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博士論文

Skeleton-based Motion Analysis and Nursing Care Posture Assessment Using Spatial Temporal Graph Convolutional Networks

(時空間グラフ畳み込みネットワークを用いた骨格ベースの動作解析と介護姿勢評価)

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Abstract

As the population ages, the demand for elderly care services will continue to increase, which includes providing specialized care, daily life support, and medical health services. As a result, informal caregiving provided by non-professionals such as family, friends, neighbors, and volunteers is becoming more prevalent. Injuries that occur during caregiving can affect the caregiving's life, especially their mental and physical health. Therefore, the correct positioning and posture during caregiving are crucial to prevent musculoskeletal disorders among caregivers. Although training programs are useful to reduce the risk of musculoskeletal disorders for informal caregivers, many of them express that it is still difficult for them to grasp the correct caregiving postures. Moreover, they struggle to obtain professional advice to correct their posture through long-term practice. Therefore, finding a targeted ergonomic posture risk assessment and guidance method is crucial to improve caregivers' posture-related risks, enhance work efficiency, and safeguard their physical health.

Rapid Entire Body Assessment (REBA) is a postural risk assessment method based on ergonomics that has been attracting attention recently, and it basically evaluates the risk from the angle of each joint of the body. However, in caregiving movements, the way of load placed on the caregiver and the time to maintain the movements vary greatly depending on the weight and posture of the cared person, so the current risk assessment using REBA is insufficient for caregiving movements. Additionally, posture recognition algorithms such as OpenPose are often used to extract skeletons. With these techniques, problems such as missing skeletons or misrecognition often occur due to image conditions or the overlapping of multiple people, and skeleton extraction may sometimes fail.

In this research, the Spatial Temporal Graph Convolution Network (ST-GCN) is applied to develop a technique for complementing missing skeletons based on behavioral features and a technique for correcting skeletons that are misrecognized due to overlapping people, and to improve the accuracy of calculating skeletal joint angles. In order to evaluate caregiving posture risk more appropriately, some parameters such as center of gravity trajectory, load duration, asymmetric load during caregiving movements are investigated and a new REBA method is proposed.

This paper consists of six chapters.

In Chapter 2, to solve the problems of skeleton misidentification and missing information by OpenPose an improved skeleton reconstruction method based on ST-GCN is propose. The method compensates for missing skeletons in terms of behavioral features and corrects incorrectly identified skeletons based on skeleton weight features. This approach improves the accuracy and robustness of pose recognition and allows more accurate estimation of skeletal joint angles and its REBA score.

In Chapter 3, to address the issue of REBA evaluation scores being too high for caregiving scenarios, a postural risk assessment method (C-REBA) is proposed by considering the characteristics of caregiving

task. Customize the traditional REBA method and add parameters such as center of gravity trajectory, load duration, and asymmetric loading to the evaluation score. the caregiving movements to assist in transferring from a bed to a wheelchair on a group of experienced nurses and a group of inexperienced caregivers are analyzed and the effectiveness of the C-REBA method is verified.

In Chapter 4, a method that combines the ST-GCN framework and C-REBA for postural risk assessment is proposed. The deep neural network algorism is applied to learn motion features and additional features such as load duration, motion frequency, center of gravity variation, and asymmetric load. So that all evaluation parameters for C-REBA rules can be obtained automatically. With this method, postural risk assessment processes in caregiving operations can be performed automatically.

In Chapter 5, "Behavior Analysis and Posture Assessment System" (BAPAS) is developed. BAPAS is a system aimed at assessing the risk of musculoskeletal disorders related to working postures in medical support work. This chapter introduces the functions and usefulness of this system and demonstrates how this system can be extended to other medical fields easily by setting parameter is settings.

Chapter 6 provides a summary of the paper as a whole and future prospect.

要 旨

高齢化の進展に伴い、専門的な介護や日常生活支援、医療健康サービスなど、高齢者介護サービスの需要は今後も増大していく。その結果、家族や友人、近隣住民、ボランティアなど、非専門職による非公式な介護がより一般的にとなりつつある。介護中に発生した怪我や損傷は、介護者の生活、特に精神的および身体的健康にさまざまな影響を与える可能性がある。従って、介護中の正しい姿勢と動きは介護者の筋骨格系疾患を防ぐために非常に重要である。研修プログラムは非正規介護者にとって筋骨格系障害のリスクを軽減するのに有用ですが、その大多数は、正しい介護姿勢を身につけるのは依然として難しいと感じている。また、彼らは正しい介護姿勢を取得するための専門的なアドバイスを長期にわたって得ることに苦労している。したがって、介護姿勢による損傷リスクを定量化することで、介護者の姿勢改善、作業効率の向上、筋骨格系疾患の軽減につながる。

人間工学に基づいた姿勢リスク評価方法として Rapid Entire Body Assessment (REBA) が最近注目されている。この方法は基本的に骨格の各関節の角度から姿勢リスクをスコアリングするものである。しかし、介護動作においては、被介護者の体重と姿勢によっても介護者への負荷のかかり方や動作を維持する時間が大きく異なるため、現状の REBA を用いたリスク評価は介護動作に対応しきれない場合が多い。また、骨格の抽出は OpenPose など姿勢認識アルゴリズムを用いることが多い。これらの技術では、画像状況や複数の人物の重なりなどにより骨格の欠落や誤認識などの問題がしばしば発生し、骨格の抽出が時にうまくいかない場合がある。

本研究では、時空間グラフ畳み込みネットワーク(ST-GCN)を用いて、欠落した骨格を行動特徴に基づき補完する技術と、人物が重なることにより誤認識された骨格を新たに生成する技術を開発することで骨格の算出精度を向上させる。また、従来の REBA スコアリング方法に対して、パワーポジションの概念を導入し、介護動作時の重心軌道、荷重継続時間、非対称荷重などを解析し、エクスラスコアとして新たに加えた C-REBA 評価方法を提案し、その有効性を検証する。さらに C-REBA スコアを算出するための評価パラメータを自動的に取得する自己学習アルゴリズムを開発する。最後に実際の臨床応用を目指して、本研究で得られた技術を実装したオンライン行動分析と姿勢評価システムを構築する。

本論文は、 6 章から構成される.

第 1 章では、本研究の背景と概要について述べる。

第 2 章では、OpenPose による骨格の誤認と情報の欠落の問題を対処するために、ST-GCN を導入し骨格の補間と再構築手法を提案する。 具体的には、時空間畳み込みネットワークを用いて、時空間的特徴に基づき姿勢の推定とアクションの予測を行う。スケルトンの完全性と連続性を判別する運動連鎖スケルトン識別ネットワークを提案し、欠落して

いるスケルトンを 2 つの近い完全なスケルトンの情報とその前後アクション特徴に基づいて補間するアルゴリズムならびに、誤認されたスケルトンに対して重みの比率の高いアクションで置き換えるアルゴリズムを開発する。本アプローチにより、姿勢認識の精度とロバスト性を向上させることができる。

第 3 章では、介護動作に対して従来の REBA 評価スコアが過剰に見積る問題に対して、介護作業の特徴を考慮した姿勢リスク評価方法（C-REBA）を提案する。介護作業にパワーポジションの概念を導入し、重心の軌跡、負荷維持時間、負荷移乗時の両足にかかる非対称荷重などを解析し、新しいエクスラスコアとして REBA スコアに追加する方法を提案する。 経験のある看護師と経験のない介護者に対して、被検者をベッドから車椅子へ移乗する補助動作を測定と解析し、C-REBA 方法の有効性を検証する。

第 4 章では、深層学習ネットワークを利用して動作特徴、負荷持続時間、動作の頻度、重心の変化、非対称負荷を学習させ、C-REBA ルールに用いる評価パラメータを自動的に取得して、介護動作における姿勢リスク評価処理をすべて自動に行うアルゴリズムを開発する。

第 5 章では、「行動分析と姿勢評価システム」(BAPAS) の開発について述べる。BAPAS は、医療支援業務における作業姿勢に関連する筋骨格系障害のリスクを評価することを目的とするウェーブアプリであり、パラメータの設定により他の医療分野にも簡単に拡張できる事例も示す。

第 6 章では、論文全体のまとめと今後の展望について述べる。

Contents

Chapter 1

Introduction

1.1 Research background

Musculoskeletal disorders (MSDs), also known as work-related musculoskeletal disorders (WMSDs), manifest as physical conditions arising from prolonged maintenance of contorted body postures, long-duration repetitive work, and highly repetitive occupational activities undertaken by workers or laborers. Examples of MSDs encompass carpal tunnel syndrome, neck pain, and lower back pain [1-2]. These disorders are characterized by the presence of pain in one or multiple regions of the body. Statistical investigations by the United States Department of Labor reveal that occupational injuries, illnesses, and absenteeism account for 59% of economic losses in the United States, with MSDs contributing to 29% to 35% of these cases [3]. Furthermore, MSDs often exhibit sudden onset during the later stages, resulting in impaired work performance. In the initial stages, these disorders may lack significant symptomatic features, leading to their potential oversight [4]. Failure to scientifically address the prolonged exposure of workers to high-risk MSDs not only compromises their work capabilities but also escalates the likelihood of safety accidents, leading to substantial social and economic losses [5]. MSDs are pervasive across diverse industries and occupations worldwide, significantly impeding workforce productivity and labor, while also imposing considerable medical expenses and inflicting severe economic ramifications on society and the nation as a whole.

According to pertinent surveys and studies, high-risk industries and populations for musculoskeletal disorders (MSDs) encompass coal miners, workers in manufacturing sectors like machinery and automotive, as well as professions such as teachers and nurses [6-7]. Among these occupations, the nursing industry exhibits a higher prevalence of work-related MSDs compared to others [8-9]. Nurses frequently endure prolonged periods of standing, bending, and lifting, imposing significant strain on their bodies. Consequently, many nurses suffer from musculoskeletal disorders including lower back pain, cervical spondylosis, and arthritis due to these demanding work conditions. These conditions not only impact the quality of life and career trajectory of nurses but also result in reduced work capacity, absenteeism, and heightened healthcare costs [10]. Presently, the global population is witnessing a noticeable aging trend. As per the World Health Organization's survey, by 2050, approximately 16% of the world's population, nearly 1.5 billion people, will be classified as elderly [11], with most developed countries defining the age of 65 as the threshold for "elderly" [12]. The proportion of individuals aged 60 and above is projected to nearly double from

12% to 22% between 2015 and 2050 [13]. Consequently, the longevity of individuals with chronic diseases is expected to increase, leading to an escalating demand for elderly care services encompassing daily life support and specialized medical care. This places a substantial burden on the healthcare industry, making nursing work more intricate and demanding. Nurses are increasingly engaged in physically laborious tasks and frequent postural adjustments, thereby heightening the risk of developing musculoskeletal disorders.

According to a report issued by the Ministry of Health, Labour and Welfare on the employment of nursing staff, the number of individuals requiring nursing care has surged to 6.76 million, while the current count of nursing staff in the healthcare industry stands at a mere 2.11 million, underscoring a significant shortage of positions within the nursing sector. Despite the high demand for nursing professionals, the turnover rate remains alarmingly high at 14.2% [14]. A comprehensive study investigating nurse turnover causes across seven countries revealed that 63.5% of nurses opt to leave or retire prematurely due to occupational ailments [15]. The aforementioned observations mainly pertain to formal nursing administered by trained caregivers. Nevertheless, it is imperative to recognize the existence of informal nursing [16]. Informal nursing denotes unpaid care provided by family members, friends, or volunteers, playing a pivotal role in the care process of individuals coping with chronic illnesses or disabilities [17]. Informal nursing has become increasingly prevalent and sought after in numerous countries [18]. Notably, in countries with a sizeable aging population, like Japan, family-based elderly care has become customary. However, providing informal care poses challenges and can significantly impact the well-being of caregivers, both psychologically and physically [19-20]. Proper nursing postures are indispensable in safeguarding caregivers from musculoskeletal disorders during the care process. Although relevant organizations offer nursing training aimed at mitigating the risk of such disorders for informal caregivers, a majority of them express dissatisfaction with the adequacy of this training in imparting a comprehensive understanding of correct nursing postures and obtaining professional guidance on correcting their postures during long-term care practices. Therefore, finding a solution to mitigate the risk of musculoskeletal disorders is paramount in improving the nursing work environment, enhancing work efficiency, and safeguarding the physical health of both formal and informal caregivers.

Positive interventions have demonstrated efficacy in preventing or reducing the risk of work-related musculoskeletal disorders (WMSDs) [21-22]. Among these interventions, the implementation of specialized assistive medical devices represents a direct approach. Notably, a study cited in reference [23] highlighted that the introduction of ceiling-mounted lifts as a standalone intervention significantly decreased WMSDs while simultaneously enhancing patient comfort and satisfaction. Other professional equipment, such as floor lifts [24], rail sliders [25], electric beds [26], and mobile assistive robots [27], have also been employed. However, the high cost and limited availability of these specialized devices in hospitals restrict their usage to specific nursing scenarios. Given the practical constraints in nursing work, researchers have proposed various ergonomic-based methods for simple posture assessment. The most widely utilized techniques include OWAS, RULA, and REBA. OWAS, developed by Ovako Oy, involves the evaluation of working postures in multiple departments of a steel mill by experienced steelworkers and ergonomists [28]. It categorizes back, arm, lower limb postures, and load handling into specific ratings, assessing the impact of posture combinations on the musculoskeletal system. Harm levels are classified into four action categories, indicating the urgency of workplace interventions. RULA aims to rapidly assess the musculoskeletal load caused by postures, muscle function, and external loads on the neck, trunk, and upper limbs [29]. Based on the total score obtained from its coding system, four action levels are recommended to guide intervention strategies for reducing the risk of injury due to physical burden. REBA, on the other hand, is an analysis tool designed to capture unpredictable work postures found in healthcare and service industries. It employs a body part diagram similar to RULA, including the upper arm, forearm, wrist, trunk, neck, and legs. This method accounts for external load/force, muscle activity resulting from static, dynamic, rapidly changing, or unstable postures, and coupling effects. Unlike OWAS and RULA, REBA offers five action levels to assess the extent of corrective measures required [30].

The posture risk assessment methods discussed above, which are based on ergonomics, rely on subjective observations and assessments made by professional ergonomists. This approach is time-consuming, labor-intensive, and prone to variations in assessment results among different assessors [31]. To overcome these limitations, some researchers have proposed the utilization of motion capture systems to automatically calculate joint angles of the human body. This can be achieved through optical markers or wearable inertial sensors for joint angle measurement. While these methods offer high accuracy, they require expensive equipment and skilled technicians for sensor calibration and data integration [32]. Consequently, they are more suitable for validation experiments in controlled laboratory settings and not practical for ergonomic posture assessment in real workspaces. As a result, researchers have shifted their focus to low-cost motion capture methods utilizing depth cameras. The Kinect series of cameras, in particular, have demonstrated human pose recognition capabilities [33-35]. The joint position calculations obtained from Kinect-based systems have shown good accuracy in providing the required joint angles for posture assessment methods such as RULA and OWAS [36]. Comparative studies have demonstrated favorable agreement between Kinect-based systems and reference optical motion capture systems, as well as expert ratings [37], indicating a promising outlook for musculoskeletal risk assessment. However, Kinect-based systems have some limitations, including body occlusion [36], reduced tracking quality in non-frontal views [38], and the omission of neck rotation [37]. With the advancements in computer vision techniques, neural network technologies have emerged to identify key skeletal joints from RGB images [39-41]. Currently, the most effective algorithm is OpenPose [42], widely employed for its stable skeletal tracking capabilities in non-frontal views and video actions.

The efficacy of the OpenPose algorithm, which has demonstrated remarkable performance and accurate assessments in industries such as construction and assembly line factories, remains uncertain in the context of nursing processes. Particularly in complex situations involving occlusion, blurriness, lighting variations, and body overlapping, challenges arise in simultaneously recognizing the poses of multiple individuals, giving rise to issues such as missing skeletal information and misidentification. These factors can impact the accuracy of joint angle calculations and result in inaccurate REBA scores. Nursing processes often involve multiple healthcare providers performing tasks for a patient simultaneously, posing potential challenges for the application of OpenPose. Therefore, it is crucial to explore body pose recognition methods suitable for nursing processes to enhance the accuracy of joint angle recognition, provide reliable references for nursing posture risk assessment, and ensure the health and safety of both healthcare providers and patients. In this regard, we propose a novel approach based on spatiotemporal graph convolutional neural networks. This method assigns behavioral labels to pose time series and utilizes behavioral characteristics to predict missing skeletal information. Additionally, by considering the behavioral feature weights of the entire task, low-weight behavioral poses can be selectively filtered out to eliminate misidentified skeletal information. Furthermore, interpolation techniques can be employed to fill in the gaps of missing skeletal information. Consequently, our method achieves high skeletal recognition accuracy during nursing tasks, even in scenarios involving multiple individuals and occlusion, thereby enhancing the precision of REBA scores.

The implementation of appropriate ergonomic posture interventions in the nursing profession has been shown to effectively reduce the risk of musculoskeletal discomfort and injuries [43-44]. Among various methods, posture feedback has been identified as the most effective intervention approach [45]. Previous studies have demonstrated that diversified posture feedback can significantly mitigate ergonomic risks for nurses [46]. Notably, interventions solely based on teaching and training have proven ineffective in reducing the risk of musculoskeletal discomfort and injuries, while those incorporating biofeedback have shown greater efficacy [47]. In light of these findings, we propose a novel behavior analysis and posture risk assessment system. This system facilitates the visualization of the trajectory of the center of gravity (COG), enabling healthcare providers to explore optimal positions by observing COG movement and comprehend the associated risk through posture risk scoring. Our system can be seamlessly integrated into Internet of Things (IoT) devices equipped with cameras and utilizes neural network models and image processing techniques to infer posture information. It then provides risk assessments and visual guidance to address discomfort and injury risks associated with nursing postures.

1.2 Research purposes

The objective of this study is to develop an assistive healthcare system that encompasses a behavior analysis and posture risk assessment system applicable to real work environments. The primary goal of this system is to enable accurate automated assessment of nursing personnel's postures and deliver personalized posture guidance to mitigate the risks associated with musculoskeletal disorders and poor posture. To achieve this, two key challenges are addressed:

(1) Tackling the issue of skeleton misidentification and missing information in nursing tasks when utilizing OpenPose for skeletal joint angle estimation.

Given the interactive nature of nursing tasks involving interactions between healthcare providers and patients, occlusions frequently occur, significantly impacting the accuracy of skeleton recognition when employing OpenPose. To overcome this challenge, we propose an enhanced skeleton reconstruction method based on a modified Spatiotemporal Graph Convolutional Network (ST-GCN). This method aims to interpolate missing skeletons based on behavioral characteristics and rectify misidentified skeletons by assigning weights based on behavioral features. By adopting this approach, the accuracy of skeleton recognition, skeletal joint angle estimation, and Rapid Entire Body Assessment (REBA) scores are improved, thereby ensuring the reliability of posture risk assessment.

(2) Addressing the issue of overestimation in the Rapid Entire Body Assessment (REBA) method for nursing postures and enhancing the applicability and reliability of REBA in the nursing industry.

The REBA method exhibits limitations when it comes to assessing posture risks in nursing, as it fails to differentiate between experienced and inexperienced healthcare providers and does not offer meaningful posture guidance specifically tailored to inexperienced providers. To overcome this, we propose an improved version of REBA known as Nursing-REBA (C-REBA), which incorporates parameters such as the trajectory of the center of gravity (COG), load duration, and asymmetric load. C-REBA effectively distinguishes between experienced and inexperienced healthcare providers and provides accurate posture scoring references for informal caregivers, thereby enhancing the practicality of C-REBA scores in nursing posture assessment.

1.3 Article structure

This paper is divided into six chapters, and the content arrangement of each chapter is as follows:

Chapter 1 provides an introduction to the background and objectives of this study.

Chapter 2 proposes an improved skeleton reconstruction method based on modified ST-GCN to address the issues of skeleton misidentification and missing in nursing tasks with OpenPose. Our method compensates for missing skeletons from the perspective of behavioral characteristics and corrects misidentified skeletons based on skeleton weight features, thereby improving the measurement accuracy of skeletal joint angles and REBA scores.

Chapter 3 presents the C-REBA method for assessing posture risks in nursing tasks, aiming to overcome the limitations of the REBA method in evaluating posture risks in nursing. This method explores a C-REBA approach that combines COG trajectory, load duration, and asymmetric load parameters, effectively distinguishing between experienced and inexperienced healthcare providers and providing accurate posture scoring references for informal caregivers.

Chapter 4 proposes an advanced method that combines the ST-GCN framework with C-REBA for posture assessment. By utilizing deep neural networks and considering behavioral and additional features, this method achieves comprehensive and automated evaluation of C-REBA scores. Experimental results confirm the reliability and feasibility of this method in various scenarios involving additional scores, including load duration, action frequency, asymmetric load, and center of gravity changes.

Chapter 5 introduces the Behavior Analysis and Posture Assessment System (BAPAS), which is a musculoskeletal disorder risk assessment system used to evaluate work postures in the assistive healthcare tasks. The BAPAS system has been successfully extended to other assistive healthcare scenarios, such as rehabilitation posture guidance and CPR posture assessment. It demonstrates excellent performance in posture recognition, assessment, and guidance. Its scalability and applicability make it a valuable tool in various healthcare environments, providing insights into musculoskeletal disorder risks and assisting in posture assessment and guidance.

Chapter 6 describes the conclusions and future prospects of this study.

Reference

[1] Hartvigsen J, Hancock M J, Kongsted A, et al. (2018). What low back pain is and why we need to pay attention. Lancet, 391(10137): 2356–2367.

[2] Barboza M C N, Milbrath V M, Bielemann V M, et al. Work-related musculoskeletal disorders and their association with occupational nursing[J]. Revista gaucha de enfermagem, 2008, 29(4): 633-638.

[3] Bureau of Labor Statistics, US Department of Labor, 2016. Nonfatal Occupational Injuries and Illnesses Resulting in Days Away from Work in 2015[EB/OL]. https://www.bls.gov/ news.release/pdf/osh2.pdf, Accessed date: 22 February 2018 Online; accessed.

[4] Nath N.D., Akhavian R., Behzadan A.H. Ergonomic Analysis of Construction Worker's Body Postures Using Wearable Mobile Sensors[J]. Applied Ergonomics, 2017(62): 107-117.

[5] Ferguson S.A., Marras W.S., Allread G., et al. Musculoskeletal disorder risk as a function of vehicle rotation angle during assembly tasks[J]. Applied Ergonomics, 2011(42):699-709.

[6] Kee D, Seo S R. Musculoskeletal disorders among nursing personnel in Korea[J]. International Journal of Industrial Ergonomics, 2007, 37(3): 207-212.

[7] Guifan S. Occupational Health and Occupational Medicine. 7th Edition. Beijing: People's Health Publishing House, 2012.

[8] Alnaser MZ, Aljadi SH. (2019). Physical therapists with work-related musculoskeletal disorders in the State of Kuwait: A comparison across countries and health care professions. Work, 63(2): 261–268.

[9] Xi Z, Suzhai T, Ning J, et al. (2020). Application of MAPO index in risk assessment of WMSDs for nursing staff carried patients with hands in China. Chinese J Ind Med, 33(2): 99–103.

[10] S P, O A. (2018). Evaluation of the prevalence of musculoskeletal disorders in nurses: a systematic review. Med Sci Int Med J, 7(3): 479–488.

[11] National Institutes of Health. Global health and aging[J]. 2018.

[12] Bilgili N, Kitiş Y. Yaşlılık ve yaşlı sağlığı[J]. 2018.

[13] World Health Organization. facts on ageing and health. 2017[J]. URL: https://www. who. int/news-room/fact-sheets/detail/10-facts-on-ageingand-health, 10.

[14] 厚生労働省 令和２年雇用動向調査結果の概要. https://www.mhlw.go.jp/toukei/itiran/roudou/koyou/doukou/21-2/index.html(アクセス日：２０２２/8/４)

[15] Simon M, Tackenberg P, Nienhaus A, et al. Back or neck-pain-related disability of nursing staff in hospitals, nursing homes and home care in seven countries—results from the European NEXT-Study[J]. International journal of nursing studies, 2008, 45(1): 24-34.

[16] Albin B, Siwertsson C, Svensson J O. Informal Care of the Elderly in Sweden-Carers' Situation[J]. Aotearoa New Zealand Social Work, 2011, 23(1/2): 66-77.

[17] Roth D L, Fredman L, Haley W E. Informal caregiving and its impact on health: A reappraisal from population-based studies[J]. The Gerontologist, 2015, 55(2): 309-319.

[18] Silva A L, Teixeira H J, Teixeira M J C, et al. The needs of informal caregivers of elderly people living at home: an integrative review[J]. Scandinavian journal of caring sciences, 2013, 27(4): 792-803.

[19] Willemse E, Anthierens S, Farfan-Portet M I, et al. Do informal caregivers for elderly in the community use support measures? A qualitative study in five European countries[J]. BMC health services research, 2016, 16: 1-10.

[20] Tatangelo G, McCabe M, Macleod A, et al. "I just don't focus on my needs." The unmet health needs of partner and offspring caregivers of people with dementia: A qualitative study[J]. International Journal of Nursing Studies, 2018, 77: 8-14.

[21] Tompa E, Dolinschi R, Alamgir H, et al. A cost-benefit analysis of peer coaching for overhead lift use in the long-term care sector in Canada[J]. Occupational and environmental medicine, 2016, 73(5): 308-314.

[22] Gold J E, Punnett L, Gore R J, et al. Predictors of low back pain in nursing home workers after implementation of a safe resident handling programme[J]. Occupational and environmental medicine, 2017, 74(6): 389-395.

[23] Alamgir H, Yu S, Fast C, et al. Efficiency of overhead ceiling lifts in reducing musculoskeletal injury among carers working in long-term care institutions[J]. Injury, 2008, 39(5): 570-577.

[24] Greenhalgh M, Blaauw E R, Crytzer T, et al. Comparison of trunk mechanics and spatiotemporal outcomes in caregivers using a robotic assisted transfer device and a mobile floor lift[J]. The Journal of Spinal Cord Medicine, 2023, 46(1): 45-52.

[25] Lin C Y, Masroor S, Bahrudin, et al. The Design and User Evaluation of Body-Transfer System via Sliding Transfer Approach for Assisting Functionally Impaired People[J]. Machines, 2023, 11(5): 555.

[26] Kopecek M, Kremlacek J. Eye-tracking control of an adjustable electric bed: construction and validation by immobile patients with multiple sclerosis[J]. Journal of NeuroEngineering and Rehabilitation, 2023, 20(1): 75.

[27] Tagliavini L, Baglieri L, Colucci G, et al. DOT PAQUITOP, an Autonomous Mobile Manipulator for Hospital Assistance[J]. Electronics, 2023, 12(2): 268.

[28] Karhu O, Kansi P, Kuorinka I. Correcting working postures in industry: A practical method for analysis[J]. Applied ergonomics, 1977, 8(4): 199-201.

[29] McAtamney L, Corlett E N. RULA: a survey method for the investigation of work-related upper limb disorders[J]. Applied ergonomics, 1993, 24(2): 91-99.

[30] Hignett S, McAtamney L. Rapid entire body assessment (REBA)[J]. Applied ergonomics, 2000, 31(2): 201-205.

[31] Fagarasanu M, Kumar S. Measurement instruments and data collection: a consideration of constructs and biases in ergonomics research[J]. International journal of industrial ergonomics, 2002, 30(6): 355-369.

[32] Trask C, Mathiassen S E, Wahlström J, et al. Data collection costs in industrial environments for three occupational posture exposure assessment methods[J]. BMC medical research methodology, 2012, 12: 1-11.

[33] Cai L, Ma Y, Xiong S, et al. Validity and reliability of upper limb functional assessment using the Microsoft Kinect V2 sensor[J]. Applied bionics and biomechanics, 2019, 2019.

[34] Clark R A, Mentiplay B F, Hough E, et al. Three-dimensional cameras and skeleton pose tracking for physical function assessment: A review of uses, validity, current developments and Kinect alternatives[J]. Gait & posture, 2019, 68: 193-200.

[35] Xu X, McGorry R W. The validity of the first and second generation Microsoft Kinect™ for identifying joint center locations during static postures[J]. Applied ergonomics, 2015, 49: 47-54.

[36] Plantard P, Shum H P H, Le Pierres A S, et al. Validation of an ergonomic assessment method using Kinect data in real workplace conditions[J]. Applied ergonomics, 2017, 65: 562-569.

[37] Manghisi V M, Uva A E, Fiorentino M, et al. Real time RULA assessment using Kinect v2 sensor[J]. Applied ergonomics, 2017, 65: 481-491.

[38] Wei T, Lee B, Qiao Y, et al. Experimental study of skeleton tracking abilities from microsoft kinect non-frontal views[C]//2015 3DTV-Conference: The True Vision-Capture, Transmission and Display of 3D Video (3DTV-CON). IEEE, 2015: 1-4.

[39] Bogo F, Kanazawa A, Lassner C, et al. Keep it SMPL: Automatic estimation of 3D human pose and shape from a single image[C]//Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part V 14. Springer International Publishing, 2016: 561-578.

[40] Mehta D, Sridhar S, Sotnychenko O, et al. Vnect: Real-time 3d human pose estimation with a single rgb camera[J]. Acm transactions on graphics (tog), 2017, 36(4): 1-14.

[41] Rhodin H, Spörri J, Katircioglu I, et al. Learning monocular 3d human pose estimation from multi-view images[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2018: 8437-8446.

[42] Cao Z, Simon T, Wei S E, et al. Realtime multi-person 2d pose estimation using part affinity fields[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2017: 7291-7299.

[43] Chanchai, W., Songkham, W., Ketsomporn, P., Sappakitchanchai, P., Siriwong, W. & Robson, M. (2016). The Impact of an Ergonomics Intervention on Psychosocial Factors and Musculoskeletal Symptoms among Thai Hospital Orderlies. International Journal of Environmental Research and Public Health, 13(5), p.464. DOI: 10.3390/ijerph13050464.

[44] Hoe, V.C., Urquhart, D.M., Kelsall, H.L., Zamri, E.N. & Sim, M.R. (2018). Ergonomic interventions for preventing work-related musculoskeletal disorders of the upper limb and neck among office workers. Cochrane Database of Systematic Reviews, 10(10). DOI: 10.1002/14651858.cd008570.pub3.

[45] Ziam, S., Lakhal, S., Laroche, E., Lane, J., Alderson, M. & Gagné, C. (2023). Musculoskeletal disorder (MSD) prevention practices by nurses working in health care settings: Facilitators and barriers to implementation. Applied Ergonomics, 106, p.103895. DOI: 10.1016/j.apergo.2022.103895.

[46] Oliver Hernández, C.; Li, S.; Merino Rivera, M.D. & Mateo Rodríguez, I. (2022). Does Postural Feedback Reduce Musculoskeletal Risk?: A Randomized Controlled Trial. Sustainability, 14(1), pp.583. DOI:10.3390/su14010583.

[47] Owlia, M., Kamachi, M. & Dutta, T. (2020). Reducing lumbar spine flexion using real-time biofeedback during patient handling tasks. Work, 66(1), pp.41–51. DOI: 10.3233/wor-203149.

Chapter 2

ST-GCN for skeleton correction

2.1 Overview

The application effectiveness of the OpenPose algorithm, renowned for its exceptional performance and precise evaluation in the architectural industry and assembly line factory contexts, remains uncertain within the healthcare domain. Particularly, when employing OpenPose for simultaneous pose estimation of multiple individuals, complex situations characterized by occlusion, blurriness, lighting variations, and body overlap can give rise to challenges such as missing skeletal information and misrecognition. These challenges have adverse implications for the accuracy of joint angle calculations and can lead to erroneous Rapid Entire Body Assessment (REBA) scores. Furthermore, in the healthcare process, there are instances where one or more caregivers simultaneously perform nursing tasks for a patient, potentially impacting the applicability of OpenPose. Consequently, there is a pressing need to explore body pose recognition methods specifically tailored to the nursing process. Such endeavors are pivotal for enhancing the accuracy of joint angle recognition, providing a reliable reference for assessing the risk associated with nursing postures, and ultimately safeguarding the health and well-being of both caregivers and patients.

Researchers have made efforts to address pose estimation challenges arising from body occlusion in nursing interactions. One approach involves using the heat map offset adjustment algorithm, which compensates for missing skeletal keypoints through left-right symmetry principles [1]. However, this method is primarily suitable for frontal camera perspectives, and deviations in camera angles may lead to corrected keypoints positioned outside the body. To overcome this limitation, the Mask RCNN method has been employed to detect human boundaries, ensuring that skeletal keypoints remain within the body's boundaries [2]. Nonetheless, compensating for occluded keypoints using symmetry principles encounters difficulties with complex movements. To restore occluded keypoints, researchers have explored the utilization of unoccluded keypoints in the Euclidean distance matrix [3]. This skeleton compensation method effectively mitigates occlusion issues but overlooks temporal attributes and their association with skeletal motion trends, resulting in discrepancies between the compensated skeleton and the actual action dynamics. Additionally, some approaches have introduced the concept of "Human Dynamics" [4], which predicts future body poses based on multiple frames in the current video, even in the absence of subsequent frames. This method has shown remarkable effectiveness in compensating for missing skeletal keypoints.

However, challenges persist regarding skeletal misidentification.

In response to the identified problem, we present a novel approach that leverages spatiotemporal graph convolutional neural networks. Our method involves assigning behavioral labels to pose time series and employing these behavioral features in a reverse manner to predict missing skeletons. Moreover, by considering the behavioral feature weights of the overall task, we can selectively filter out low-weighted behavioral poses to eliminate misidentified skeletons. The missing skeletons are subsequently interpolated using an interpolation method. As a result, our proposed method achieves enhanced accuracy in skeleton recognition, particularly in multi-person and occlusion scenarios encountered during caregiving tasks, thereby enabling more precise estimation of Rapid Entire Body Assessment (REBA) scores.

2.2 Study design

2.2.1 Overview of methods

Within our investigation, we have introduced a novel approach for discriminating the kinematic chain skeleton, enabling the assessment of pose skeleton integrity and differentiation between loss and misidentification. By examining the heterogeneity of action features derived from the ST-GCN network and their corresponding skeleton mappings within a predetermined temporal threshold, we were able to identify cases of skeleton misidentification from a pose-based kinematic chain perspective. To optimize the compensation for skeletal loss, we have proposed a temporal-based skeleton interpolation method. This method involves leveraging temporal features, traversing complete skeletons before and after the temporal sequence, and applying interpolation algorithms to rectify missing skeleton data. For instances of skeleton misidentification, we have presented a technique to enhance the heterogeneity of action features. This technique entails optimizing action features with lower weights within the defined temporal range, compensating for gaps by utilizing consistent action features from previous and subsequent temporal sequences, and updating the associated skeletons mapped with the action features to rectify misidentification of the pose skeleton. An illustrative overview of our skeleton compensation method is depicted in Figure 2.1.

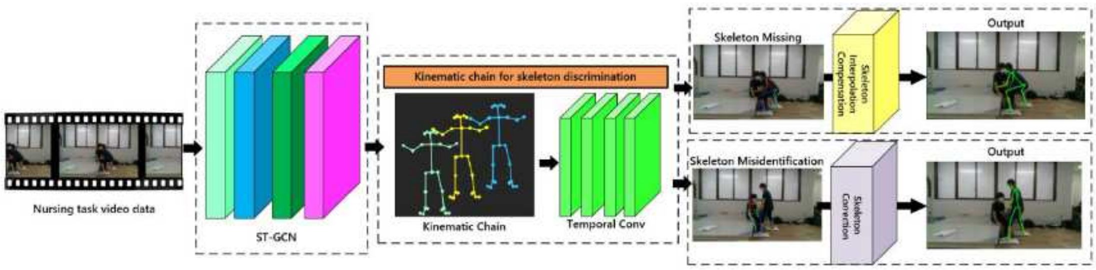

Figure 2.1. Overview of our skeleton compensation method.

Furthermore, our research process encompasses several distinct steps, which are visually depicted in Figure 2.2. Firstly, we deliberately selected the prevalent patient transfer task within the nursing care field to evaluate the efficacy of our method in caregiver-patient interaction scenarios. Secondly, RGB cameras were employed to capture video recordings of the nursing tasks, while wearable sensors were utilized to accurately measure the angular changes in various joints of the human body. Subsequently, the recorded nursing task videos underwent processing using both the OpenPose algorithm and our novel proposed method. This processing facilitated the calculation of skeletal joint angles and Rapid Entire Body Assessment (REBA) scores. Lastly, we conducted a meticulous comparative analysis, assessing the accuracy of our approach by juxtaposing the outcomes derived from OpenPose, our proposed method, and the joint angles and REBA scores directly measured by the sensors.

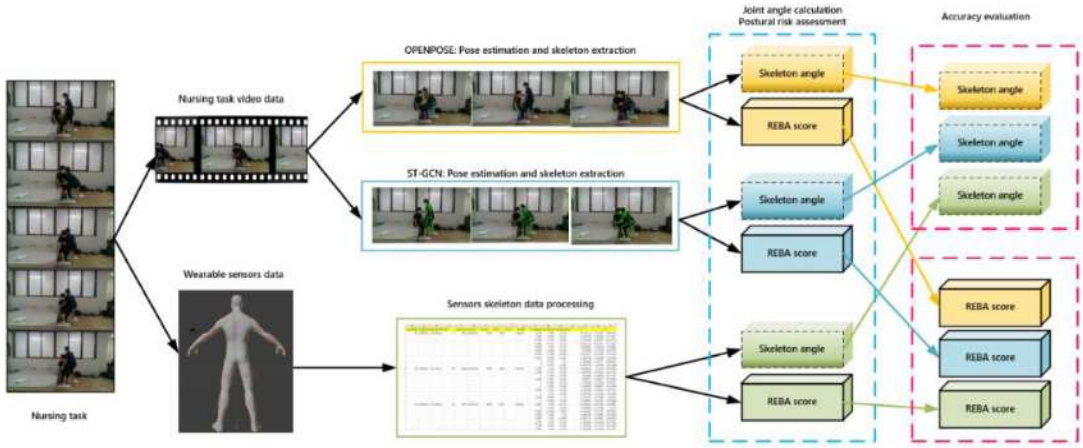

Figure 2.2 Overview of experiment and validation.

2.2.2 Experiment design

We recruited a group of eight experienced nurses from the Rehabilitation Department of the author's affiliated hospital. Table 2.1 provides details regarding their ages, weights, and heights. It is important to note that these nurses had no record of musculoskeletal diseases within the past year. To simulate the patient, a male volunteer with a height of 168cm and weight of 62kg was enlisted. The task assigned to the eight nurses involved transferring the patient from the bed to the wheelchair while ensuring consistent sitting posture and movements throughout the process.

We utilized an Intel RealSense Depth Camera D435 to capture videos of the caregiving tasks, with the camera positioned at a distance of 3 meters from the caregivers. To measure the angles of various joints in the body, we employed a motion capture system comprising multiple WitMotion WT901C TTL 9 Axis IMU Sensors. These sensors have demonstrated strong correlation with results obtained from optical motion capture systems, and they are widely utilized in fields such as rehabilitation medicine and ergonomic analysis [5-7]. Furthermore, IMU sensors exhibit robust resistance to occlusion, enhancing their suitability for evaluating the accuracy of visual-based angle measurements [8-9]. For this study, a total of 10 IMU sensors were employed, primarily targeting major joints including the neck, torso, legs, upper arms, and lower arms. The specific placement positions of these sensors are depicted in Figure 2.3. The data transmission was facilitated by a PC equipped with Microsoft Windows 10 operating system, Intel (R) Core (TM) i7-8750H 2.00 GHz CPU, 8 GB RAM, and Nvidia GeForce GTX 1050Ti GPU. To mitigate drift inaccuracy in the sensors during the caregiving tasks, each task was completed within a 20-second timeframe by each participant, and the IMU sensors were recalibrated after the completion of each caregiving task.

Table 2.1 Demographics of the participants.

	Gender	Age	Weight(kg)	Height(cm)
Nurse 1	Male	31	61	171
Nurse 2	Female	30	51.5	163
Nurse 3	Male	30	62	168
Nurse 4	Male	27	79	175
Nurse 5	Male	25	65	171
Nurse 6	Male	28	65	168
Nurse 7	Male	36	57	163
Nurse 8	Female	26	48	161

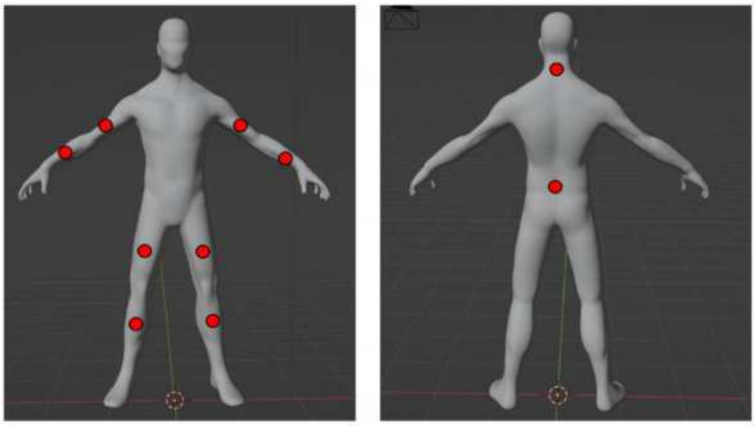

Figure 2.3 Inertial sensor location.

We conducted an experiment and collected data from multiple participants in 2022. Each participant recorded three sets of data, and the average value was considered as the final result. Following the completion of the caregiving tasks, the OpenPose and ST-GCN modules automatically generated pose and skeletal joint information for various time sequences. The coordinates of the skeletal joints were synchronized with the PC, represented as two-dimensional pixel coordinates. Additionally, the joint angle data obtained from the IMU sensors were also synchronized with the PC. To streamline the process, we developed an automated ergonomic assessment system, where the skeleton data input system automatically evaluated joint scores and Rapid Entire Body Assessment (REBA) scores.

2.2.3 Statistical analysis

Statistical analysis was performed using SPSS 27 software (SPSS Inc) and GraphPad Prism 9 (GraphPad Inc). Paired t-test was employed for analyzing paired continuous data. Mean values and standard deviations were reported for all statistical tests, and a p-value less than 0.05 was considered statistically significant.

2.3 Improved ST-GCN for skeleton reconstruction

The spatial-temporal graph convolutional network (ST-GCN), introduced by Yan et al. [10], is an advanced deep neural network approach designed for the recognition of human skeletal actions. In this method, a spatial-temporal graph is employed to encode the spatial positions and temporal dynamics of human skeletal joints. Each joint is denoted as a node in the graph, while the connections between nodes capture the interdependencies among joints, encompassing both skeletal connectivity and motion trajectories. Furthermore, each node encodes feature information pertaining to the joint across multiple temporal instances. By leveraging spatial-temporal graph convolutional layers, the ST-GCN network effectively processes the spatial-temporal graph data, enabling the propagation of information and feature extraction from the joints. These convolutional layers consider both the interconnections among nodes and the temporal aspects, allowing for the capture of action patterns and correlations through neighboring nodes and their temporal relationships. Through training, the ST-GCN network acquires discriminative feature representations, facilitating accurate recognition of human skeletal actions. Beyond action recognition, the versatility of this network extends to real-time action generation, pose estimation, and various related tasks. Remarkably, the ST-GCN has exhibited exceptional accuracy and robustness on human skeletal datasets, endowing it with considerable value in the realm of human action recognition. For visual reference, the original network structure is depicted in Figure 2.4.

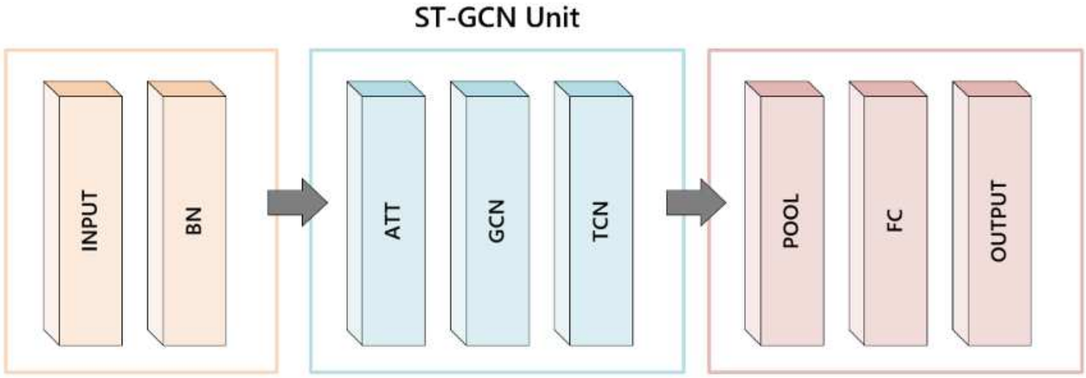

Figure 2.4. The original ST-GCN network structure

Upon scrutinizing the original structure of the ST-GCN network, it becomes evident that its fundamental ST-GCN unit comprises an attention mechanism (ATT), graph convolutional neural network (GCN), and temporal convolutional neural network (TCN) interconnected sequentially. This sequential architecture for skeletal feature extraction poses a challenge in maintaining the coherence between spatial and temporal features, resulting in notable disparities between predicted action labels and the corresponding true actions. To tackle this predicament, we have introduced modifications to the original ST-GCN structure, as depicted in Figure 2.5a. These modifications encompass four key adjustments. Firstly, we have reconfigured the ST-GCN unit by decoupling the GCN and TCN modules. In this reconfiguration, the GCN, batch normalization (BN), and rectified linear unit (ReLU) activation function are interconnected to form the spatial feature extraction unit (Figure 2.5b). Subsequently, the spatial feature extraction unit is linked with the TCN to construct the spatiotemporal feature extraction unit (Figure 2.5c). This deliberate design ensures the adequate assimilation of skeletal features at the temporal level. Secondly, we have augmented the spatial feature extraction unit with a residual structure, while the spatiotemporal feature extraction unit is fortified with dense connections to enhance the efficacy of spatial and temporal feature propagation, thereby alleviating the concern of gradient explosion. Lastly, and of paramount importance, we have revamped the ST-GCN unit by establishing parallel connections between the spatial feature extraction layer and the spatiotemporal feature extraction layer (Figure 2.5a), with the primary objective of fostering a strong alignment between predicted labels and actual actions.

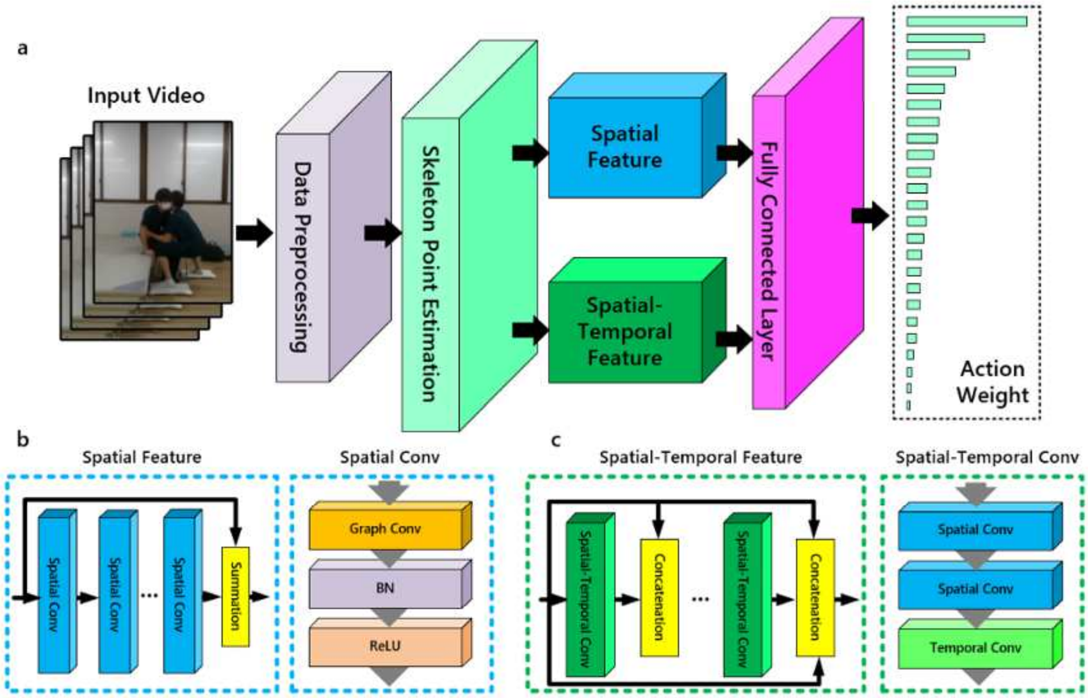

Figure 2.5. Spatial temporal graph convolutional neural network.

Within our refined framework, the spatial feature layer, denoted as Spatial Conv, assumes a pivotal role in capturing the interconnected characteristics among skeletal nodes and their neighboring counterparts, employing the spatial information derived from key nodes within the skeletal graph. Its impact on human pose estimation is rooted in its capacity to depict local features and amalgamate the features of neighboring nodes associated with each skeletal joint. To model spatial relationships, we leverage a topological structure and graph convolution technique, which effectively extracts information from neighboring nodes through a comprehensive partitioning strategy [5]. The spatial convolutional layer integrates graph convolution, thereby amalgamating spatial and neighborhood information originating from interconnected skeletal points. In order to foster stability and capture the nonlinear relationships between joints, batch normalization and the rectified linear unit (ReLU) activation function are employed. Multiple spatial convolutional layers collectively form the extraction unit, interconnected via a residual framework, which aims to address challenges related to gradients.

The spatiotemporal feature layer serves the purpose of extracting action trend features from skeletal joint nodes across frames within the skeletal graph. This extraction process is instrumental in delineating the action trends between corresponding joint nodes in successive frames, which holds paramount importance for posture maintenance and risk assessment. By capturing the spatial adjacency information of skeletal joint nodes and employing temporal convolutional layers, the spatiotemporal feature layer facilitates the update of joint nodes based on temporal cues. Analyzing these features enables a comprehensive comprehension of action trends and posture risks within the human skeletal structure. The convolutional layers responsible for temporal feature extraction encompass a stack of Spatial Conv and Temporal Conv layers, collectively referred to as Spatial-Temporal Conv. To overcome challenges such as gradient vanishing and enhance feature propagation efficiency, a dense connection approach [11] is implemented, consolidating multiple spatiotemporal convolutional layers into the spatiotemporal feature extraction unit.

2.3.1 Kinematic chain for skeleton discrimination

The integration of spatial and temporal features within the label mapping relationship enables the determination of action weights for different postures, where the highest-weighted action label represents each distinct posture. In order to tackle the challenges posed by missing skeleton data or instances of skeleton misidentification in complex scenarios, we have introduced a Kinematic Chain Skeleton Discrimination Network in the final layer of the Spatial Temporal Graph Convolutional Neural Network (ST-GCN). This incorporation allows for the effective assessment of skeleton integrity and the identification of cases involving skeletal misidentification. Notably, we have developed a novel method for skeleton discrimination utilizing kinematic chains, which goes beyond the scope of previous research [9]. Our kinematic chain-based approach not only evaluates the completeness of skeleton poses in each frame but also incorporates the comparison of fused action weight features. Abnormal action weights within a specified temporal sequence are classified as misidentified actions and skeletons, and corrective feedback is provided in terms of both action and skeleton information.

Each skeletal connection is defined as the linkage between adjacent keypoints within the human skeletal structure, denoted as a feature vector that represents the direction from one skeletal keypoint to its neighboring node. These vectors collectively form a 2×M matrix K, where M represents the predetermined number of skeletal keypoints in the human body structure. The matrix $\Psi = K^T K$ serves as a discriminating feature for skeletal integrity, where the diagonal elements of Ψ depict the squared lengths of skeletal joints, while the remaining elements indicate the weighted angles between pairs of skeletal keypoints, serving as internal indicators. Drawing inspiration from kinematic chains, we introduce a temporal kinematic chain, defined as follows:

$$\Phi = K_{t+i}^T K_{t+i} - K_t^T K_t \tag{2.1}$$

Where, i represents the temporal interval between successive frames within the temporal kinematic chain. The diagonal elements within matrix Φ depict alterations in skeletal joint lengths, while the remaining elements signify changes in angles between pairs of skeletal keypoints. Figure 2.6 provides a visual representation of the temporal kinematic chain relationship between two adjacent skeletal keypoints, denoted as K1 and K2. Within the temporal kinematic chain, the input values consist of alterations in skeletal joint lengths between K1 and K2, denoted as K_1^t and K_1^{t+i}, as well as dissimilarities in angles between keypoints K_2^t and K_2^{t+i}. These dissimilarities represent the disparities in skeletal joint lengths between two frames separated by a time interval of *i*, along with the angular variations between neighboring skeletal keypoints, exemplified by the discrepancies between θ_{12}^t and θ_{12}^{t+i}.

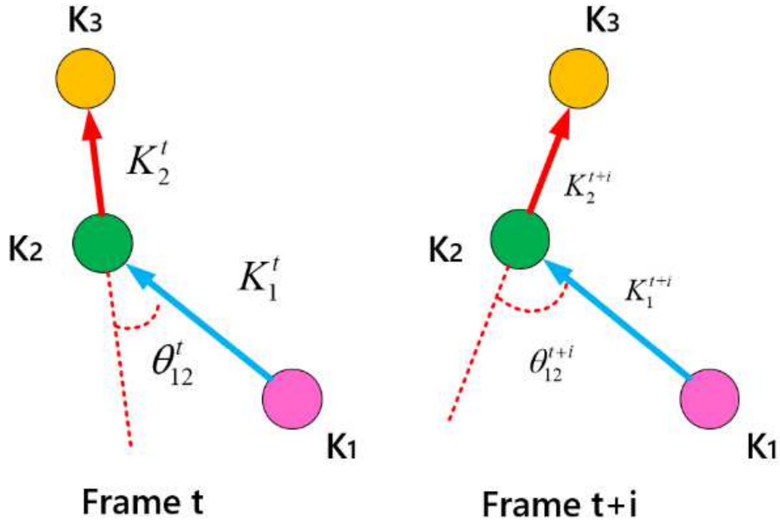

Figure 2.6. Illustration for temporal kinematic chain between two neighboring skeletal keypoints.

We establish the prediction of temporal kinematic chains by connecting the coordinates of skeletal keypoints, which are subsequently inputted into a Temporal Convolutional Network (TCN) to construct a posture discrimination network. This methodology not only accounts for the integrity of posture skeletons across frames but also ensures the coherence of weight variations in action feature changes across frames. It optimizes abnormal action weights and provides feedback for skeleton compensation or correction. Building upon the framework of a Generative Adversarial Network, we construct the posture discrimination network and employ this framework to generate regularization loss $Loss_g$ for pose estimation. Furthermore, we introduce rotation matrices to enhance robustness under diverse viewing angles, as exemplified by the following equation:

$$Loss_g^{'} = Loss(RX) \tag{2.2}$$

Where, R represents the rotation matrix $Rotation(\alpha, \beta)$, whereas α, β respectively denote the chosen angles along the x and y axes. In the experimental configuration, α is randomly selected from the interval [−0.2π, 0.2π], while β is randomly selected from the range [−π, π].

2.3.2 Skeleton interpolation compensation

In cases where the skeletal discrimination network identifies a missing skeleton state, the skeleton interpolation compensation network is activated to localize the temporal position of the missing skeletal keypoints. This process involves traversing the preceding and subsequent temporal skeletons and selecting complete skeletal sequences with shorter temporal intervals as references for skeletal interpolation. To ensure the generated skeleton aligns with realistic kinematic features, a compensation algorithm takes into account the action characteristics of the temporal sequence. For the interpolation compensation process, we set the range of traversal for the preceding and subsequent temporal skeletons to ten frames, based on findings from a referenced study [12] which determined that a range of ten frames at a sampling frequency of 50Hz provides optimal kinematic skeletal interpolation data. Accordingly, the missing skeletal temporal stage serves as the starting point, and the skeletal data from the preceding ten frames and subsequent ten frames are explored. The flowchart illustrating the skeletal interpolation compensation process is presented in Figure 2.7. When the skeleton discrimination network detects a missing skeleton state, the missing information is transmitted to the interpolation compensation network. This network integrates the skeletal information from the preceding and subsequent ten frames surrounding the missing skeletal keypoints, utilizing two neighboring complete skeletons with closer temporal distances as references. By incorporating action characteristics based on temporal features, the interpolation compensation network effectively compensates for the missing skeletal information, resulting in accurate skeletal compensation.

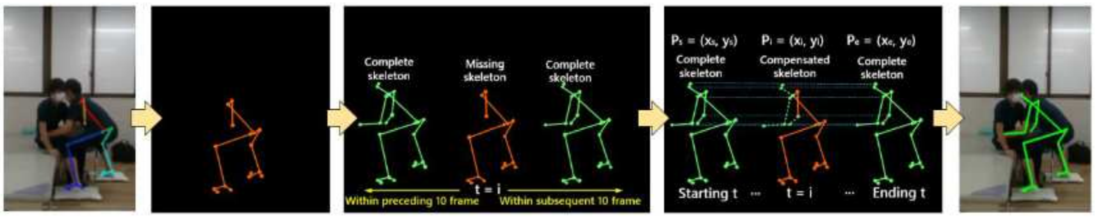

Figure 2.7 ST-GCN for skeleton missing interpolation compensation.

Assuming that the motion velocity of skeletal keypoints remains independent and constant within the missing region, when there are n missing skeletal keypoints between the temporal sequences, $P_s(x_s, y_s), P_e(x_e, y_e)$, P_s, and P_e respectively represent the starting and ending points of the complete skeletal information with a temporal distance of ten frames. The missing point is denoted as $P_1(x_1, y_1), P_2(x_2, y_2), \ldots, P_n(x_n, y_n)$. The equation for computing the interpolated compensatory coordinates of the missing skeleton keypoints is as follows.

$$x_i = (1-t)x_s + tx_e \tag{2.3}$$

$$y_i = (1-t)y_s + ty_e \tag{2.4}$$

$$t = \frac{i}{n+1}(i = 1, 2, \ldots, n) \tag{2.5}$$

2.3.3 Skeleton correction

To optimize heterogeneous action features in the case of skeletal misidentification, we have devised a method that takes into account the differences in action characteristics and determines the weights of the temporal sequences. Within these relevant temporal sequences, we calculate the proportion of action weights based on a predefined time threshold, while automatically filtering abrupt action features and compensating for missing temporal sequences with consistent action characteristics. By mapping the updated action features to the skeletal feature set, new skeletons are generated to replace the misidentified ones. For the temporal standard settings, we employ the same traversal method as in cases of skeletal loss. Starting from the misidentified skeleton temporal sequence, we traverse the pose weight information of the preceding and succeeding ten frames to determine the pose. The final determining feature is selected based on the highest-weighted feature within the temporal sequence, thereby replacing the anomalous action feature. Simultaneously, this feature is mapped to the corresponding skeletal feature, effectively replacing the misidentified skeleton. The entire process is depicted in Figure 2.8. For instance, if we consider B as the starting point for anomalous action feature weights and traverse ten frames before and after, all frames exhibit A features. Consequently, the B feature will be identified as an anomalous action feature by the skeletal correction network, and A will replace B as the action feature. The corresponding skeletal feature will also be adjusted accordingly, leading to the rectification of the misidentified skeleton.

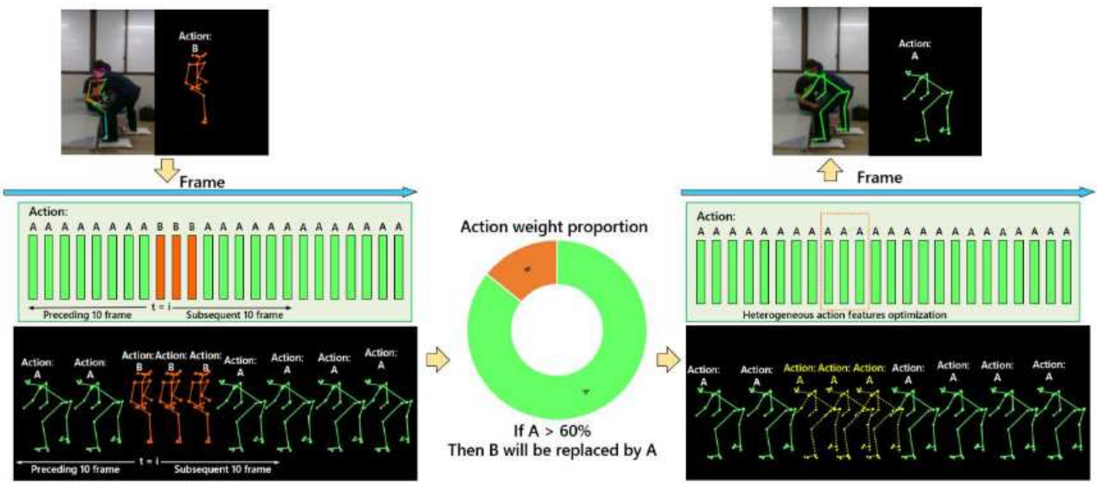

Figure 2.8. Skeleton correction for misidentified frames.

In order to mitigate estimation errors in the current frame that may lead to the neglect of preceding and succeeding frames, we introduce the utilization of the Kalman filtering algorithm for performing noise smoothing on the time series of coordinates for each skeletal point [6]. This integration ensures improved consistency between the corrected skeleton and the actual movement.

While considering the independent calculation of each skeletal point without accounting for skeletal constraints, we observe a natural correlation between the horizontal and vertical actions of the skeleton. Furthermore, when action trends are disregarded, the temporal states before and after exhibit similar characteristics. As a result, the following mathematical equations are satisfied.

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k \tag{2.6}$$

$$\hat{P}_k^- = AP_{k-1}A^T + Q \tag{2.7}$$

$$K_k = \frac{P_k^- C^T}{CP_k^- C^T + R} \tag{2.8}$$

$$\hat{x}_k = \hat{x}_k^- + K_k\left(y_k - C\hat{x}_k^-\right) \tag{2.9}$$

$$P_k = \left(I - K_k C\right)P_k^- \tag{2.10}$$

This study utilized PyCharm 2020.3.2 to perform interpolation and smoothing operations on human skeletal points based on time sequences.

2.4 Accuracy evaluation factors

2.4.1 Joint angle calculation

In the nursing task video, the human skeletal structure is predicted using the OpenPose and ST-GCN algorithms, followed by the calculation of joint angles from the skeletal points using the same methods. Each caregiver is identified with a total of 25 skeletal points, as shown in Figure 2.9. To comply with the scoring rules of the Rapid Entire Body Assessment (REBA), a comprehensive evaluation tool for assessing posture risks, a total of eight joint angles need to be computed. The calculation of these joint angles and their corresponding relationships with the skeletal points can be found in Table 2.2. By referencing the skeletal points associated with different joint angles as indicated in Table 2.2, the corresponding joint angles can be determined using inverse trigonometric functions based on the cosine theorem. Given that the nursing task primarily involves the use of the arms, the wrist angle will be treated as a constant value for angle measurement and pose risk assessment purposes in this study.

Table 2.2 Joint angles list.

Joint angle	Involved skeletal points
Trunk flexion angle	∠1, 8, 8’
Neck flexion angle	∠0, 1, 1’
Left leg flexion angle	∠12, 13, 14
Right leg flexion angle	∠9, 10, 11
Left upper arm flexion angle	∠5’, 5, 6
Right upper arm flexion angle	∠2’, 2, 3
Left lower arm flexion angle	∠5, 6, 7
Right lower arm flexion angle	∠2, 3, 4

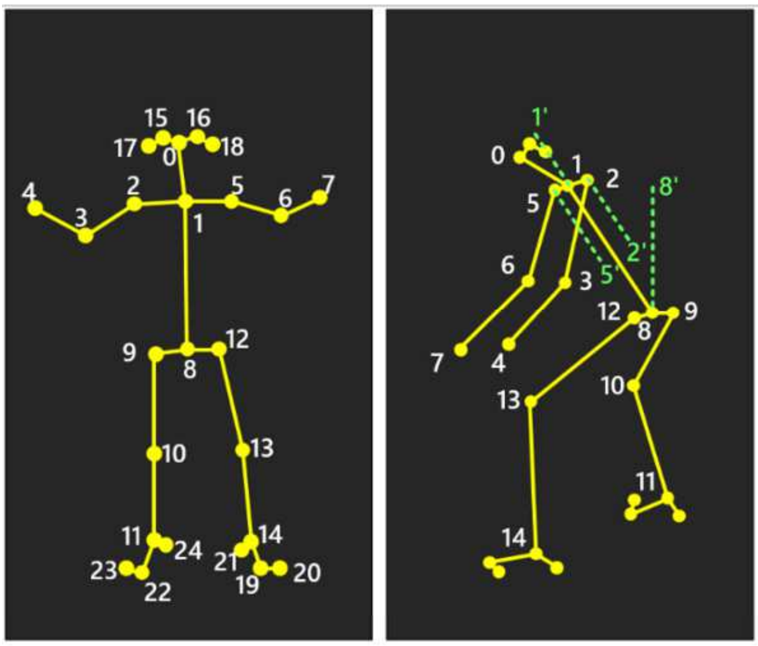

Figure 2.9 Skeleton angle calculation method.

The REBA method has been selected as a comprehensive tool for assessing ergonomic risks in the workplace, aiming to promptly evaluate the risk of work-related musculoskeletal disorders (WMSDs) associated with various postures. Its primary objective is to identify work positions that require additional attention and improvement in order to mitigate the risk of bodily discomfort and injury during work activities. The REBA algorithm involves the assessment of angle variations in key joints of the skeleton, including the trunk, neck, legs, upper arms, forearms, and wrists, as well as considerations for external loads and hand coupling capability. Based on the evaluation, REBA scores are assigned on a scale ranging from 1 to 12, with higher scores indicating a greater risk of WMSDs, as presented in Table 2.3.

Table 2.3. REBA risk level list.

REBA Risk Level			
Action Level	REBA Score	Risk Level	Correction Suggestion
0	1	Negligible	None Necessary
1	2-3	Low	Maybe Necessary
2	4-7	Medium	Necessary
3	8-10	High	Necessary Soon
4	11-15	Very High	Necessary Now

2.4.2 Accuracy calculation

In order to evaluate the accuracy of our approach in assessing posture risk, a comprehensive comparison was conducted between OpenPose, inertial sensors, and our method with regards to joint angles and REBA scores. The nursing task videos were meticulously divided into individual frames, and for each frame, the joint angles and REBA scores were calculated independently, as outlined in Table 2.4. To assess the performance of our method, the mean absolute error (MAE) of the joint angles and the precision of the REBA scores were employed as evaluation metrics. The MAE quantifies the absolute discrepancy between the joint angles computed by different methods, capturing the true magnitude of the error regardless of its direction. The mathematical equation for calculating MAE is provided as follows:

$$MAE_1 = \frac{\sum_{i=1}^{n} |A_i - A_{si}|}{n} \tag{2.11}$$

$$MAE_2 = \frac{\sum_{i=1}^{n} |A_{oi} - A_{si}|}{n} \tag{2.12}$$

Where, MAE_1 represents the mean average absolute error of joint angles measured by our method and the inertial sensors. MAE_2 represents the mean average absolute error of joint angles measured by OpenPose and the inertial sensors. The precision calculation for the REBA scores is primarily based on the REBA scores computed from the measurements of the inertial sensors. Assuming the number of frames with consistent REBA scores between the inertial sensors and our method is denoted as Fm, and the total number of frames is denoted as F, the precision calculation is determined by the following mathematical equation:

$$Acc = \frac{F_m}{F} \times 100\% \tag{2.13}$$

Table 2.4 Accuracy calculation parameters.

	Nursing task video	Frame 1	Frame 2	Frame i	Frame n
OpenPose	Joint angle	A_{o1}	A_{o2}	A_{oi}	A_{on}
	REBA	R_{o1}	R_{o2}	R_{oi}	R_{on}
Inertial sensor	Joint angle	A_{s1}	A_{s2}	A_{si}	A_{sn}
	REBA	R_{s1}	R_{s2}	R_{si}	R_{sn}
Ours	Joint angle	A_1	A_2	A_i	A_n
	REBA	R_1	R_2	R_i	R_n
Accuracy	Joint angle error	[A_{o1}, A_{s1}, A_1]	[A_{o2}, A_{s2}, A_2]	[A_{oi}, A_{si}, A_i]	[A_{on}, A_{sn}, A_n]
	REBA score error	[R_{o1}, R_{s1}, R_1]	[R_{o2}, R_{s2}, R_2]	[R_{oi}, R_{si}, R_i]	[R_{on}, R_{sn}, R_n]

2.5 Result

2.5.1 Skeletons missing and misidentifications

During the implementation of OpenPose for posture risk assessment in nursing tasks, significant challenges arise due to the intricate interactions and overlapping body configurations between nurses and patients. These challenges often give rise to incomplete or inaccurate skeletal estimations, leading to deviations and fluctuations in joint angles, as illustrated in Figure 2.10a. For instance, as depicted in Figure 2.10b, when a misidentified skeleton corresponds to the upper arm, substantial fluctuations in the upper arm angle occur, resulting in discontinuous states. In contrast, our method addresses the issue of misidentification (Figure 2.10c), ensuring a stable and continuous state for the joint angles of the upper arm. Similarly, in scenarios where the skeleton is missing, such as the legs, there may be deviations or even a complete absence of leg angles. However, our method optimizes the identification of the skeleton, thereby achieving the continuity of leg angle measurements.

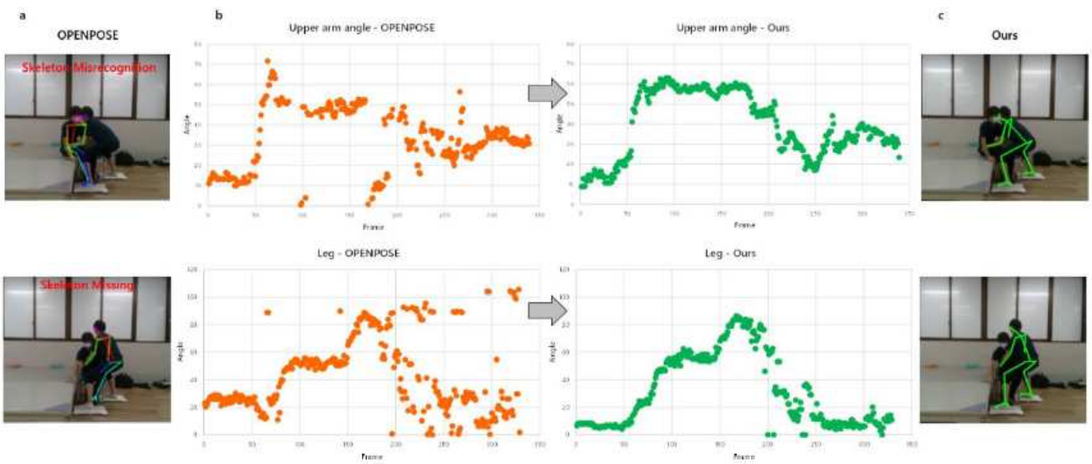

Figure 2.10. The effects of skeleton compensation and correction on joint angles.

In order to evaluate the performance of our approach, we conducted a comprehensive analysis comparing the rates of overall skeleton missing and misidentification across all frames, as presented in Table 2.5. The findings demonstrated that our approach achieved a remarkable skeletal misidentification rate of 2.18%. Furthermore, in terms of the skeleton missing rate, except for the right lower arm (Lower arm-R) which was affected by limb occlusion, substantial compensation effects on skeleton missing were observed for all other cases. These outcomes underscore the effectiveness and potential of our approach in optimizing the challenges associated with skeleton missing and misidentification in the field of skeletal analysis.

Table 2.5. Overall skeleton missing rate and misidentification rate for all frames.

Joints	Skeleton missing rate		Skeleton misidentification rate	
	OpenPose	Ours	OpenPose	Ours
Trunk	0.18%	0.07%	20.60%	2.18%
Leg-R	16.79%	5.96%		
Upper arm-R	22.42%	10.36%		
Lower arm-R	64.68%	51.67%		
Neck	22.06%	7.01%		
Leg-L	8.47%	1.78%		
Upper arm-L	11.19%	0.29%		
Lower arm-L	12.75%	0.58%		

2.5.2 Joint angle error

To assess the accuracy of our approach in measuring joint angles, we conducted a comparative analysis of angle errors among various methods. The analysis involved three distinct groups, each focused on evaluating the errors within a specific context. $E_{angle1} = A_{oi} - A_{si}$ represented the error between the joint angles obtained from OpenPose and the ground truth values; $E_{angle2} = A_i - A_{si}$ represented the error between our method and the ground truth values; $E_{angle3} = A_i - A_{oi}$ represented the error in joint angle errors between our method and OpenPose (Table 2.6).

Table 2.6 Errors between different joint angles.

Joints	E_{angle1} (N=8)	Paired t-test p-value P1	E_{angle2} (N=8)	Paired t-test p-value P2	E_{angle3} (N=8)	Paired t-test p-value P3
Trunk	-0.166±18.526	P=0.628	-0.019±2.345	P=0.659	-0.017±18.800	P=0.961
Leg-R	3.880±18.591	P<0.001	-0.060±2.324	P=0.160	0.882±6.090	P<0.001
Upper arm-R	3.145±10.742	P<0.001	-0.186±4.475	P=0.025	0.755±10.136	P<0.001
Lower arm-R	3.969±30.840	P<0.001	-0.226±4.427	P=0.006	-0.108±18.481	P=0.752
Neck	-1.956±14.891	P<0.001	-0.072±2.281	P=0.087	1.963±14.436	P<0.001
Leg-L	-1.069±7.174	P<0.001	-0.125±4.512	P=0.134	-4.098±30.771	P<0.001
Upper arm-L	-1.014±10.605	P<0.001	-0.059±2.292	P=0.165	0.773±9.903	P<0.001
Lower arm-L	2.473±27.971	P<0.001	0.006±4.586	P=0.942	-3.001±27.793	P<0.001

We presented a detailed analysis of joint angle errors based on comprehensive experimental results (Table 2.6). When comparing joint angle errors between OpenPose and ground truth values (E_{angle1}), all angles, except Trunk angles (P1=0.628), displayed significant statistical differences (P1<0.001), indicating substantial joint angle deviations. Conversely, our method exhibited minimal errors compared to ground truth values (E_{angle2}), with significant statistical differences observed only in Upper arm-R (P2=0.025) and Lower arm-R (P2=0.006) joint angles. This highlighted the reliability of our method in calculating skeletal joint angles. Additionally, significant differences were found in joint angle errors (P3<0.001) between our method and OpenPose (E_{angle3}), except for Trunk (P3=0.961) and Lower arm-R angles (P3=0.752), demonstrating the effectiveness of our approach in enhancing pose estimation accuracy and improving the precision of skeletal joint angle calculation.

The stability and accuracy of joint angle measurements were assessed using the mean absolute error (MAE) as an evaluation metric, with smaller MAE values indicating higher measurement accuracy. Our method consistently achieved an overall MAE (MAE1) below 10°, demonstrating superior accuracy in joint angle measurement, as illustrated in Figure 2.11. In contrast, OpenPose exhibited an MAE exceeding 10° for all joints, except the trunk, indicating substantial fluctuations in measurement errors. Statistical analysis revealed significant differences in both MAE1 and MAE2 across all joint angles (P<0.05). These discrepancies can be attributed to the challenges encountered by OpenPose, including skeleton loss and misidentification issues during the estimation of nursing care poses, resulting in frequent variations in angle differences and increased error fluctuations. In contrast, our proposed method effectively addressed these challenges by optimizing skeleton loss and misidentification, leading to reduced error fluctuations and significantly enhanced accuracy in joint angle calculations, as evidenced by the lower MAE values and reduced error fluctuations depicted in Figure 2.11.

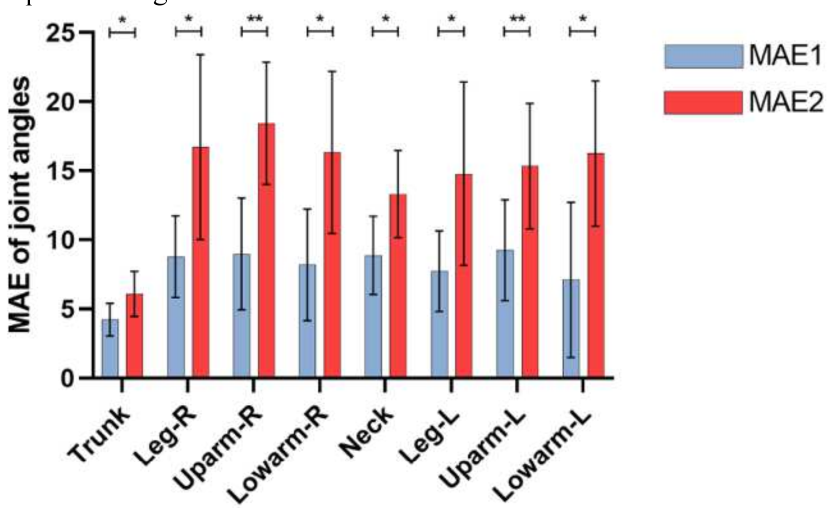

Figure 2.11. MAE of different joint angles. NS=not significant, *p<0.05, **p<0.01, ***p<0.001.

2.5.3 REBA score difference

To verify the performance of our method in REBA scoring, we conducted a comparative analysis of the error in REBA scores among different skeletal joints. $E_{REBA1} = R_{oi} - R_{si}$ denoted the error between OpenPose and the ground truth values, while $E_{REBA2} = R_i - R_{si}$ signified the error between our method and the ground truth values. The results, in accordance with the REBA scoring rules, were presented in Table 2.7.

Table 2.7. Errors between joint angle score and REBA score.

Joints	E_{REBA1} (N=8)	Paired t-test p-value	E_{REBA2} (N=8)	Paired t-test p-value
Trunk	-0.001±0.207	P=0.788	0±0.159	P=1
Leg-R	0.255±0.568	P<0.001	0.015±0.465	P=0.066
Upper arm-R	-0.176±0.644	P<0.001	-0.005±0.302	P=0.296
Lower arm-R	-0.154±0.635	P<0.001	0.235±0.448	P<0.001
Neck	0.003±0.132	P=0.124	-0.003±0.395	P=0.638
Leg-L	-0.027±0.282	P<0.001	0.012±0.506	P=0.186
Upper arm-L	0.013±0.282	P=0.013	0.001±0.186	P=0.619
Lower arm-L	0.098±0.309	P<0.001	0.234±0.508	P=0.325
REBA	0.116±1.128	P<0.001	-0.003±0.208	P=0.373

Based on the comprehensive results presented in Table 2.7, notable differences (P<0.001) were observed in the joints scores and REBA scores between the OpenPose and the ground truth values (E_{REBA1}), except for Trunk (P=0.788), Neck (P=0.124). These observations indicated that the reliability of REBA scores derived from the OpenPose method for assessing nursing care task postures was suboptimal, with considerable deviations. Conversely, when considering the REBA scores obtained through our proposed method (E_{REBA2}), a significant difference was only observed for the Lower arm-R score (P<0.001) compared to the ground truth values, while no significant differences were detected for other joint scores. Moreover, the final REBA scores showed no significant discrepancy compared to the ground truth values (P=0.373). These outcomes demonstrated that the REBA scores computed using our method closely aligned with the ground truth values, highlighting the substantial feasibility and reliability of our approach for assessing nursing task posture.

Furthermore, in order to assess the efficacy of our proposed method in addressing the challenges of skeleton loss and misidentification specifically in nursing care task scenarios, we conducted a comprehensive performance comparison against several existing methods. These methods include Tsai et al. [2], which employs a left-right skeletal symmetry skeleton compensation approach; Guo et al. [3], utilizing a Euclidean distance matrix skeleton compensation technique; and Kanazawa et al. [4], which employs a Human Dynamics-based temporal skeleton compensation method. The precision of REBA scores was chosen as the evaluation metric for this comparative analysis. A summary of the results obtained from this comprehensive evaluation can be found in Table 2.8.

Table 2.8. Accuracy of REBA score by different methods in nursing care tasks.

Joints	Acc				
	OpenPose	Tsai et al.	Guo et al.	Kanazawa et al.	Ours
Trunk	91.92%	90.34%	92.36%	95.32%	95.65%
Leg-R	81.43%	86.61%	86.42%	88.33%	87.47%
Upper arm-R	71.61%	72.41%	72.98%	75.79%	76.95%
Lower arm-R	47.76%	59.87%	60.14%	62.87%	64.31%
Neck	76.96%	82.86%	87.95%	86.97%	87.96%
Leg-L	82.94%	83.14%	89.76%	91.61%	90.81%
Upper arm-L	80.25%	85.27%	92.31%	91.89%	92.13%
Lower arm-L	84.26%	87.35%	91.14%	95.57%	91.68%
REBA	58.33%	63.29%	76.63%	80.46%	87.34%

The findings in Table 2.8 indicated that OpenPose achieved accuracy exceeding 90% for specific skeletal joints, yet its final accuracy in REBA scoring remains at 58.33%. This was associated with the issues of skeleton loss and misidentification, which caused low accuracy of REBA. In contrast, our approach attained an 87.34% accuracy, outperforming alternative methods and improved the skeleton loss and misidentification in nursing care tasks. Importantly, our method exhibited promising potential for pose assessment in action interaction-based nursing tasks.

2.6 Discussion

In this chapter, we have identified the challenges of skeleton misidentification and missing that arise when applying the OpenPose method to assess postures in nursing tasks. These challenges lead to deviations and fluctuations in skeletal joint angles, thereby impacting the accuracy of REBA scoring. To address this issue, we propose an improved approach based on ST-GCN that compensates for and rectifies missing skeletons by leveraging behavior-level information. This approach enables precise tracking of nurses' skeletons, even in scenarios involving overlapping bodies and dynamic interactions during nursing tasks. Consequently, it enhances the continuity and stability of skeletal joint angle calculations, resulting in improved accuracy in REBA scoring. To validate the reliability and feasibility of our method, we compare joint angles, joint angle scores, and REBA scores with the ground truth values obtained from inertial sensors. Given the dynamic nature of the nursing task process, joint angles and scores exhibit corresponding changes over time.

Therefore, we conduct paired t-tests to compare the frame-by-frame errors in joint angles and scores. The results reveal significant disparities between the joint angles and scores obtained from OpenPose and the ground truth values, primarily attributed to the impact of skeleton misidentification and missing. In contrast, our method exhibits no significant differences between the joint angles, scores, and the ground truth values, indicating the efficacy of our approach in compensating for missing skeletons and correcting misidentified skeletons through behavioral features. This ensures robust skeleton tracking and enhances the precision of joint angles and scores.

It is worth noting that significant angle errors are observed in the upper arm and lower arm joints, which can be attributed to the interactions between caregivers and patients during caregiving activities, resulting in a loss of arm joint tracking features. This limitation is commonly encountered in pose recognition algorithms and can only be overcome by employing marker-based or wearable sensor measurement methods. In terms of REBA scoring accuracy, our proposed method achieves an impressive accuracy of 87.34%, surpassing other existing methods. Compared to the OpenPose method, our approach exhibits a remarkable 29.01% improvement in accuracy, effectively addressing the limitations of OpenPose in nursing task scenarios and enhancing the accuracy of joint angles and REBA scoring, thereby ensuring reliable posture risk assessment outcomes. While there is still room for improvement in the accuracy of our method, particularly for the leg, upper arm, and lower arm joints, the significantly higher errors observed in these joints suggest that skeleton misidentification predominantly affects the recognition of leg and arm joints in nursing task postures. Therefore, future research on nursing task posture recognition should focus on further refining the accuracy of these specific joints.

Our proposed method offers distinct advantages compared to existing approaches. While previous studies have demonstrated the reliability of OpenPose in predicting joint angles for simple poses [13-15], its performance in complex scenarios involving multiple person interactions and occluded bodies is suboptimal. To enhance skeleton prediction accuracy, some researchers have employed label correction techniques to improve multi-person skeleton detection using OpenPose [16]. Others have utilized heatmap offset adjustment algorithms, leveraging the left-right symmetry principle of the human body skeleton, to compensate for missing skeletal keypoints [1]. However, these methods are primarily suitable for poses captured from a frontal camera perspective, and deviations in camera angles may lead to corrected skeletal points located outside the body. To address this issue, Mask RCNN has been employed for body boundary detection, effectively constraining skeletal points within the body boundary [2]. Nevertheless, misidentification challenges persist in the case of multiple individuals. To overcome this, researchers have explored the use of graph neural networks, effectively leveraging feature information from key and neighboring nodes in the human skeleton to discern skeletal point associations between different individuals. Furthermore, graph attention networks have been proposed to learn relevant weights between continuous feature skeleton graphs. However, these methods tend to capture limited low-order semantic information and lack high-order semantic feature information. Drawing inspiration from spatiotemporal graph convolutional neural networks, we introduce a novel approach that compensates for missing or misidentified skeletons based on behavioral feature weights from preceding and succeeding temporal frames. The results section and accuracy comparisons with other methods demonstrate the superior performance of our approach in REBA assessment score accuracy for caregiving tasks. This highlights the effectiveness of our method in mitigating issues related to skeleton misidentification and missing skeletons in OpenPose while achieving excellent skeleton recognition accuracy. Our method exhibits high accuracy and reliability in posture risk scoring for caregiving tasks based on human ergonomics.

In the field of ergonomics, various methods exist for assessing posture risk, including OWAS, RULA, and others. However, our study specifically selected REBA scores as the validation criterion for several reasons. Firstly, previous studies employing visual posture risk assessment methods have used REBA, RULA, and OWAS scores concurrently as evaluation indicators, revealing a linear positive correlation among these three methods [8]. Therefore, the scoring trends observed from these methods are consistent. While incorporating all three methods as validation indicators would provide a more comprehensive evaluation, the choice of assessment method can vary depending on the specific work scenario. For instance, in assessing posture among construction workers, employing only the OWAS score as an evaluation indicator can yield scientifically valid results [17]. Similarly, when evaluating the risk of musculoskeletal disorders in lifting postures with a limited sample size, RULA alone can serve as the assessment standard. Ultimately, we selected REBA due to its inclusion of leg angle evaluations. The primary contribution of our method lies in improving the accuracy of skeletal joint angles, and REBA is the only method that comprehensively demonstrates the assessment results of joint angles across the entire body. Therefore, the evaluation results obtained from REBA are better suited to demonstrate the effectiveness of our method.

Moreover, this study aims to compare our method with the OpenPose method in terms of the accuracy of skeletal joint angle prediction within the realm of 2D pose estimation algorithms. The REBA assessment scoring criteria encompass not only joint angle scoring but also supplementary scoring for joint rotation and additional points. To ensure consistent scores across all methods, we manually established parameters for rotation and extra points intervention. While there is a wealth of research on posture risk assessment based on 3D pose estimation [18-20], which has yielded commendable recognition accuracy, 3D pose estimation does have certain limitations. The extensive computational requirements of 3D pose estimation make it less suitable for real-time pose estimation, often necessitating the use of depth cameras or specialized sensors to acquire depth data, thereby increasing hardware and data acquisition complexities. In contrast, 2D pose estimation algorithms exhibit greater robustness in complex conditions such as lighting variations and occlusions compared to 3D pose estimation methods. Consequently, our method offers high feasibility and can be readily implemented on commonly used smartphones or surveillance cameras in a lightweight model format. Naturally, future research could explore the application of 3D pose estimation in healthcare, and investigating the comparative effects of 3D and 2D approaches would be of considerable significance.

2.7 Conclusion

In this chapter, we present an improved skeletal reconstruction method based on ST-GCN. Our approach employs a compensation and correction strategy at the behavioral level to accurately track the nurse's skeleton in scenarios involving body overlap and movement interaction. This enhances the continuity and stability of skeletal joint angle calculations, resulting in improved accuracy of REBA scores. To validate the performance of our method, we conduct a comparative analysis of skeletal joint angles, REBA scores, and accuracy against ground truth values. The results demonstrate that our method achieves joint angles and REBA scores that are statistically indistinguishable from the ground truth values when compared to the OpenPose method. Moreover, our approach effectively mitigates issues related to skeletal missing and misidentification in nursing tasks, leading to enhanced accuracy of skeletal joint angles and REBA scores. Notably, our method surpasses other skeletal correction methods in terms of the accuracy of REBA scores for nursing task postures, achieving an impressive accuracy rate of 87.34%. By optimizing the tracking accuracy of skeletons in nursing tasks, our method enhances the efficiency and precision of posture risk assessment in the nursing domain, with potential positive implications for the health and safety of healthcare workers. Furthermore, our method offers easy integration into IoT devices equipped with cameras, such as smartphones and surveillance cameras, enabling posture information inference using neural network models and image processing techniques. This capability enables risk assessment and visual guidance for discomfort and injury in nursing postures. Looking ahead, the realization of an integrated intelligent nursing posture assessment system becomes a possibility.

Reference

[1] Huang C C, Nguyen M H. Robust 3D skeleton tracking based on openpose and a probabilistic tracking framework[C]//2019 IEEE International Conference on Systems, Man and Cybernetics (SMC). IEEE, 2019: 4107-4112.

[2] Tsai M F, Huang S H. Enhancing accuracy of human action Recognition System using Skeleton Point correction method[J]. Multimedia Tools and Applications, 2022, 81(5): 7439-7459.

[3] Guo X, Dai Y. Occluded joints recovery in 3d human pose estimation based on distance matrix[C]//2018 24th International Conference on Pattern Recognition (ICPR). IEEE, 2018: 1325-1330.

[4] Kanazawa A, Zhang J Y, Felsen P, et al. Learning 3d human dynamics from video[C]//Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2019: 5614-5623.

[5] Miyajima S, Tanaka T, Imamura Y, et al. Lumbar joint torque estimation based on simplified motion measurement using multiple inertial sensors[C]//2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2015: 6716-6719.

[6] Liang F Y, Gao F, Liao W H. Synergy-based knee angle estimation using kinematics of thigh[J]. Gait & Posture, 2021, 89: 25-30.

[7] Figueiredo L C, Gratão A C M, Barbosa G C, et al. Musculoskeletal symptoms in formal and informal caregivers of elderly people[J]. Revista Brasileira de Enfermagem, 2021, 75.

[8] Kim W, Sung J, Saakes D, et al. Ergonomic postural assessment using a new open-source human pose estimation technology (OpenPose)[J]. International Journal of Industrial Ergonomics, 2021, 84: 103164.

[9] Tsuchiya Y, Kusaka T, Tanaka T, et al. Calibration method for lumbosacral dimensions in wearable sensor system of lumbar alignment[C]//2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2015: 3909-3912.

[10] Yan S, Xiong Y, Lin D. Spatial temporal graph convolutional networks for skeleton-based action recognition[C]//Proceedings of the AAAI conference on artificial intelligence. 2018, 32(1).

[11] Wu C, Wu X J, Kittler J. Spatial residual layer and dense connection block enhanced spatial temporal graph convolutional network for skeleton-based action recognition[C]//proceedings of the IEEE/CVF international conference on computer vision workshops. 2019: 0-0.

[12] Howarth S J, Callaghan J P. Quantitative assessment of the accuracy for three interpolation techniques in kinematic analysis of human movement[J]. Computer methods in biomechanics and biomedical engineering, 2010, 13(6): 847-855.

[13] Li, L., Martin, T. & Xu, X. A novel vision-based real-time method for evaluating postural risk factors associated with musculoskeletal disorders. Appl. Ergon. 87, 103138 (2020).

[14] Li, Z., Zhang, R., Lee, C.-H. & Lee, Y.-C. An evaluation of posture recognition based on intelligent rapid entire body assessment system for determining musculoskeletal disorders. Sensors 20(16), 4414 (2020).

[15] Lin, PC., Chen, YJ., Chen, WS. et al. Automatic real-time occupational posture evaluation and select corresponding ergonomic assessments. Sci Rep 12, 2139 (2022). https://doi.org/10.1038/s41598-022-05812-9.

[16] Kato N, Li T, Nishino K, et al. Improving multi-person pose estimation using label correction[J]. arXiv preprint arXiv:1811.03331, 2018.

[17] Yan X, Li H, Wang C, et al. Development of ergonomic posture recognition technique based on 2D ordinary camera for construction hazard prevention through view-invariant features in 2D skeleton motion[J]. Advanced Engineering Informatics, 2017, 34: 152-163.

[18] Yuan H, Zhou Y. Ergonomic assessment based on monocular RGB camera in elderly care by a new multi-person 3D pose estimation technique (ROMP)[J]. International Journal of Industrial Ergonomics, 2023, 95: 103440.

[19] Plantard P, Auvinet E, Le Pierres A S, et al. Pose estimation with a kinect for ergonomic studies: Evaluation of the accuracy using a virtual mannequin[J]. Sensors, 2015, 15(1): 1785-1803.

[20] Zhou X, Huang Q, Sun X, et al. Towards 3d human pose estimation in the wild: a weakly-supervised approach[C]//Proceedings of the IEEE international conference on computer vision. 2017: 398-407.

Chapter 3

Improved REBA for caregiving

3.1 Overview

This chapter presents a targeted caregiving postural risk assessment method, employing a simulated patient transfer scenario with participants having varying levels of caregiving experience. Initially, the Rapid Entire Body Assessment (REBA) method showed limited sensitivity in discerning differences between experienced and inexperienced groups. However, an analysis of the center of gravity (COG) trajectory revealed notable posture distinctions between the two groups. Leveraging these disparities, we explored parameter adjustments to the REBA rules, resulting in the development of the Caregiving-REBA (C-REBA) method, which incorporates COG trajectory, load-bearing time, and asymmetric load factors. Experimental findings demonstrated that C-REBA effectively distinguished between experienced and inexperienced caregivers, particularly in the caregiving task stages 2-4.

3.2 Study design

3.2.1 Experiment setting

The daily work in the caregiving industry is individualized and involves many complex working postures. Patient transfer, one of the most common postures in the caregiving, is chose for our research. Subjects were recruited by convenience sampling, and the subjects were selected under following criteria:

Eight professional nurses from the department of Rehabilitation Therapy at co-author's hospital were invited and served as the Experienced Group (Exp Group). The inclusion criteria for the Exp Group were: (1) age between 25 and 35 years old, (2) at least 5 years of professional caregiving experience, (3) no history of back injury or pain in the past year [1].

Ten inexperienced volunteers were recruited. The inclusion criteria for the Inexperienced Group (Inexp Group) were: (1) age between 20 and 35 years old, (2) without any caregiving experience, (3) no history of back injury or pain in the past year.

One nurse at co-author's hospital was acted as the patient (age: 30 years old, height: 168 cm, weight: 62 kg). Other eight nurses (Exp Group) and ten volunteers (Inexp Group) were requested to transfer the patient from bed to wheelchair. The sitting posture and movements of the patient were kept consistent. Their age, height and weight were shown in Table 3.1.

Table 3.1 Demographics of the participants.

Demographic	Exp Group (N=8)	Inexp Group (N=10)	P value
Age	29.125±3.48	26.9±6.11	0.348
Weight(kg)	61.06±9.5	62.97±7.73	0.644
Experience(year)	6.25±3.15	0	<0.001
Height(cm)	167.5±4.84	169.89±5.07	0.328

The Intel RealSense Depth Camera D435 was employed to capture caregiving postures, while the kinematic analysis system based on the OpenPose algorithm provided skeleton joint data. The OpenPose-based ergonomic assessments demonstrated resilience to non-ideal task conditions [2]. Validating a previous study, the Wii Balance Board was utilized as a reliable tool for assessing standing balance [3]. Two Wii Balance Boards (Nintendo Co., Ltd.) were utilized to measure ground reaction forces of each foot and subsequently calculate the trajectories of the center of pressure (COP). Each participant (Exp Group, n=8; Inexp Group, n=10) assumed suitable caregiving postures while standing on the Wii Balance Board, with the distance between their feet measured beforehand. To comprehensively analyze and refine the entire patient transfer process, the caregiving process was divided into five stages (Figure 3.1):

Stage 1: The caregiver placed their hands in a hugging position around the patient's waist, adjusted the posture, and prepared to start.

Stage 2: The caregiver began to lift the patient and the patient was about to leave the support of the bed.

Stage 3: The caregiver lifted the patient to the proper point, and prepared to rotate the patient to the side of wheelchair.

Stage 4: The caregiver rotated the patient to the side of wheelchair and the patient was about to be put down.

Stage 5: The caregiver placed the patient on the wheelchair.

Figure 3.1 Representative pictures of the 5 stages of caregiving task.

3.2.2 Data collection and statistical analysis

The experiments were performed and data was collected in 2022, with each subject recording three sets of data. The final results were obtained by calculating the average values. Upon completion of the caregiving task, the kinematic analysis system generated posture skeleton joint information in pixel coordinates, which was synchronized with the PC terminal. Furthermore, the trajectory information of the center of pressure (COP) and center of gravity (COG) was also synchronized. To obtain the REBA assessment result, we developed a system utilizing a neural network model to evaluate joint angles from the experimental videos.

SPSS 16.0 software (SPSS Inc) and GraphPad Prism 9 (GraphPad Inc) were used for statistical analysis. The Shapiro-Wilk test was used to check whether the mean differences of all variables were normally distributed since the sample size was less than 20. The student t-test method was used for continuous data from two groups that met normal distribution, and the 1-way ANOVA method was used for continuous data from two groups that did not meet normal distribution. For some statistical tests, the mean value and standard deviation were reported, and P-values less than 0.05 were considered as statistically significant.

3.2.3 Ethics

This study was approved by the Ethics Committee at the Center for Clinical Research of Yamaguchi University Hospital (H2019-182), and written informed consent was obtained. All participants signed informed consent forms prior to the study.

3.3 Rapid Entire Body Assessment (REBA) method

3.3.1 Related work

The assessment of postural loads from an ergonomic standpoint necessitates the consideration of multiple factors, encompassing vibration, coupling, movement frequency, load size, and duration [4]. Within the field of ergonomics, three primary methods are commonly utilized for evaluating risk factors related to musculoskeletal disorders: the Ovako Working Posture Analysing System (OWAS) [5], the Rapid Upper Limb Assessment (RULA) [6], and the Rapid Entire Body Assessment (REBA) [7]. Among these methods, REBA stands out as a comprehensive approach that enables the assessment of postural loads across the entire body. It involves the observation and evaluation of workers' postures, joint angles, and muscle loads, mapping these parameters to specific grades and scores within a scoring table. By doing so, it determines the risk level associated with working postures and provides recommendations for improvement to mitigate potential health issues associated with poor ergonomics [8].

The reliability of the Rapid Entire Body Assessment (REBA) as an ergonomic assessment tool has been substantiated through comparisons with other conventional methods, affirming its efficacy [9]. The selection of REBA is warranted due to its inclusive evaluation of all body parts, encompassing recognized awkward postures, loads, and various types of activities, including repetitive and static tasks. Furthermore, the versatile nature of REBA enables its application across diverse occupations, such as forestry timber harvesting [10], mining industries [11], dentistry [12], and hospital nursing [13-14].

3.3.2 REBA rules

The primary purpose of the Rapid Entire Body Assessment (REBA) method is to provide a quick assessment of postural loads and identify working postures that require attention and improvement. Its objective is to reduce the risk of work-related physical discomfort and injuries. The assessment process involves evaluating the angle changes of major joints according to the REBA rules. REBA divides the body into two independent assessment parts: Part A and Part B (Figure 3.2a). Part A assesses the neck, trunk, and legs, while Part B assesses the upper arms, lower arms, and wrists. Each part is assigned individual scores based on the evaluation of specific criteria outlined in Table A. The scores for the trunk, legs, and neck are added together to determine the Part A score. This score is then combined with the Extra A score, which takes into account the strain and load associated with the work. Similarly, Part B score, Extra B score, and Score B are calculated using the same methodology. The Extra B score considers the coupling ability of the hands. The scores from Part A and Part B are integrated into Table C to generate the Score C. The final REBA score is obtained by adding the Score C to the Extra C score (Figure 3.2b). The Extra C score is determined based on the difficulty level of the activity being assessed.

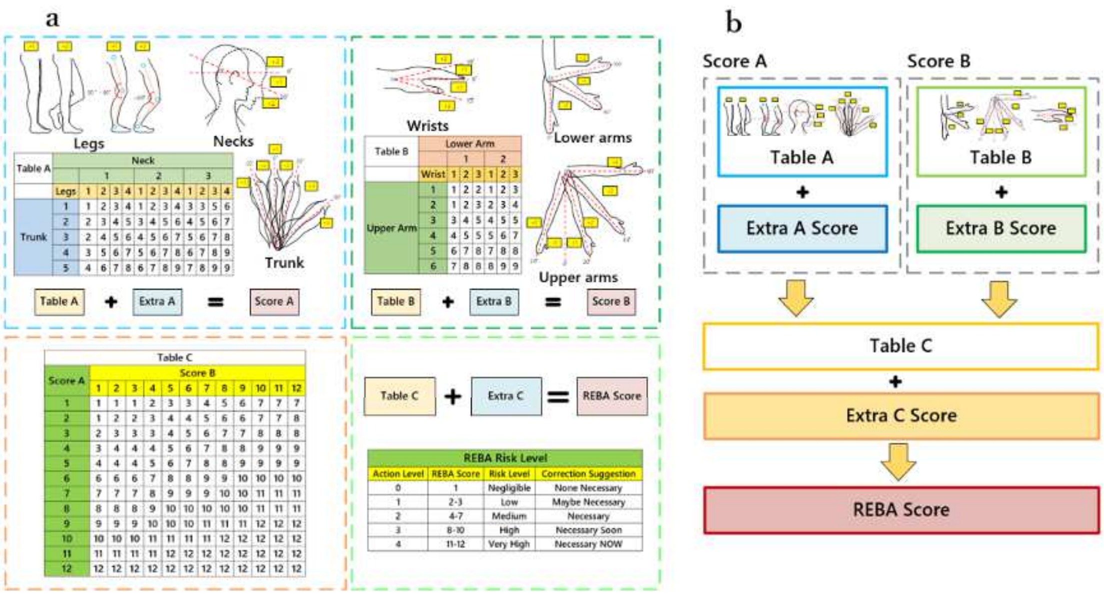

Figure 3.2 REBA scoring rules.

The REBA score, ranging from 1 to 12, serves as an indicator of the risk level associated with musculoskeletal disorders, discomfort, and injuries. Caregivers and practitioners can utilize the REBA score, along with action levels, to evaluate the extent of risk posed by postural loads and timely adjust high-risk postures. Comprehensive scoring rules and guidelines for REBA can be found in the existing literature [7]. The systematic assessment offered by REBA empowers caregivers and organizations to proactively address ergonomic risks and implement necessary modifications to work environments, tasks, and postures. By incorporating the recommendations derived from REBA assessments, the objective is to enhance the well-being of workers, mitigate the occurrence of musculoskeletal discomfort and injuries, and improve overall productivity and efficiency.

3.3.3 REBA's adaptability

The accurate assessment of postural loads plays a critical role in identifying and mitigating the risk of work-related musculoskeletal disorders (MSDs). Among the various methods available, the Rapid Entire Body Assessment (REBA) has emerged as a widely utilized approach for evaluating ergonomic postural loads across different industries. With its extensive application, the REBA method effectively assesses postural loads and offers recommendations to mitigate the risk of MSDs. It takes into account multiple factors, including joint angles, muscle loads, and overall body posture, to determine the varying levels of risk associated with different working postures. Through the assignment of scores and their integration within a comprehensive evaluation framework, REBA provides a quantitative measure of ergonomic risks, aiding in informed decision-making and intervention strategies.

Nevertheless, the broad applicability of the Rapid Entire Body Assessment (REBA) method may present limitations when applied to diverse work environments. Each industry and occupation possess unique characteristics, including distinct tasks, work postures, and associated risks. Researchers in the literature [15] discovered that the REBA method tends to overestimate the risk levels of musculoskeletal disorders when estimating the frequency distribution of risk levels in work tasks. Consequently, they developed a more targeted approach for personal risk assessment of musculoskeletal disorders among workers. In a rapid examination of musculoskeletal disorders in nurseries, the quantitative results obtained from REBA indicated that 45% of cases exhibited issues such as risk overestimation [16]. In response to the problem of overestimating the risks of musculoskeletal disorders in workers through REBA, the literature [17] proposed an improved method known as MOREBA for assessing postural risks. The findings demonstrate that this method is better suited for evaluating working postures in specific situations.

We employed the REBA method to assess the caregiving postures in both the Exp and Inexp Groups. The results (Figure 3.3) revealed that in the Inexp Group, the average REBA scores were in the high-risk range (above 8 points) across all stages. Similarly, the average REBA scores for the Exp Group in stages 1 to 4 were also in the high-risk range. These findings suggest an overestimation of risk levels in caregiving postures by the REBA method. Furthermore, there were no significant differences between the Exp and Inexp Groups in the assessment of caregiving postures at each individual stage (Stage 1: p=0.319; Stage 2: p=0.343; Stage 3: p=0.183; Stage 4: p=0.0596; Stage 5: p=0.113). This indicated that the REBA method could not distinguish the Exp and Inexp Groups in caregiving postures, and lacks sensitivity and specificity in assessing postural loads. Therefore, the REBA method is not suitable for providing guidance and reference for inexperienced caregivers, as it does not adequately assess the ergonomic demands of caregiving postures.

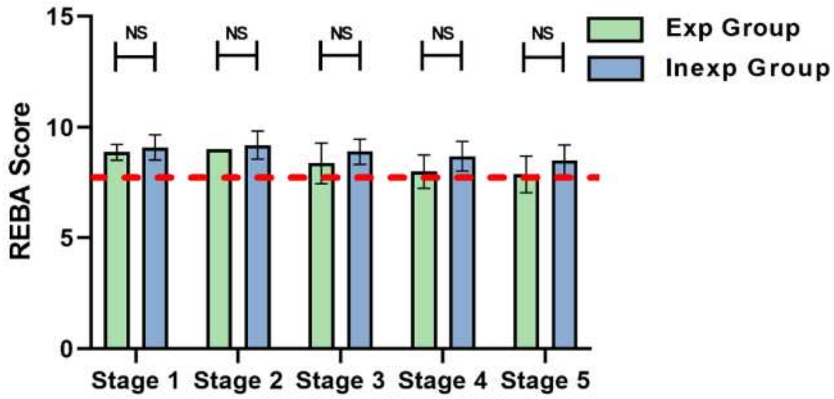

Figure 3.3 Evaluation results of caregiving posture with REBA method.

In order to enhance the versatility of the Rapid Entire Body Assessment (REBA) method and ensure its applicability across diverse contexts, customization based on the specific characteristics of the work environment is crucial. This tailored approach will result in a more focused and effective ergonomic assessment of postural loads, enabling workers to make appropriate adjustments to their caregiving postures. Therefore, to enhance the relevance and efficacy of postural load assessments, it is imperative to adapt the REBA method to meet the unique requirements of different work scenarios. By customizing the REBA method to suit the characteristics of a specific work environment, a targeted and context-specific ergonomic assessment approach can be established. This customized approach will facilitate a more accurate evaluation of postural loads and, subsequently, provide personalized recommendations for workers to optimize their caregiving postures. These adjustments aim to minimize the risk of musculoskeletal disorders (MSDs) and promote the overall well-being and safety of workers.

3.4 Center of gravity (COG)

3.4.1 Related work

The point of concentration of total body mass without affecting translational inertia properties, known as the body center of gravity (COG), is of utmost importance for maintaining balance and stability during various physical activities, including walking, running, and sports [18-19]. Moreover, it plays a pivotal role in optimizing safety and efficiency in fields such as ergonomics, industrial design, and rehabilitation [20]. During lifting tasks, the body undergoes a transition from a lower to a higher position, necessitating deliberate lowering of the COG in order to maintain balance [21]. Concurrently, maintaining an upright posture in the upper body minimizes muscle activation and enhances postural stability [22]. These factors alleviate pressure on the waist and mitigate the risk of musculoskeletal disorders. However, the impact of these findings on the evaluation of nursing postures from an ergonomic risk perspective has been largely overlooked. Experienced caregivers, benefiting from extensive training, possess the knowledge of optimal postures and positions. This expertise enables them to adopt power positions that aid in preventing musculoskeletal injuries. Power position refers to the ideal physical posture and body alignment that ensures balance and maximizes strength output during lifting activities, thereby reducing the risk of muscular injuries [23]. Experienced caregivers are inclined to adjust the COG height to achieve a power position with minimal physical strain. There exists a correlation between trunk bending height and postural instability, and bearing loads in a tilted manner can further contribute to body instability [24]. Power position holds significant importance in caregiving tasks. Previous studies have primarily focused on applying the REBA rules for assessing caregiving postures, disregarding the relationship between COG changes and power position.

3.4.2 Calculation of COG

The determination of the center of gravity (COG) position involves a comprehensive methodology that combines the weight proportion of each body part [25] with the skeleton data extracted using the OpenPose algorithm (Figure 3.4). We adopt an approach rooted in the center of gravity calculation methods outlined in literature [26] and literature [27], which provide valuable guidelines for acquiring the COG position. By considering the weight proportion of individual body parts, we assign relative weights to different segments of the skeleton, enabling the calculation of their combined impact on the overall COG. The skeleton data obtained from OpenPose furnishes crucial insights into joint positions and connections, forming the fundamental basis for our calculations.

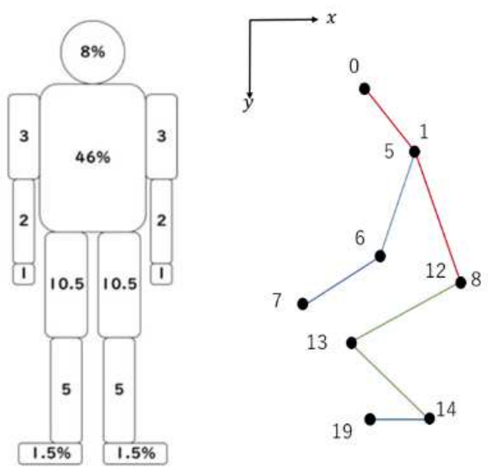

Figure 3.4 Weight ratio of each part of the body and skeleton coordinate points of OpenPose.

Assume that w_n represents the weight proportion of each part, W represents the proportion of the total weight of the part to be considered, x_n represents the coordinates of the center of gravity of each part, m_0 represents the weight of the subject, m represents the center of gravity position x_g, and the center of gravity position $x_g^{'}$ when a weight is applied It can be expressed by the following equations.

$$x_g = \sum \frac{w_n}{W} \times x_n \tag{3.1}$$

$$x_g^{'} = \sum \left\{ \frac{m_0 * w_n}{m_0 * W + m} * x_n \right\} + \frac{m}{m * W + m} * x_7 \tag{3.2}$$

In addition, the overall center of gravity position x_g, the center of gravity position x_{gw} when considering the waist load moment, and the center of gravity position x_{gk} when considering the knee load moment are expressed by the following equations.

$$x_g = \frac{8}{97}\frac{x_0 + x_1}{2} + \frac{46}{97}\frac{x_1 + x_8}{2} + \frac{6}{97}\frac{x_5 + x_6}{2} + \frac{4}{97}\frac{x_6 + x_7}{2} + \frac{2}{97}x_7 + \frac{21}{97}\frac{x_{12} + x_{13}}{2} + \frac{10}{97}\frac{x_{13} + x_{14}}{2} \tag{3.3}$$

$$x_{gw} = \frac{8}{66}\frac{x_0 + x_1}{2} + \frac{46}{66}\frac{x_1 + x_8}{2} + \frac{6}{66}\frac{x_5 + x_6}{2} + \frac{4}{66}\frac{x_6 + x_7}{2} + \frac{2}{66}x_7 \tag{3.4}$$

$$x_{gk} = \frac{8}{87}\frac{x_0 + x_1}{2} + \frac{46}{87}\frac{x_1 + x_8}{2} + \frac{6}{87}\frac{x_5 + x_6}{2} + \frac{21}{87}\frac{x_{12} + x_{13}}{2} + \frac{2}{87}x_7 \tag{3.5}$$

3.4.3 The difference in COG

We used camera to capture the entire process of patient transfer and implemented COG trajectory visualization (Figure 3.5a). The Exp Group showed a trajectory of the COG first dropping, then rising, and dropping again during patient transfer (Figure 3.5b). They tended to lowered their COG to keep their upper body upright for reducing the torque in the waist, and keep the trunk as straight as possible. On the contrary, the COG trajectory of the Inexp Group showed an initial rising, and then directly dropping (Figure 3.5c), Inexp Group caregivers, unfamiliar with power position, tended to bend their trunk as much as possible to lifted the patient.

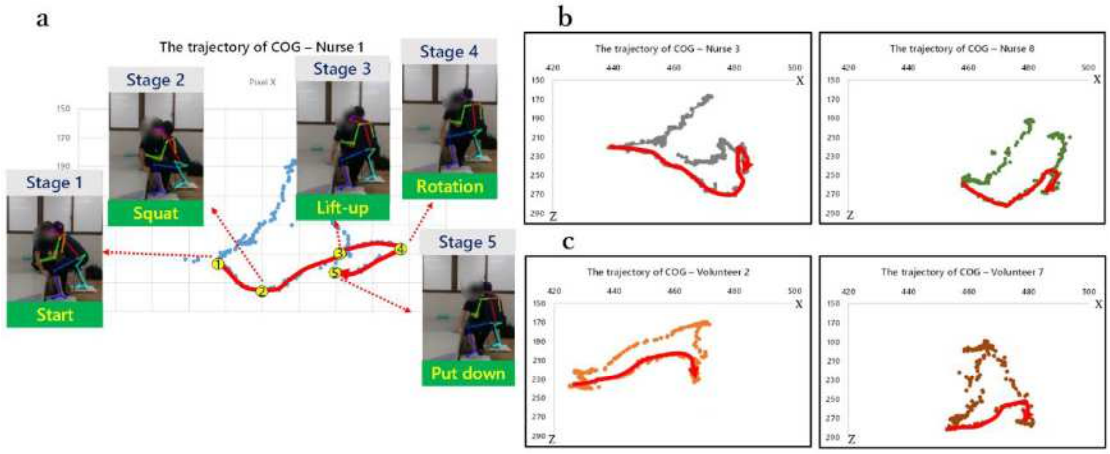

Figure 3.5 The difference in the trajectory of the pixel COG between Exp Group and Inexp Group.

The height changes of the COG were visualized, where notable differences between Exp Group and Inexp Group was found during patient transfer (Figure 3.6a). The Exp Group showed a downward trend in COG changes during Stage 2 of patient transfer, but Inexp Group showed an opposite upward trend. During Stage 2, the Exp Group used a body backward movement to lower the COG and maintained an upright trunk to increase body stability. The Inexp Group lifted the patient by bending over directly, which increased the burden on their waist. The difference of Stage 2 ($p<0.001$), 3 ($p=0.002$) and 4 ($p=0.003$) was statistically significant, suggesting that Stage 2, 3 and 4 might be meaningful intervention stages for caregiving posture (Figure 3.6b). The visualization results provided a reference for Inexp Group, which reminded them to adjust their caregiving posture and reduce the risk of musculoskeletal discomfort and injury.

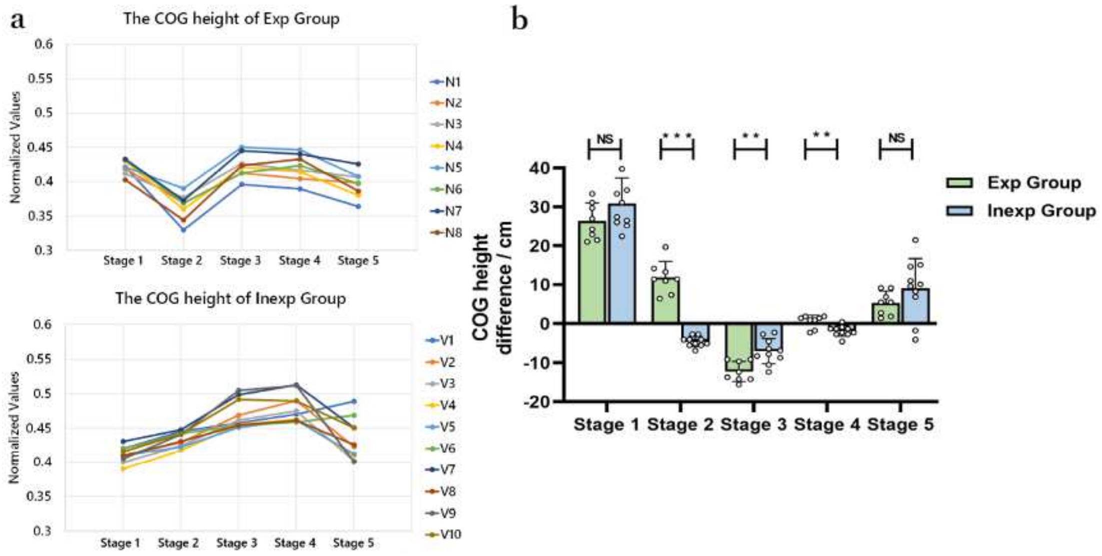

Figure 3.6 Difference analysis of height change of COG.

In addition, the COG heights from Stage 1 to the highest lifting position (Stage 3 or Stage 4) were also compared between the Exp Group and Inexp Group. The Exp Group utilized power positions to control COG heights at the Stage 1, minimizing the fluctuation and reducing the work performed by gravity and waist burden. The Inexp Group showed an overall tendency of higher COG heights from Stage 1 to Stage 3 and Stage 4, indicating that the Inexp Group hold the patient at a higher height during the caregiving task. This also increased the waist burden and risk of injury. Therefore, incorporating COG changes into the REBA score holds the potential to make it more applicable to the caregiving process.

3.5 Caregiving-REBA

The REBA method had limitations in assessing the risk of caregiving postures as it failed to differentiate experienced and inexperienced caregivers, and it couldn't provide meaningful postural guidance for inexperienced caregivers. We found that the original evaluation rules for the Extra A and Extra C scores are limited in their applicability to caregiving work. It's closely related the difference in COG. Accordingly, we adapted the REBA method as followed.

3.5.1 C-Extra A

The asymmetric load in caregiving work is an important factor of musculoskeletal discomfort and injury [22]. We redefined the scoring rules of Extra A by adding the factor of the asymmetric load according to the changing trend of COG. With two Wii Balance Board sensors, we measured the ground reaction forces on the left foot COP1 and right foot COP2 from all the participants during transfer operation. Figure 3.7a showed the results of statistical analysis of the load difference between the left and right foot. It was evident that the inter-foot load difference quartile in the Inexp Group was larger than the Exp Group. Experienced caregivers had less fluctuations in the load difference. While inexperienced caregivers had large fluctuations. We attempted to use the quartile value of the Exp Group as an evaluation criterion to assess the difference in asymmetric loading of the Inexp Groups. The inter-foot load quartile value of the Exp Group showed that values of the first quartile and the third quartile were 9.99kg and 24.54kg (Figure 3.7a). We added new scores in the C-Extra A rule by defining the load difference range as provided in Figure 3.7b.

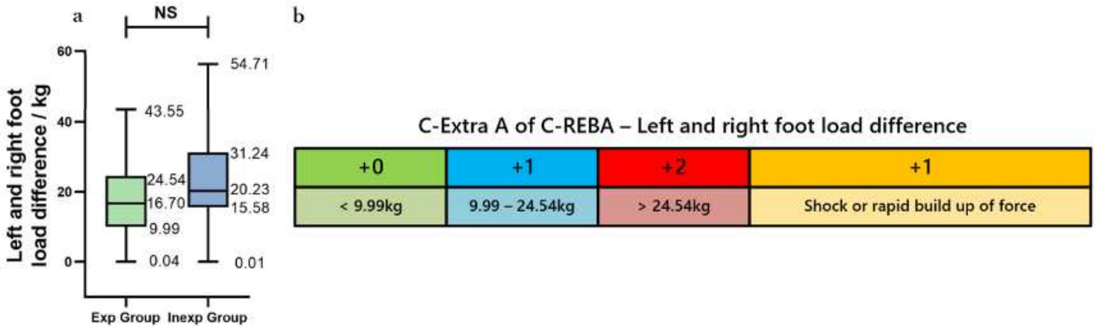

Figure 3.7 Left and right foot load difference range and the C-Extra A score.

We defined the Wii Balance Board plane as the horizontal plane, and the image COG trajectory plane as the vertical plane. To realize the automatic evaluation of C-REBA at the pixel level, we firstly converted the difference in load between the left and right feet (Figure 3.7b) into the corresponding COP trajectory score range A-B-C-D (horizontal plane) in the Wii Balance Board (Figure 3.8a). COG could be approximated by Wii Balance Board COP measurements in the statically equivalent situation [26]. In the setting of score range, we assumed a static equivalence situation. Then mapped the COP trajectory score range (horizontal plane) into COG trajectory score range (vertical plane) approximately according to the ratio conversion between the COG x axis and the COP x axis (Figure 3.8b, Figure 3.5a). The distance between the foot ankles was defined as L, and it was divided into five ranges according to the difference in load in Figure 3.8b (0-A and D-1:>24.54kg; A-B and C-D:9.99-24.54kg; B-C: <0.99kg). The range of each part in the pixel level were calculated in percentage to L.

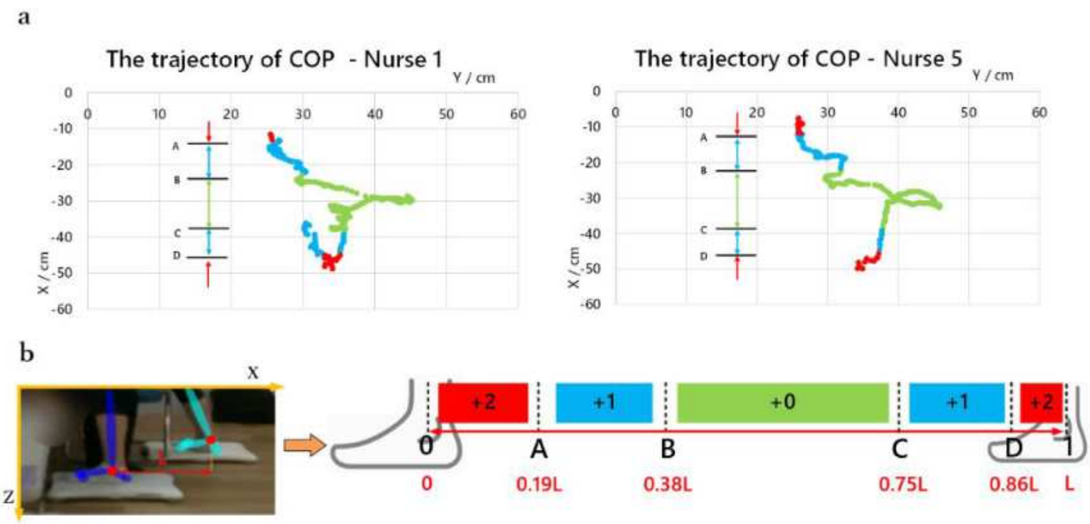

Figure 3.8 The load difference range between the left and right feet matched to the distance range.

3.5.2 C-Extra C

We collected data on the loading time in caregiving work and found significant difference ($p<0.001$) of load bearing time between the two groups. The median load bearing time of the Inexp Group was even 1.65 times higher than the Exp Group (Figure 3.9a). Therefore, for Extra C score in C-REBA, we set the evaluation standard for loading time at 3.87 seconds, which was 1.5 times the median loading time of the Exp Group. Similarly, based on the fact that the less the COG height changes, the less work the waist does and the easier to maintain the power position, we determined the difference in the COG changes from the initial stage to the highest point of COG trajectory. We found that the median COG height change of the Inexp Group was significantly larger than that of the Exp Group (Figure 3.9b, $p<0.001$). Further, we set the evaluation standard for Extra C score in C-REBA at 7.54 cm, which was 2 times of the 75% quantile COG height of the Exp Group. Therefore, the adapted C-Extra C score is redefined (Table 3.2).

Table 3.2 The C-Extra C scoring rule of C-REBA.

Score	Rule
+1	Large body tipping due to COG instability
+1	Load-bearing time over 3.87s
+1	The COG height difference between the stage1 and the highest point exceeds 7.54 cm

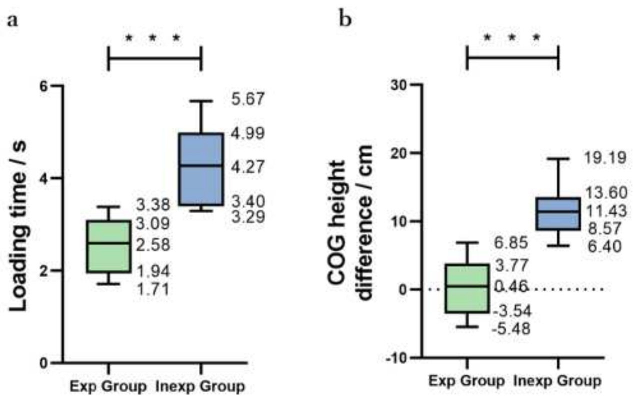

Figure 3.9 The loading bearing time and COG height difference.

3.6 Comparison of REBA and C-REBA

3.6.1 The difference of REBA and C-REBA scoring results

When Exp Group and Inexp Group caregivers were evaluated by our C-REBA method, there were significant differences between the Exp and Inexp Groups at each individual stage (Stage 1: $p<0.01$; Stage 2: $p<0.001$; Stage 3: $p<0.001$; Stage 4: $p<0.001$; Stage 5: $p<0.05$). This indicates that the C-REBA method could be well-differentiated in each stage of caregiving task (Figure 3.10), also it's suitable for providing guidance and reference for inexperienced caregivers. More specifically, the mean C-REBA scores for the Exp Group in stages 1-5 were all below eight points, at a medium risk level. For the Inexp Group, on the contrary, the mean C-REBA scores were above eight points except stages 1 and 5. It indicated that the caregiving posture in stages 2, 3, and 4 needed to be corrected to reduce musculoskeletal discomfort and injury risks. It also suggests that stages 2, 3, and 4 might be the most meaningful caregiving posture intervention stages.

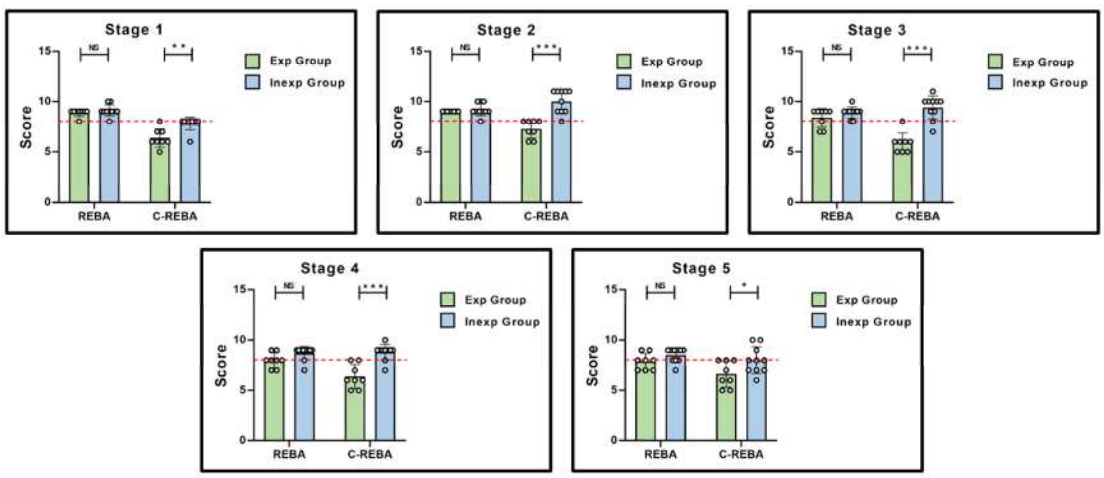

Figure 3.10 The difference of REBA and C-REBA scoring results.

3.6.2 Ablation experiment result

To verify the improvement of C-Extra A and C-Extra C in C-REBA, we set up ablation experiments to verify the REBA scoring rules, REBA with C-Extra A scoring rules, and C-REBA (REBA with C-Extra A and C-Extra C) scoring rules. The scoring results of REBA and REBA with C-Extra A were significantly different (Table 3.3, all groups and all stages $p1<0.05$). The evaluation rules for C-Extra C focused on the caregiving power position and the load-bearing time. For the Exp Group, they were familiar with the caregiving power position, and the load-bearing time was relatively short. Therefore, C-Extra C rules had little effect on the Exp Group. However, for the Inexp Group, there were significant differences in stages 2 ($p<0.001$), 3 ($p<0.001$), and 4 ($p=0.035$) in the scoring results of REBA with C-Extra A and C-REBA, indicating that the Inexp Group had a greater change in the COG and a longer load-bearing time in these stages. Thus, urgent intervention was needed in these stages. In addition, we calculated the proportion of high-risk (scores above eight points) frames in the caregiving process to assess the risk adaptability of these methods.

Table 3.3 The influence of C-Extra A and C-Extra C on the REBA results.

	Stage	REBA	REBA with C-Extra A	C-REBA	p1	p2	p3
Exp Group (N=8)	Stage1	8.88±0.35	6.38±0.92	6.38±0.92	P<0.001	P<0.001	1.0
	Stage2	9.00±0	7.25±0.89	7.25±0.89	P<0.001	P<0.001	1.0
	Stage3	8.38±0.92	6.13±0.83	5.88±0.99	P<0.001	P<0.001	0.592
	Stage4	8.00±0.76	6.63±1.06	6.38±1.19	0.01	0.005	0.663
	Stage5	7.88±0.83	6.63±1.30	6.63±1.30	0.037	0.037	1.0
Inexp Group (N=10)	Stage1	9.10±0.57	7.40±0.52	7.70±0.67	P<0.001	P<0.001	0.277
	Stage2	9.20±0.63	8.00±0.82	10.00±1.15	0.002	0.096	P<0.001
	Stage3	8.90±0.57	8.20±0.42	9.60±0.84	0.006	0.061	P<0.001
	Stage4	8.70±0.67	8.10±0.57	8.80±0.79	0.044	0.779	0.035
	Stage5	9.30±0.67	7.30±0.95	8.00±1.33	P<0.001	0.022	0.192

Note: p1 represents the p value of REBA and REBA with C-Extra A, p2 represents the p value of REBA and C-REBA, and p3 represents the p value of REBA with C-Extra A and C-REBA.

3.6.3 The proportion of high-risk frames in caregiving work

There was a significant difference (Table 3.4, all groups and all stages $p1<0.05$) in the results of the proportion of frames with high-risk (scores above 8) between the REBA and C-REBA methods. For the Inexp Group, the proportion of frames with high-risk in stages 2, 3, and 4 was high, indicating that the caregiving postures needed to be corrected in these stages. These results suggested that C-REBA avoided the problem of overassessment of caregiver posture. Also, the C-REBA method evaluated the COG changes in the caregiving power position and load bearing time, and provided reliable posture risk feedback for the caregivers.

Table 3.4 The proportion of high-risk frames in caregiving work.

	Stage	REBA	C-REBA	P
Exp Group (N=8)	Stage1	92%±8%	20%±7%	P<0.001
	Stage2	91%±6%	18%±4%	P<0.001
	Stage3	91%±5%	6%±4%	P<0.001
	Stage4	93%±7%	6%±3%	P<0.001
	Stage5	92%±5%	13%±4%	P<0.001
Inexp Group (N=10)	Stage1	93%±8%	50%±18%	P<0.001
	Stage2	94%±6%	82%±6%	0.001
	Stage3	94%±6%	81%±13%	0.019
	Stage4	97%±2%	74%±13%	P<0.001
	Stage5	92%±8%	46%±14%	P<0.001

3.7 Discussion

Although the REBA method is widely used in the nursing industry, its risk assessment criteria need to be adjusted according to different scenarios. Raman et al. considered REBA to be an easy-to-apply and fairly reliable tool for alerting clinical dental nurses to ergonomic risks [28]. Law et al. used the existing REBA assessment system to assess the risk of musculoskeletal disorders in transferring patients [29]. However, our study found that the REBA method overestimated the artificial caregiving scenarios and could not distinguish the experienced and inexperienced caregivers. As Yazdanirad et al. found in the risk-adaptation test, the REBA method overestimated the risk level of musculoskeletal disorders [17], which was consistent with our findings. Hence, we explored the key factors involved in caregiving tasks and made adjustments to the additional scoring rules of the REBA method. Our C-REBA method offers caregivers a more accurate and targeted evaluation of the risk levels associated with caregiving postures.

The original Extra A scoring rule is related to the load on the body, ignoring the injury to the body caused by the asymmetrical load. Asymmetric loads tend to cause muscle injury on one side of the body, making great impact. We found notable differences in caregiving power position and COG change trajectory between experienced and inexperienced caregivers, and then reconstructed the scoring rules of Extra A from the perspective of COG trajectory. The asymmetric load could be directly reflected in the position change of the COG between the feet. Keeping the COG position in the middle of the feet largely avoided the impact of the asymmetric load. It was also closely related to the caregiving power position. We converted asymmetrical loads into the COG position trajectory between the feet to monitor the trend of asymmetrical loads and incorporated it into the evaluation rule of C-Extra A. It ensured that C-REBA realized comprehensive evaluation of caregiving tasks from the level of asymmetrical load.

The original Extra C rule focused on maintaining fixed positions and repeating small ranges action. There were differences in load-bearing time and range of caregiving movements between Inexp Group and Exp Group. The load-bearing time was directly proportional to the risk of musculoskeletal discomfort and injury. The greater the change in COG height, the more work the waist did, which was related to the maintenance of power position [30-31]. The effects of load bearing time and COG height changes were ignored by the original REBA method. We took the Exp group as the standard of load bearing time and COG height variation, and integrated it into the evaluation rules of the Extra C rules. The evaluation results of C-REBA indicated that the role of C-Extra C was to distinguish the Exp Group from the Inexp Group. Our research also pointed out that stages 2, 3, 4 to be the most meaningful postural intervention phases for the inexperienced caregivers. Therefore, we integrated the load-bearing time and COG height changes factors into the C-Extra C rules.

3.8 Conclusion

In this chapter, we identified the incomplete applicability of the REBA rules in caregiving scenarios. By investigating the differences between the Exp and Inexp Groups, we preliminarily explored parameter adjustments for the REBA rules and proposed the C-REBA method. The C-REBA method incorporated crucial factors, including asymmetrical load assessment, changes in COG height, and duration of load-bearing. As a result, the proposed C-REBA effectively differentiated the experienced and inexperienced caregivers, offering posture assessment references and guidance for inexperienced caregivers. As the development of this method, its application could be extended to other caregiving movements by adjusting the parameters with the collected data.

Reference

[1] Hwang, J., Kuppam, V.A., Chodraju, S.S.R., Chen, J. & Kim, J.H. (2019). Commercially Available Friction-Reducing Patient-Transfer Devices Reduce Biomechanical Stresses on Caregivers' Upper Extremities and Low Back. Human Factors: The Journal of the Human Factors and Ergonomics Society, 61(7), pp.1125–1140. DOI: 10.1177/0018720819827208.

[2] Kim, W., Sung, J., Saakes, D., Huang, C., & Xiong, S. (2021). Ergonomic postural assessment using a new open-source human pose estimation technology (OpenPose). International Journal of Industrial Ergonomics, 84, 103164. DOI: 10.1016/j.ergon.2021.103164.

[3] Clark, R.A., Bryant, A.L., Pua, Y., McCrory, P., Bennell, K. & Hunt, M. (2010). Validity and reliability of the Nintendo Wii Balance Board for assessment of standing balance. Gait & posture, 31(3), pp.307–10. DOI: 10.1016/j.gaitpost.2009.11.012.

[4] Tanaka, R., Ishii, Y., Yamasaki, T. & Kawanishi, H. (2019). Measurement of the total body center of gravity during sit-to-stand motion using a markerless motion capture system. Medical Engineering & Physics, 66, pp.91–95. DOI: 10.1016/j.medengphy.2018.12.020.

[5] Karhu O, Kansi P, Kuorinka I. (1977). Correcting working postures in industry: A practical method for analysis. Applied Ergonomics, 8(4), pp.199–201. DOI:10.1016/0003-6870(77)90164-8.

[6] McAtamney, L. & Nigel Corlett, E. (1993). RULA: a survey method for the investigation of work-related upper limb disorders. Applied Ergonomics, 24(2), pp.91–99. DOI: 10.1016/0003-6870(93)90080-s.

[7] Hignett, S. & McAtamney, L. (2000). Rapid Entire Body Assessment (REBA). Applied Ergonomics, 31(2), pp.201–205. DOI: 10.1016/s0003-6870(99)00039-3.

[8] Andreas G W J, Johanssons E. Observational methods for assessing ergonomic risks for work-related musculoskeletal disorders. A scoping review[J]. Revista Ciencias de la Salud, 2018, 16(SPE): 8-38.

[9] Schwartz, A. H., Albin, T. J., & Gerberich, S. G. (2019). Intra-rater and inter-rater reliability of the rapid entire body assessment (REBA) tool. International Journal of Industrial Ergonomics, 71, 111-116. DOI: 10.1016/j.ergon.2019.02.010.

[10] Enez, K., & Nalbantoğlu, S. S. (2019). Comparison of ergonomic risk assessment outputs from OWAS and REBA in forestry timber harvesting. International Journal of Industrial Ergonomics, 70, 51-57. DOI: 10.1016/j.ergon.2019.01.009.

[11] Norhidayah, M. S., Mohamed, N. M. Z. N., Mansor, M. A., & Ismail, A. R. (2016). A study of postural loading in Malaysian mining industry using rapid entire body assessment. In MATEC web of conferences (Vol. 74, p. 00014). EDP Sciences. DOI: 10.1051/matecconf/20167400014.

[12] Jahanimoghadam, F., Horri, A., Hasheminejad, N., Nejad, N. H., & Baneshi, M. R. (2018). Ergonomic evaluation of dental professionals as determined by rapid entire body assessment method in 2014. Journal of

Dentistry, 19(2), 155. PMCID: PMC5960736.

[13] Iridiastadi, H., Vani, T. & Yamin, P.A.R. (2020). Biomechanical Evaluation of a Patient-Handling Technology Prototype. International Journal of Technology (IJTech), 11(1), pp.180-189. DOI: 10.14716/ijtech.v11i1.1332.

[14] Davison, C., Cotrim, T.P. & Gonçalves, S. (2021). Ergonomic assessment of musculoskeletal risk among a sample of Portuguese emergency medical technicians. International Journal of Industrial Ergonomics, 82, p.103077. DOI: 10.1016/j.ergon.2020.103077.

[15] Yazdanirad, S., Pourtaghi, G., Raei, M. & Ghasemi, M. (2022). Developing and validating the personal risk assessment of musculoskeletal disorders (PRAMUD) tool among workers of a steel foundry. International Journal of Industrial Ergonomics, 88, p.103276. DOI: 10.1016/j.ergon.2022.103276.

[16] Sabino L, Melo R B, Carvalho F. Ergonomic work analysis at plant nurseries of a portuguese municipality[C]//Advances in Physical Ergonomics & Human Factors: Proceedings of the AHFE 2018 International Conference on Physical Ergonomics & Human Factors, July 21-25, 2018, Loews Sapphire Falls Resort at Universal Studios, Orlando, Florida, USA 9. Springer International Publishing, 2019: 273-285.

[17] Yazdanirad, S., Pourtaghi, G., Raei, M. et al. Development of modified rapid entire body assessment (MOREBA) method for predicting the risk of musculoskeletal disorders in the workplaces. BMC Musculoskelet Disord 23, 82 (2022). https://doi.org/10.1186/s12891-022-05011-7.

[18] Tucker, C.A., Ramirez, J., Krebs, D.E. & Riley, P.O. (1998). Center of gravity dynamic stability in normal and vestibulopathic gait. Gait & Posture, 8(2), pp.117–123. DOI: 10.1016/s0966-6362(98)00030-7.

[19] Chou, L.-S., Kaufman, K.R., Hahn, M.E. & Brey, R.H. (2003). Medio-lateral motion of the center of mass during obstacle crossing distinguishes elderly individuals with imbalance. Gait & Posture, 18(3), pp.125–133. DOI: 10.1016/s0966-6362(02)00067-x.

[20] Gassett, R. S., Hearne, B., & Keelan, B. (1996). Ergonomics and body mechanics in the work place. Orthopedic Clinics of North America, 27(4), 861-879. DOI: 10.1016/S0030-5898(20)32129-5.

[21] Rosker, J., Markovic, G. & Sarabon, N. (2011). Effects of vertical center of mass redistribution on body sway parameters during quiet standing. Gait & Posture, 33(3), pp.452–456. DOI: 10.1016/j.gaitpost.2010.12.023.

[22] Wu, G. & MacLeod, M. (2001). The control of body orientation and center of mass location under asymmetrical loading. Gait & Posture, 13(2), pp.95–101. DOI: 10.1016/s0966-6362(00)00102-8.

[23] Ferland, P. M., & Comtois, A. S. (2019). Classic powerlifting performance: A systematic review. The Journal of Strength & Conditioning Research, 33, S194-S201. DOI: 10.1519/JSC.0000000000003099.

[24] Guo, L. & Xiong, S. (2020). Effects of working posture, lifting load, and standing surface on postural instability during simulated lifting tasks in construction. Ergonomics, 63(12), pp.1571–1583. DOI: 10.1080/00140139.2020.1807614.

[25] Ackland T R, Lohman T G, Sundgot-Borgen J, et al. Current status of body composition assessment in sport: review and position statement on behalf of the ad hoc research working group on body composition health and

performance, under the auspices of the IOC Medical Commission[J]. Sports medicine, 2012, 42: 227-249.

[26] González, A., Hayashibe, M., & Fraisse, P. (2012). Estimation of the center of mass with Kinect and Wii balance board. In 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems (pp. 1023-1028). IEEE. DOI: 10.1109/IROS.2012.6385665.

[27] Cotton, S., Vanoncini, M., Fraisse, P., Ramdani, N., Demircan, E., Murray, A. P., & Keller, T. (2011). Estimation of the centre of mass from motion capture and force plate recordings: a study on the elderly. Applied Bionics and Biomechanics, 8(1), 67-84. DOI: 10.3233/ABB-2011-0006.

[28] Raman, V., Ramlogan, S., Sweet, J. & Sweet, D. (2020). Application of the Rapid Entire Body Assessment (REBA) in assessing chairside ergonomic risk of dental students. British Dental Journal, pp.1–6. DOI: 10.1038/s41415-020-1855-5.

[29] Law, M.J.J., Ridzwan, M.I.Z., Mohd Ripin, Z., Abd Hamid, I.J., Law, K.S., Karunagaran, J. & Cajee, Y. (2022). REBA assessment of patient transfer work using sliding board and Motorized Patient Transfer Device. International Journal of Industrial Ergonomics, 90, p.103322. DOI: 10.1016/j.ergon.2022.103322.

[30] Hecker, K. A., Carlson, L. A., & Lawrence, M. A. (2019). Effects of the safety squat bar on trunk and lower-body mechanics during a back squat. The Journal of Strength & Conditioning Research, 33, S45-S51. DOI: 10.1519/JSC.0000000000002912.

[31] Falch, H. N., Kristiansen, E., & van den Tillaar, R. (2023). A Biomechanical Comparison between Squatbar® and Olympic Barbell. Biomechanics, 3(2), 258-266. DOI: 10.3390/biomechanics3020022.

Chapter 4

Improved ST-GCN for C-REBA assessment

4.1 Overview

This chapter presents an innovative posture assessment approach that combines the optimized Spatial Temporal Graph Convolutional Network (ST-GCN) framework with the C-REBA method. The ST-GCN framework is utilized to extract temporal features from postures, allowing for the inference of posture load duration and action frequency features based on behavioral characteristics and time series analysis. Moreover, this method introduces a dual-layer collaborative neural network, where the Faster R-CNN model is employed to extract asymmetric load features in the task, while the Long Short-Term Memory (LSTM) network captures variations in the center of gravity of the posture. By leveraging confidence maps, the two neural networks synergistically fuse these features to predict scores for center of gravity variation and asymmetric load. The C-REBA scores encompass joint angle scores as well as additional scores, distinguishing it from existing posture detection methods that solely compute joint angle scores. The proposed method employs a deep neural network framework that considers both behavioral features and additional features during training, enabling automatic prediction of these additional scores and facilitating a comprehensive and automated assessment of C-REBA scores. To validate the effectiveness of the method, verification experiments were conducted in diverse scenarios involving additional scores such as load duration, action frequency, asymmetric load, and center of gravity variation. The experimental results demonstrate the reliability and feasibility of our approach in accurately assessing postures in these scenarios.

In summary, this chapter introduces an innovative and sophisticated approach that merges the ST-GCN framework with C-REBA for posture assessment. By harnessing the power of deep neural networks and incorporating behavioral features along with additional factors, this method enables a comprehensive and automated evaluation of C-REBA scores. Experimental findings provide compelling evidence of the method's robustness and viability in diverse scenarios encompassing various additional scores, including load duration, action frequency, asymmetric load, and center of gravity variation.

4.2 Related work

Musculoskeletal disorders pose a significant threat to the healthcare industry, primarily attributed to the cumulative joint and skeletal loads resulting from repetitive and improper postures

[1-3]. In response, ergonomics experts have proposed various work posture assessment methods, among which the Rapid Entire Body Assessment (REBA) method has gained prominence [4-6]. Initially, these methods relied on on-site observations by ergonomics experts, who assigned scores based on their subjective assessments. However, such observational approaches not only demand substantial time for manual analysis but also introduce significant variability due to subjective inputs from assessors [7-8]. In fact, a study by researchers [9] revealed a correlation coefficient of less than 0.5 among the results obtained from four trained RULA assessors. To address this issue, researchers [10] have advocated minimizing the involvement of multiple assessors in posture assessments to enhance the reliability of the evaluation outcomes.

To tackle these challenges, researchers have proposed semi-automatic posture risk assessment methods that utilize motion capture inputs, including optical markers and wearable inertial sensors [11-13]. These methods involve sensor-based labeling of joint positions and calculating joint angles using spatial vectors, enabling semi-automatic scoring of posture risks based on the Rapid Entire Body Assessment (REBA) method. While these approaches demonstrate high accuracy in capturing human motion, they are accompanied by high equipment costs and require technical expertise for data collection and processing. Consequently, researchers have explored low-cost motion capture techniques employing depth cameras like Kinect v1 [14-15]. This method automatically detects 25 major joint keypoints from depth images and aligns them with the scoring rules of REBA by computing the angles between the keypoints, thereby obtaining posture assessment results. This approach eliminates the need for laborious labeling and calibration. However, it is important to note that this method exhibits lower accuracy and significant deviations in joint angle calculations.

In recent years, remarkable advancements have been made in computer vision research, particularly in the field of human pose estimation. Researchers have proposed a supervised machine learning-based method for both 2D and 3D human pose estimation using a single camera [16-17]. The 2D pose estimation enables the recognition of major keypoints of the human body from one or multiple RGB images, while the 3D human pose estimation involves multi-view reconstruction and external camera calibration. Subsequently, the angle information is computed using spatial vectors to facilitate semi-automatic assessment based on the Rapid Entire Body Assessment (REBA) method. Among the existing methodologies, the OpenPose open-source library has emerged as the most effective approach [18-19]. In comparison to the human pose recognition results provided by Kinect v2, OpenPose offers a larger number of facial and foot joints and exhibits enhanced tracking capabilities under occlusion or non-frontal tracking conditions. However, while the scoring rules of REBA encompass additional scoring options beyond joint angle scoring, current methods solely obtain human pose features for joint angle scoring. Consequently, manual observation and parameter input are still required for evaluating these additional scoring factors. To achieve a fully automatic assessment of REBA by incorporating the additional scoring as automatic evaluation parameters, we propose a deep neural network framework based on the Spatial Temporal Graph Convolutional Network (ST-GCN). This framework can effectively train the external features of the additional scoring factors, and by integrating the predicted values of the model, a fully automated assessment of REBA can be achieved.

4.3 ST-GCN for C-REBA assessment

The OpenPose framework performs recognition of skeleton features, which consists of 25 nodes representing specific joints of the human body. These joint positions can be concatenated to form a skeletal diagram, as depicted in Figure 3.4. The resulting output from OpenPose is stored in Json files, containing the pixel coordinates of the 25 joints. For the evaluation of human body posture using the C-REBA method, ten joint angles are required, including those of the neck, trunk, legs, upper arms, lower arms, and wrists on both sides. To automatically compute these angle features, vectors parallel or perpendicular to the coronal, sagittal, and transverse body planes are derived based on the midpoint of the shoulder joint and the left/right hip joint. Subsequently, these vectors are utilized to project other body segment vectors and calculate the desired joint angles. Detailed explanations of the angle calculation for OpenPose can be found in references [20-22], and for our research, we have adopted these referenced methods for the calculation of OpenPose joint angles.

4.3.1 Load bearing time and action frequency

We present a novel approach for predicting postural risks in human posture, termed C-REBA, based on the Spatial Temporal Graph Convolutional Network (ST-GCN). Our network is constructed on a sequence of skeletal maps, enabling the extraction of dynamic skeletal features encompassing spatial, temporal, and external activity factors, which are integrated into the REBA algorithm for postural risk prediction. Leveraging spatial features, we generate a skeleton graph consisting of 25 nodes and calculate the joint angle scores using the OpenPose joint angle calculation method. Additional factors in the C-REBA rules, such as carrying time, center of gravity change, asymmetric loading, and frequency of action, form supplementary points. The temporal convolutional layer of ST-GCN is employed to capture motion patterns between skeleton maps, facilitating the evaluation of load duration by exploiting temporal convolutional features specific to behavioral characteristics. Action frequency features are derived through vector calculations between behavioral and temporal features. To address other additional features, we propose a two-layer collaborative neural network model for their training. As depicted in Figure 4.1, the spatial feature layer of ST-GCN predicts 25 skeleton points, generating a complete skeleton. The spatiotemporal feature layer arranges all skeletons in chronological order, learning the motion patterns between them, and assigns the highest-weighted action feature to each complete skeleton. Figure 4.2 illustrates a comprehensive nursing action, with skeletons at different stages corresponding to independent action features. Action frequency is obtained by calculating the correlation between action features and time features.

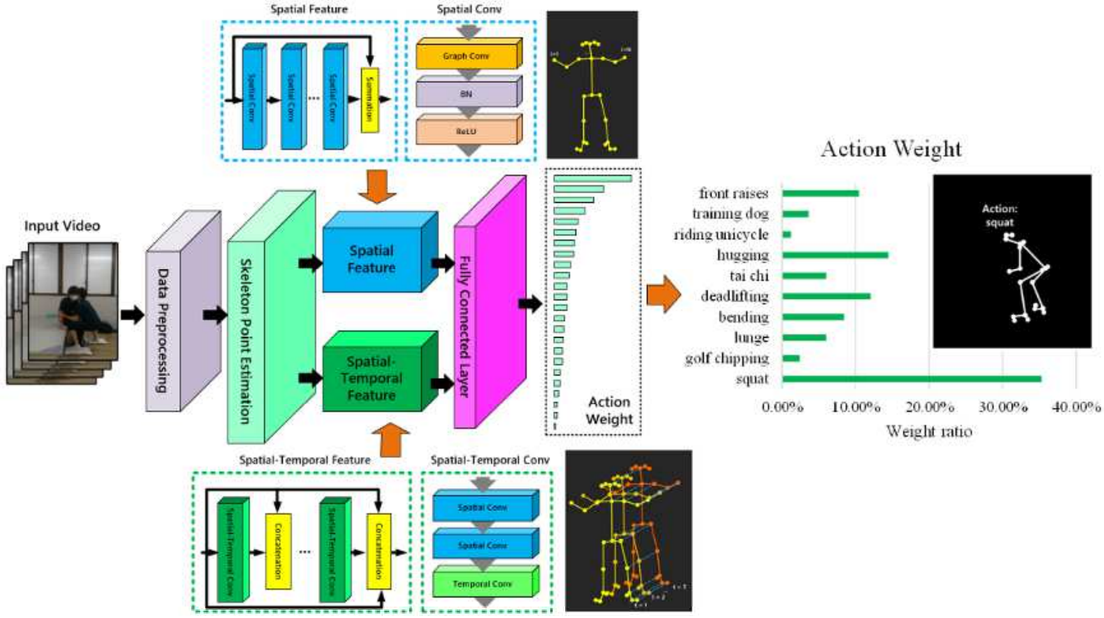

Figure 4.1. ST-GCN for load bearing time and action frequency prediction.

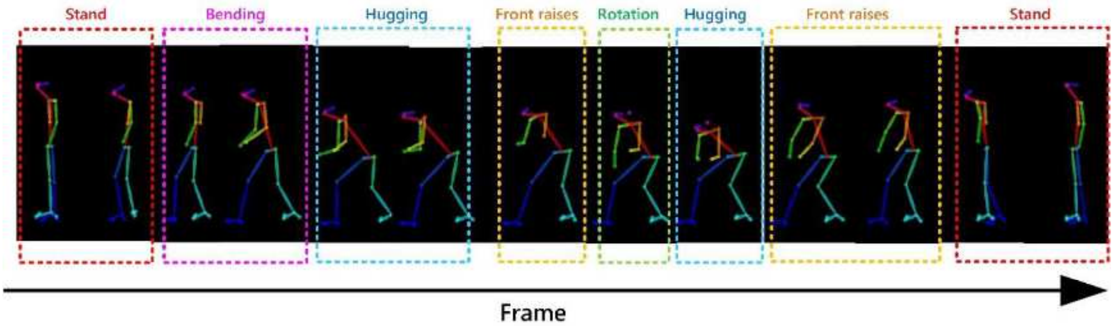

Figure 4.2. Correspondence between skeleton and action features during caregiving task.

4.3.2 Asymmetric load and change of COG

The presence of asymmetric load, where one foot bears a greater burden than the other, can disrupt the equilibrium of muscle forces in the body, leading to uneven stress and pressure on the joints. This imbalance has the potential to contribute to joint conditions such as arthritis and synovitis. Moreover, asymmetric load can lead to postural deviations, unstable gait, and abnormal walking patterns, which impose additional strain and load on the muscles and bones [23]. In order to capture the features associated with asymmetric load, we propose a novel approach that utilizes image analysis to compute the discrepancy in load distribution. Specifically, we convert the range of load differences into a range of distances between the left and right foot, as depicted in Figure 4.3.

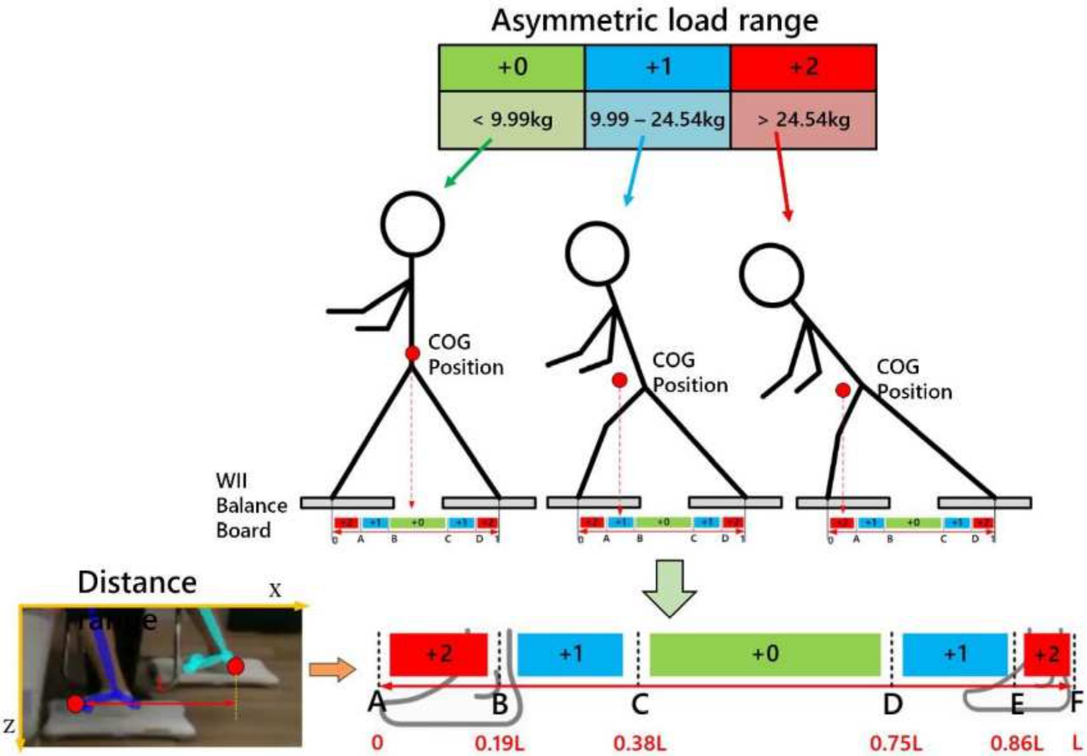

Figure 4.3. A method of converting the load difference range into the distance range.

As shown in Figure 3.8a, COP1 and COP2 were measured by the two Wii Balance Boards, and the fused COP was calculated by COP1 and COP2. Assumed that the ground reaction forces were F_1 and F_2 corresponding to COP1 and COP2, F_c was corresponding to fused COP, the load difference force between the left and right feet was ΔF, and the distance between the feet was L. Then the location in x-axis of F_c could be calculated as follows.

$$F_c = F_1 + F_2 \tag{4.1}$$

$$\Delta F = F_2 - F_1 = \frac{2X_c - (X_1 + X_2)}{X_2 - X_1} F_c \tag{4.2}$$

$$\frac{X_c}{L} = \frac{\Delta F (X_2 - X_1)}{2F_c L} + \frac{(X_1 + X_2)}{2L} \tag{4.3}$$

Calculating X_c along the range of ΔF by Eq.(4.2) and taking its average, then the load difference score range could be converted into the distance score range of COP on the x-axis which was given by $\Delta F < 9.99$ kg corresponding to $0.38 < \frac{X_c}{L} < 0.75$, $9.99 < \Delta F < 24.54$ kg corresponding to $0.19 < \frac{X_c}{L} < 0.38$ or $0.75 < \frac{X_c}{L} < 0.86$, and $\Delta F > 24.54$ kg corresponding to $\frac{X_c}{L} < 0.19$ or $\frac{X_c}{L} > 0.86$. Figure 4.4b showed the load difference value marked in (ΔF<9.99kg, green; 9.99-24.54kg, blue; >24.54kg, red) on each point corresponding to COP.

Considering the quasi-static state, COG trajectory calculated by the OpenPose algorithm is approximated to the COP trajectory obtained by Wii Balance Board [24], the center coordinate of COG in x-axis (Figure 4.4c) could be assumed same as X_c of COP (Figure 4.4a). By doing so, instead of using Wii Board, X_c could be calculated from the camera image. Therefore, the scores in Figure 4.4c could be automatically determined by calculating COG trajectory in x-coordinate.

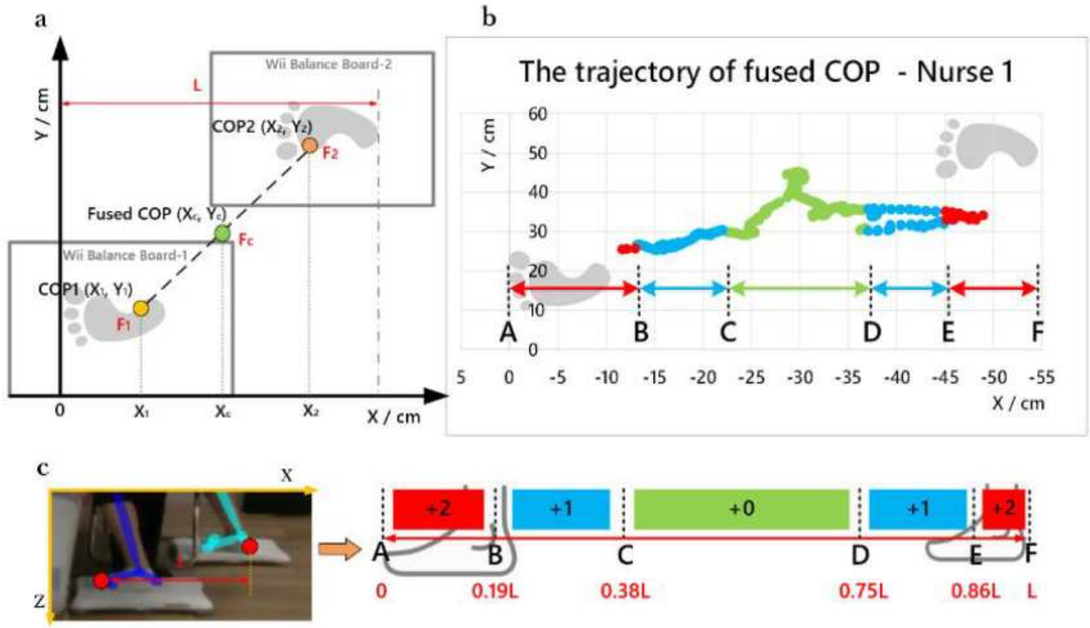

Figure 4.4 The load difference range between the left and right feet matched to the distance range.

Once the features of asymmetric load have been acquired, they are linked to the corresponding Json files within the frames, which constitute the features to be trained by the neural network. Likewise, the feature denoting the variation in the center of gravity is computed utilizing the methodologies elucidated in the preceding section and stored within the respective Json files as trainable features. In order to generate additional predictive scores for the asymmetric load and center of gravity variation features, we establish a two-layer collaborative neural network model, as illustrated in Figure 4.5.

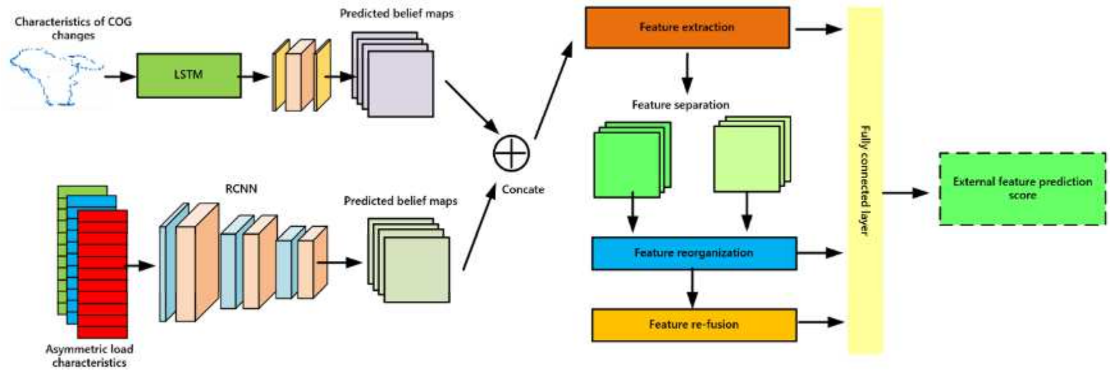

Figure 4.5 Two-layer collaborative neural network for extra feature.

1. For the extraction of center of gravity variation features, we utilize Long Short-Term Memory (LSTM) networks as the foundational network. To classify the center of gravity variation in the given task, clustering methods are employed, enabling the mapping of variations to different levels of posture stability. The features corresponding to different stability levels are stored in respective clusters, where each cluster serves as a storage unit. Through the transformation of the feature sequence, a predictive confidence map is generated, facilitating the analysis and prediction of center of gravity variations.

2. Feature extraction pertaining to asymmetric load is conducted using Faster RCNN as the underlying network. In accordance with the scoring rules of C-REBA, the features associated with asymmetric load are categorized into three levels, and each sample is assigned the appropriate level label. To ensure the coherence between the asymmetric load features and the computed values and balance board test values, we treat the computed values and test values as distinct input variables for feature fusion. Subsequently, hierarchical feature extraction is employed, taking into account the level of asymmetric load, thereby generating distinct confidence maps for subsequent feature fusion processes.

3. The process of feature fusion and prediction scoring involves the concatenation of confidence maps generated by the final two layers of the two-layer collaborative neural network, while adhering to unified constraints. These combined features are subsequently fed into the feature fusion layer and feature separation layer in a sequential manner, enabling the recombination of the extracted features. Ultimately, a fully connected layer is employed to ascertain the fusion prediction scoring for the features associated with asymmetric load and center of gravity variation.

By leveraging the two-layer collaborative neural network model, we are able to adeptly extract and amalgamate features pertaining to asymmetric load and center of gravity variation, thereby facilitating the prediction of corresponding supplementary scores. This approach enables the automated acquisition of C-REBA's additional feature scores across diverse scenarios, effectively circumventing the potential subjective inconsistencies associated with human judgment. Notably, the two-layer collaborative neural network layer is seamlessly integrated into the comprehensive framework of ST-GCN in a modular fashion, as visually depicted in Figure 4.6.

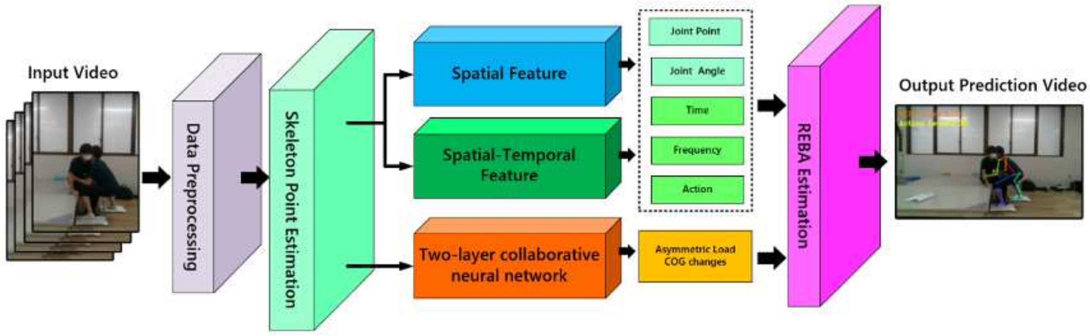

Figure 4.6 Improved ST-GCN incorporating additional feature extraction networks.

4.3.3 Dataset and model training

Given the nursing-oriented focus of our method, relying solely on publicly available datasets for training would yield results that are overly generalized. To address this limitation, we conducted patient transfer experiments with the participation of twenty volunteers, during which we recorded experimental videos using RGB cameras (Figure 4.7). To mitigate data redundancy, we extracted image frames at a rate of one frame every 10 frames from each experimental video. We also added some data records of daily life postures to expand the diversity of posture features. The performance of the neural network model heavily relies on the size of the dataset used for training. Consequently, to compensate for the small sample size of the original data, we employed data augmentation techniques such as flipping, rotation, scaling, cropping, and translating to expand the batch size of the dataset. Additionally, in order to tackle problems arising from overfitting and object occlusion during model training, we implemented a random key point hiding method to enhance the algorithm's robustness. Leveraging the sensitivity of the convolutional layer to negative values, we assigned negative coordinates to the missing joint points, capitalizing on the property of the ReLU function to filter out negative values. This approach effectively distinguishes the occluded parts from the rest of the skeleton. By employing this data augmentation method, we ensured the preservation of invariance within the original dataset while simultaneously augmenting the data volume of the bone joint points. Ultimately, we obtained a total of 3794 video clips for training, with each clip undergoing pose estimation to generate a 25-node skeleton. Corresponding Json files were generated for each data sample to facilitate model training. The training parameters and equipment settings employed in the model are presented in Table 4.1 and Table 4.2, respectively.

Figure 4.7 Dataset collection experiment.

Table 4.1 Training parameter setting.

Parameters	Values
Epoch	10000
Regularization	0.001
Dropout rate	0.5
Initial learning rate	0.05
Batch size	64
Weight attenuation coefficient	0.005
Momentum	0.9

Table 4.2 Software and hardware setting.

Framework	PyTorch
Programming language version	Python 3.7
Platform	PyCharm Community Edition 2020.3.2
Terminal device	Intel Xeon CPU E5-1560 v4 @ 3.60 GHz and two Titan V workstations. AMD Ryzen 7 3800X 8-Core Processor x 16 @3.90GHz, 128 GB RAM, GPU GeForce GTX1660Ti

4.4 Extra score application scenarios

In order to comprehensively evaluate the efficacy of the C-REBA automated assessment method utilizing ST-GCN, we conducted a validation study incorporating additional scoring features, namely load duration, action frequency, asymmetric load, and center of gravity variation. These features contribute to a more comprehensive suite of evaluation metrics, enabling a thorough analysis of the automated assessment method across various aspects. By comparing the ST-GCN-based C-REBA method with the semi-automated assessment method based on OpenPose, we can gain insights into the impact of the additional scoring features in different application scenarios. The OpenPose method heavily relies on pose detection environments and is subject to certain limitations in terms of accuracy and robustness. The comparison with the OpenPose-based method allows us to assess the advantages and performance of the ST-GCN-based C-REBA method in different features and application scenarios.

4.4.1 Load bearing time and action frequency

In order to comprehensively assess the automated scoring of C-REBA, we incorporated the duration of load-bearing and action frequency as crucial features. The duration of load-bearing provides insights into the length of time an individual endures specific actions, which is particularly relevant for evaluating healthcare professionals involved in prolonged, repetitive movements. Prolonged load-bearing durations can contribute to increased muscle fatigue and discomfort. Similarly, action frequency plays a vital role in assessing fatigue and workload by quantifying the number of repetitions or frequency of actions. To evaluate the practical application of load-bearing duration and action frequency in automated C-REBA scoring, we conducted a simulation involving a volunteer performing patient transfers, a common task in healthcare settings. The volunteer had no physical limitations that could impede their ability to independently carry out the task, and video clips of their postures were recorded using an Intel RealSense Depth Camera D435. The collected data underwent preprocessing and was input into the ST-GCN model to derive behavioral weighting features throughout the task. By mapping the behavioral features with the corresponding time features, we determined the duration and frequency of different behaviors. The top 5 behavioral weights were selected for visualization, as depicted in Figure 4.8. Through these experiments and analyses, we gained insights into the practical effectiveness of load-bearing duration and action frequency in the automated scoring of C-REBA, as well as a deeper understanding of their impact across diverse application scenarios.

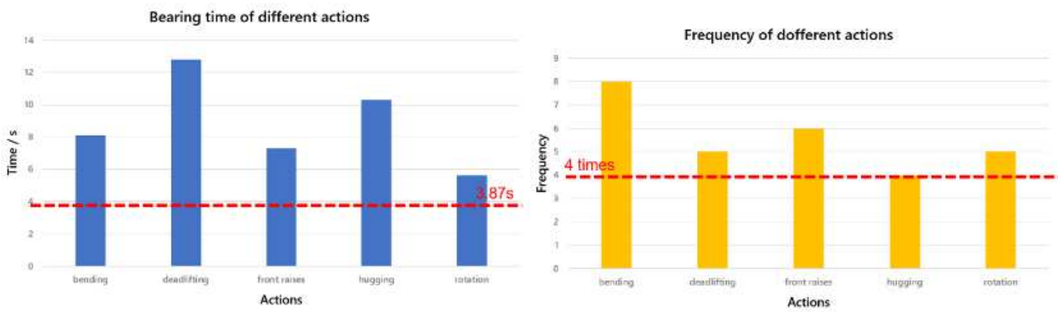

Figure 4.8 The top five behavioral characteristics ranked by weight.

In accordance with the scoring criteria of C-REBA, when a posture endures a load-bearing time exceeding 3.87 seconds, an additional point is awarded. Similarly, if the action frequency surpasses 4 times within one minute, an additional point is granted. Notably, in the additional scoring logic of ST-GCN, only the top five behavioral weights that fulfill both aforementioned additional scoring rules are eligible for extra points. To illustrate, for load-bearing time scoring, all five of the highest-ranked behaviors must exhibit a duration exceeding 3.87 seconds to receive the additional scoring point. The same principle applies to the scoring rule for action frequency. The comprehensive impact of these two scoring rules, along with the additional points, on the overall C-REBA score is depicted in Figure 4.9. "A" denotes the semi-automated C-REBA scoring results solely based on OpenPose calculations, while "B" represents the C-REBA scoring outcomes derived from ST-GCN calculations. Notably, in the second task cycle, scenario B satisfies the criteria for additional points in load-bearing time, while in the fifth cycle, it meets the criteria for additional points in action frequency. Notably, scenario B exhibits a significant increase in score compared to scenario A.

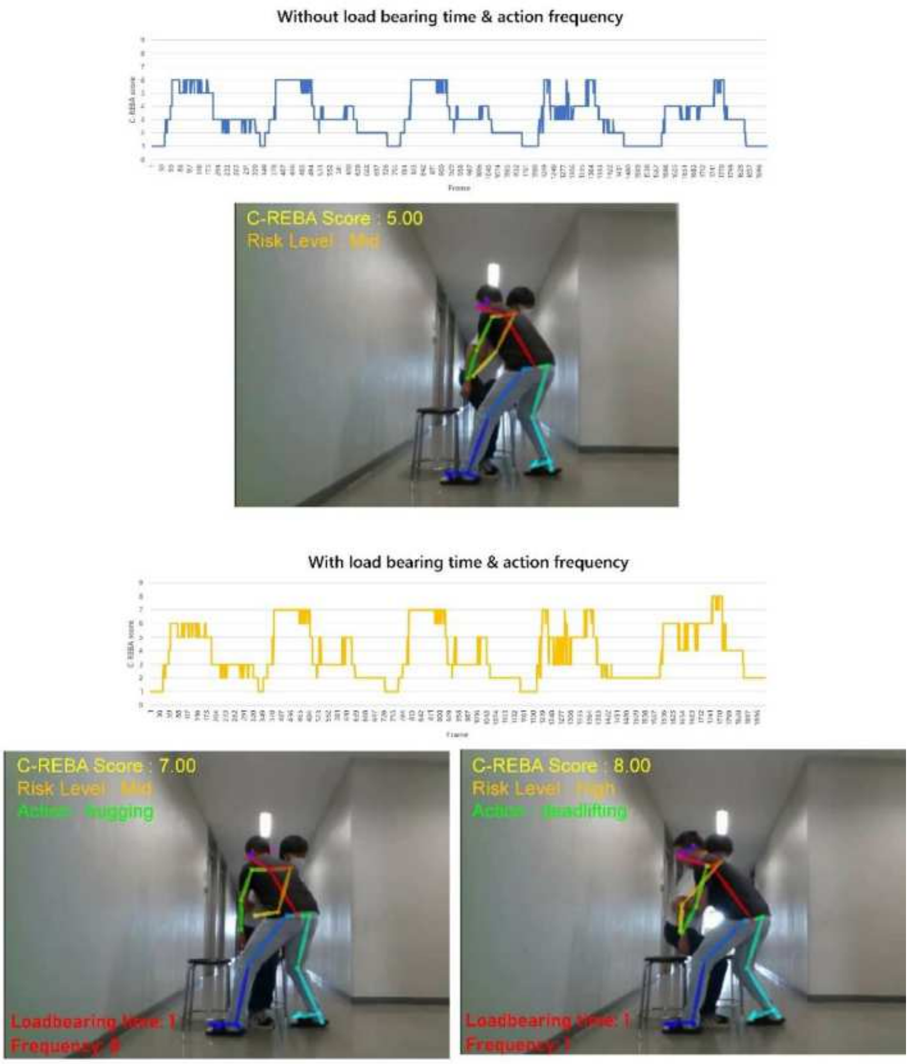

Figure 4.9 Visualization of total scores and bonus points after two scoring rules.

4.4.2 Asymmetric load

Accurately assessing asymmetric load, which refers to the imbalanced distribution of load-bearing between the left and right feet or hands, is crucial due to its potential to induce muscle imbalances and joint problems. This assessment holds particular significance for healthcare professionals who frequently exert force on one side of their body or for caregivers with limited experience. C-REBA employs the monitoring of asymmetric load through pixel centroid position, enabling the quantification of its magnitude based on load levels. These quantified asymmetric load features are subsequently fed into the dual-layer collaborative neural network of ST-GCN to predict corresponding additional scores. To evaluate the performance of asymmetric load in the pose scoring of the ST-GCN model, we enlisted a volunteer to simulate patient transfers—a common task in healthcare settings. The volunteer possessed no musculoskeletal or physiological impairments that could impede their ability to carry out the task independently. Video clips of the task's postures were captured using an Intel RealSense Depth Camera D435, while the actual values of asymmetric load were measured using the WII Balance Board. The experimental data obtained from this test are presented in Figure 4.10.

C-Extra A of C-REBA – Left and right foot load difference

+0	+1	+2	+1
< 9.99kg	9.99 – 24.54kg	> 24.54kg	Shock or rapid build up of force

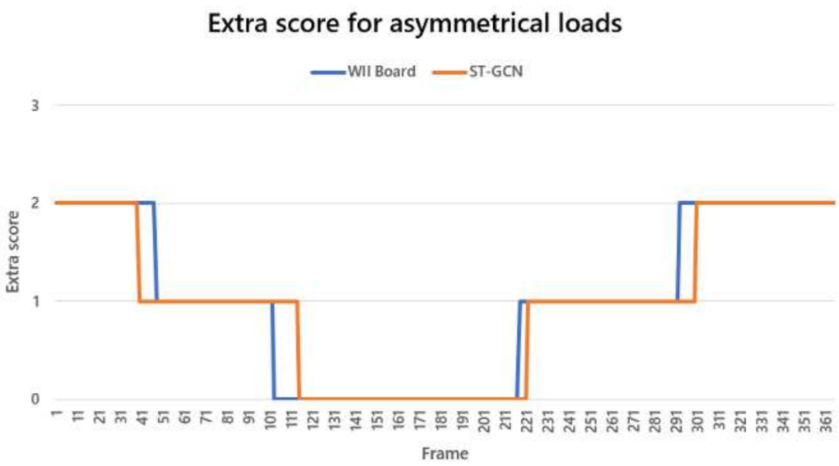

Figure 4.10 Difference in asymmetric load values measured by WII balance board and ST-GCN.

To ensure comparability, the test values obtained from the WII Balance Board for the asymmetric load feature were measured in kilograms (kg), representing the load, while the predicted values derived from ST-GCN were in pixel positions (unit: pixels). Both datasets underwent normalization based on the additional scoring criteria, with the y-axis representing the additional scoring values for asymmetric load and the x-axis representing the time series. Remarkably, the

Pearson correlation coefficient between the two datasets yielded a value of 0.93, indicating a substantial correlation between the ST-GCN-based prediction of asymmetric load and the measured values from the WII Balance Board. This high correlation underscores the reliability of the predicted asymmetric load scores. Figure 4.11 showcases the overall score and the impact of additional points after incorporating the consideration of asymmetric load. A comparison between scenarios C and D reveals that the presence of asymmetric load is primarily concentrated in the first and second halves of the caregiver task.

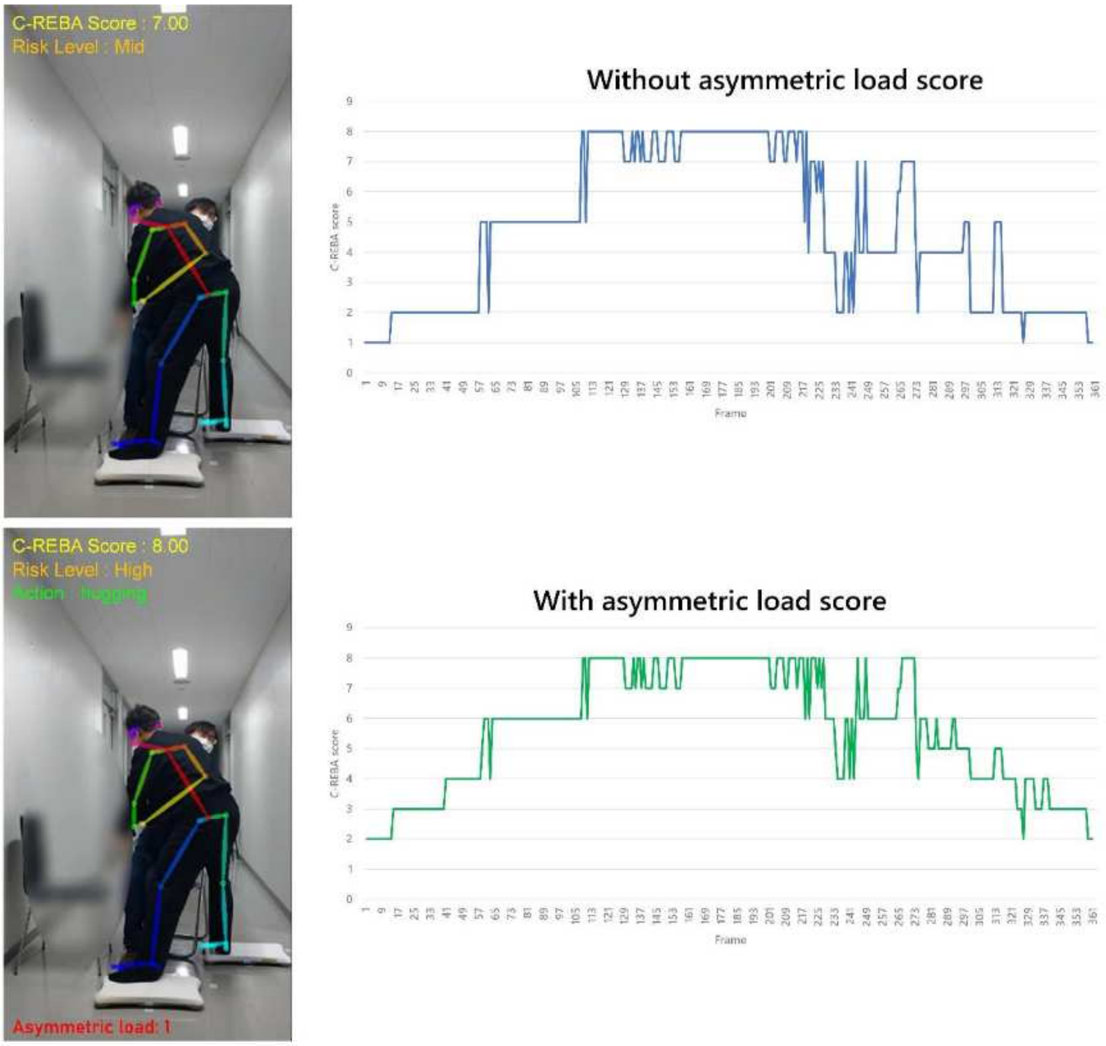

Figure 4.11 Visualization of total and bonus points after accounting for asymmetrical loading.

4.4.3 Change of COG

The body's center of gravity represents the point where the body's mass is concentrated, while preserving its translational inertia and playing a critical role in maintaining overall body stability. In the context of caregiving tasks, a larger range of center of mass trajectory variation is more likely to lead to unstable postures, thereby increasing the risk of falls and musculoskeletal injuries. As highlighted in the preceding section on center of gravity differences, inexperienced caregivers tend to exhibit larger ranges of center of mass variation during patient transfers, whereas experienced caregivers demonstrate relatively smaller ranges. To assess the additional scoring evaluation of center of gravity variation in ST-GCN, we enlisted two volunteers to simulate patient transfers, assuming the roles of healthcare professionals. Volunteer 1 deliberately generated a larger range of center of gravity variation during the caregiving task, while Volunteer 2 aimed to maintain a smaller range of variation. Importantly, both volunteers were free from any musculoskeletal or physiological limitations that could impede their ability to independently perform the task. The Intel RealSense Depth Camera D435 was employed to capture video clips of the postures involved in the task, enabling the visualization of center of gravity variation trajectories at the pixel level, as depicted in Figure 4.12.

Figure 4.12 Visualization of the center of gravity of Volunteer 1 and Volunteer 2 in the caregiving task.

The center of gravity trajectory feature serves as an input to the dual-layer collaborative neural network of ST-GCN, where the long-short term memory network extracts stability grading features based on the variation trajectory of the center of gravity. In accordance with the additional scoring rules of C-REBA, an additional score is granted when the range of center of gravity variation exceeds 7.54 cm. Within the supplementary scoring logic of ST-GCN, a large variation range is determined if the distance between the lowest and highest points of the center of gravity trajectory surpasses 7.54 cm, thereby warranting the addition of extra points. Notably, to address the heterogeneity arising from height discrepancies, the center of gravity variation values employed herein are normalized based on the height of each individual. The comprehensive impact of the additional points and the resulting overall scores, after incorporating considerations of center of gravity variation, are demonstrated in Figure 4.13. Volunteer 2 showcased a task performance characterized by a smaller range of center of gravity variation, leading to lower C-REBA scores for the majority of the duration when compared to Volunteer 1. However, following the identification of excessive center of gravity variation features, Volunteer 1 consistently attained higher overall C-REBA scores in the later stages as compared to Volunteer 2.

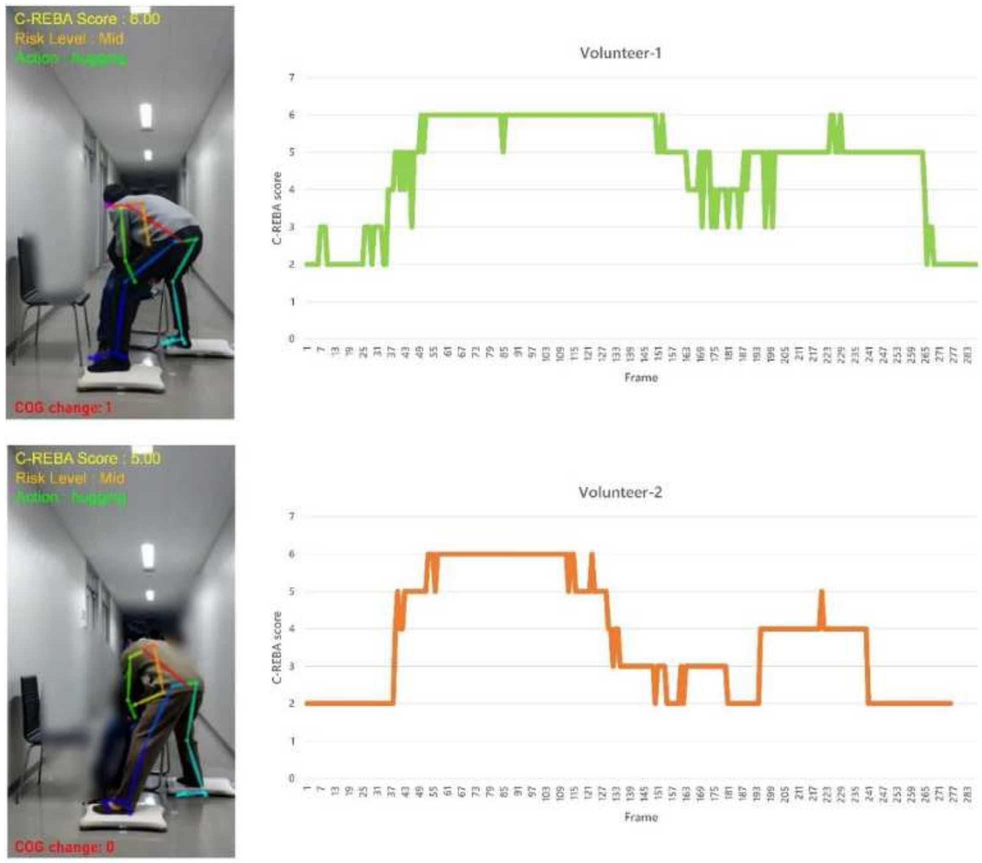

Figure 4.13 Visualization of extra scoring for Volunteer 1 and Volunteer 2 in COG changes.

4.4.4 Computing costs

In order to assess the computational efficiency and speed of our automatic evaluation model for additional scores, we meticulously configured the experimental conditions and employed identical hardware equipment. The test set, comprising a total of 2803 frames, was utilized to ascertain the performance of our method in terms of time consumption, memory usage, and frames per second. Furthermore, we conducted a comprehensive performance analysis by comparing our approach to several existing methods, including Tsai et al. [25], which utilizes a left-right skeletal symmetry skeleton compensation method; Guo et al. [26], which employs a Euclidean distance matrix skeleton compensation method; and Kanazawa et al. [27], which relies on a Human Dynamics-based temporal skeleton compensation method. The summarized results of this comparative evaluation can be found in Table 4.3, providing insights into the performance of our method relative to the aforementioned approaches.

Table 4.3 Computational cost and speed comparison of different methods.

Method	Time consuming (s)	Memory usage (MB)	Frame per second (fps)
OpenPose	434	1126.4	6.45
Tsai et al.	302	1003.6	9.28
Guo et al.	303	906.3	9.25
Kanazawa et al.	298	786.1	9.41
Ours	256	716.8	10.95

The findings in Table 4.3 indicated that OpenPose achieved huge computational cost 1126.4MB, which reduced the calculation speed, its final computational speed remains at 6.45 fps. This was associated with the issues of large-scale skeleton points calculation. In contrast, our approach attained the computational speed at 10.95 fps, outperforming alternative methods and improved the skeleton points computational cost. Importantly, our method exhibited promising potential for computational cost and speed in action interaction-based nursing tasks.

4.5 Discussion

The primary objective of this study was to integrate the ST-GCN framework with C-REBA rules, aiming to achieve automated assessment of task posture risks and thereby enhance the comprehensiveness and applicability of posture assessment methods. Through the integration of the optimized ST-GCN framework with C-REBA, a variety of features encompassing time, behavior, asymmetric load, and center of gravity variation were collectively trained, with each feature corresponding to a specific network layer for effective feature learning and prediction. To validate the efficacy of this integrated approach, we conducted rigorous experimental verification across multiple additional scoring assessment scenarios, including load duration, action frequency, asymmetric load, and center of gravity variation. These comprehensive assessments served to validate the effectiveness and reliability of our proposed methodology.

The experimental findings from the validation of load duration and action frequency revealed that the load duration feature exerted a more significant impact, resulting in an approximate increase of 1 point on the total C-REBA score. In terms of action frequency, adhering to the additional scoring rules of C-REBA, a frequency exceeding 4 actions within one minute was required to meet the scoring criteria. Within the scoring logic of ST-GCN, the action frequency needed to surpass 4 times for the top 5 ranked actions to qualify for additional points. Notably, in practical caregiving scenarios, this scoring criterion was less frequent and typically observed in action scenarios associated with rehabilitation treatment planning. During the validation experiment on asymmetric load, the predicted scores obtained through ST-GCN for asymmetric load exhibited a correlation of over 93% with the measured values, demonstrating the reliability of this method. The overall C-REBA scores based on asymmetric load revealed that the occurrence of asymmetric load was concentrated in the early and late stages of patient transfer. It was observed that different individuals exhibited inconsistent habits of applying force to bilateral muscles, as evidenced by the scoring results indicating the participants' preferences regarding the side of muscle force. This underscores the importance of encouraging participants to maintain bilateral consistency to mitigate the risk of unilateral musculoskeletal disorders. In the C-REBA rules, the scoring for asymmetric load was categorized as Extra A, and the impact of the asymmetric load feature on the overall score ranged from 0 to 2 points, depending on changes in joint angles. During the validation experiment on center of gravity variation, the center of gravity variation values were normalized based on the height of each individual to account for heterogeneity arising from height differences. Comparing the data from two groups—one with larger center of gravity variation and the other with smaller center of gravity variation—it was observed that this feature had a discernible impact on the overall C-REBA score during time periods when the model detected center of gravity variation surpassing the specified threshold. In the caregiving process, the additional scoring based on this feature was concentrated in the later stages, indicating that the C-REBA scores of Volunteer 1, who exhibited larger center of gravity variation, were higher in the later stages. The center of gravity variation feature influenced the overall score by approximately 1 point.

Currently, several research methods exist for automated C-REBA assessment, including wearable sensors, Kinect depth cameras, and OpenPose. However, these methods solely evaluate joint angles, and the assessment of additional scores still relies on manual judgment, leading to subjectivity and result instability. In contrast to previous approaches, we propose an enhanced ST-GCN methodology. The primary framework of ST-GCN is utilized to forecast the temporal features of skeletal behavior, with behavior labels being weighted to simultaneously incorporate time and action frequency features. Conversely, posture features such as asymmetric load and center of gravity variation necessitate separate neural networks for feature extraction. To ensure the comprehensive integration of additional scoring feature extraction in C-REBA, we combine long-short term memory units and Faster RCNN networks, embedding them within the overarching ST-GCN framework. Our method exhibits significant advantages in handling additional scoring features, encompassing load bearing time, action frequency, center of gravity variation, and asymmetric load. By incorporating the learnable features of C-REBA's additional scoring factors into the ST-GCN framework, it becomes possible to automatically predict the scores of additional scorings while training the behavioral features, thereby enhancing the objectivity and stability of assessment outcomes.

The proposed method presented in this chapter showcases innovation and advantages in automating C-REBA posture assessment. Nonetheless, several limitations warrant consideration. Firstly, the size and diversity of the dataset utilized may restrict the generalizability of the method. The current dataset may only encompass posture samples from specific domains or particular types of actions, thus necessitating further validation to assess the effectiveness of the assessment in diverse environments or tasks. Future research endeavors should focus on collecting larger and more diverse datasets, encompassing a broader range of posture scenarios, to enhance the applicability and generalization performance of the method. Secondly, the computational complexity of the algorithm could pose limitations in its practical application. Deep neural networks typically demand substantial computational resources and time during both training and inference. To enhance the feasibility of this method in real-world applications, techniques such as model compression, hardware acceleration, or distributed computing can be employed to mitigate the computational complexity. Furthermore, the method holds significant potential in the assistive healthcare domain and can be fine-tuned based on different scenario datasets to extend automated posture assessment to a wider range of medical contexts. For instance, precise assessment of patients' posture and load during rehabilitation treatment can aid doctors in devising more effective rehabilitation plans and monitoring patient progress. It can also find applications in areas such as elderly care and sports training, assisting individuals in maintaining good posture and overall health.

4.6 Conclusion

The proposed integrated posture assessment method, which combines the improved ST-GCN model and C-REBA, has yielded outstanding outcomes across multiple scoring scenarios. Through the integration of the ST-GCN framework and a dual-layer collaborative neural network, we have successfully extracted the additional scoring factors of C-REBA rules and adeptly fused these features using confidence maps. In comparison to conventional methodologies, our approach facilitates the automatic prediction of the additional scores, thereby enhancing the comprehensiveness and automation of C-REBA scoring. Experimental validation results unequivocally establish the reliability and feasibility of our method in scenarios involving load duration, action frequency, asymmetric load, center of gravity variation, and other additional scoring factors. By accurately assessing these supplementary scores, we acquire a more holistic understanding of the load imposed on postures, consequently improving the assessment of task safety and human health risks. This deep neural network-based method, which encompasses multiple posture features and additional scores, achieves automated scoring and comprehensive evaluation. Furthermore, its potential extension to various assistive healthcare scenarios holds great promise, contributing to heightened work efficiency and diminished musculoskeletal risks for healthcare professionals. As a result, it plays a pivotal role in safeguarding the physical well-being of both healthcare personnel and patients alike.

Reference

[1] Kim I J. The role of ergonomics for construction industry safety and health improvements[J]. Journal of Ergonomics, 2017, 7(2): 2-5.

[2] Punnett L, Wegman D H. Work-related musculoskeletal disorders: the epidemiologic evidence and the debate[J]. Journal of electromyography and kinesiology, 2004, 14(1): 13-23.

[3] Vieira E R, Kumar S. Working postures: a literature review[J]. Journal of occupational rehabilitation, 2004, 14: 143-159.

[4] Karhu O, Kansi P, Kuorinka I. (1977). Correcting working postures in industry: A practical method for analysis. Applied Ergonomics, 8(4), pp.199–201. DOI:10.1016/0003-6870(77)90164-8.

[5] McAtamney, L. & Nigel Corlett, E. (1993). RULA: a survey method for the investigation of work-related upper limb disorders. Applied Ergonomics, 24(2), pp.91–99. DOI: 10.1016/0003-6870(93)90080-s.

[6] Hignett, S. & McAtamney, L. (2000). Rapid Entire Body Assessment (REBA). Applied Ergonomics, 31(2), pp.201–205. DOI: 10.1016/s0003-6870(99)00039-3.

[7] Burdorf A, Derksen J, Naaktgeboren B, et al. Measurement of trunk bending during work by direct observation and continuous measurement[J]. Applied ergonomics, 1992, 23(4): 263-267.

[8] Fagarasanu M, Kumar S. Measurement instruments and data collection: a consideration of constructs and biases in ergonomics research[J]. International journal of industrial ergonomics, 2002, 30(6): 355-369.

[9] Robertson M, Amick III B C, DeRango K, et al. The effects of an office ergonomics training and chair intervention on worker knowledge, behavior and musculoskeletal risk[J]. Applied ergonomics, 2009, 40(1): 124-135.

[10] Dockrell S, O'Grady E, Bennett K, et al. An investigation of the reliability of Rapid Upper Limb Assessment (RULA) as a method of assessment of children's computing posture[J]. Applied ergonomics, 2012, 43(3): 632-636.

[11] Battini D, Persona A, Sgarbossa F. Innovative real-time system to integrate ergonomic evaluations into warehouse design and management[J]. Computers & Industrial Engineering, 2014, 77: 1-10.

[12] Huang C, Kim W, Zhang Y, et al. Development and validation of a wearable inertial sensors-based automated system for assessing work-related musculoskeletal disorders in the workspace[J]. International Journal of Environmental Research and Public Health, 2020, 17(17): 6050.

[13] Valero E, Sivanathan A, Bosché F, et al. Musculoskeletal disorders in construction: A review and a novel system for activity tracking with body area network[J]. Applied ergonomics, 2016, 54: 120-130.

[14] Dutta T. Evaluation of the Kinect™ sensor for 3-D kinematic measurement in the workplace[J]. Applied ergonomics, 2012, 43(4): 645-649.

[15] Xu X, McGorry R W. The validity of the first and second generation Microsoft Kinect™ for identifying joint

center locations during static postures[J]. Applied ergonomics, 2015, 49: 47-54.

[16] Bogo et al., 2016，F. Bogo, A. Kanazawa, C. Lassner, P. Gehler, J. Romero, M.J. Black Keep it SMPL: automatic estimation of 3D human pose and shape from a single image Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) (2016), pp. 561-578, 10.1007/978-3-319-46454-1_34.

[17] Cao et al., 2017Z. Cao, T. Simon, S.E. Wei, Y. Sheikh, Realtime multi-person 2D pose estimation using part affinity fields Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017 2017-Janua (2017), pp. 1302-1310, 10.1109/CVPR.2017.143.

[18] Cao Z, Simon T, Wei S E, et al. Realtime multi-person 2d pose estimation using part affinity fields[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2017: 7291-7299.

[19] Cai L, Ma Y, Xiong S, et al. Validity and reliability of upper limb functional assessment using the Microsoft Kinect V2 sensor[J]. Applied bionics and biomechanics, 2019, 2019.

[20] Li L, Xu X. A deep learning-based RULA method for working posture assessment[C]//Proceedings of the Human Factors and Ergonomics Society Annual Meeting. Sage CA: Los Angeles, CA: SAGE Publications, 2019, 63(1): 1090-1094.

[21] Manghisi V M, Uva A E, Fiorentino M, et al. Real time RULA assessment using Kinect v2 sensor[J]. Applied ergonomics, 2017, 65: 481-491.

[22] Yu Y, Yang X, Li H, et al. Joint-level vision-based ergonomic assessment tool for construction workers[J]. Journal of Construction Engineering and Management, 2019, 145(5): 04019025.

[23] Zaman R, Quarnstrom J, Xiang Y, et al. Hybrid predictive model for assessing spinal loads for 3D asymmetric lifting[C]//International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers, 2022, 86212: V002T02A022.

[24] González, A., Hayashibe, M., & Fraisse, P. (2012). Estimation of the center of mass with Kinect and Wii balance board. In 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems (pp. 1023-1028). IEEE. DOI: 10.1109/IROS.2012.6385665.

[25] Tsai M F, Huang S H. Enhancing accuracy of human action Recognition System using Skeleton Point correction method[J]. Multimedia Tools and Applications, 2022, 81(5): 7439-7459.

[26] Guo X, Dai Y. Occluded joints recovery in 3d human pose estimation based on distance matrix[C]//2018 24th International Conference on Pattern Recognition (ICPR). IEEE, 2018: 1325-1330.

[27] Kanazawa A, Zhang J Y, Felsen P, et al. Learning 3d human dynamics from video[C]//Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2019: 5614-5623.

Chapter 5

Behavior analysis and posture assessment system

5.1 Overview

This chapter unveils the development of the Behavior Analysis and Posture Assessment System (BAPAS), a comprehensive tool merging previously discussed algorithms and devices. BAPAS aims to assess job postures in assistive medical tasks and provide valuable insights into the risk of musculoskeletal disorders. The system comprises a cloud-based server acting as the central processing unit, accessible through diverse user platforms such as PCs, tablets, and mobile devices. BAPAS leverages user-captured or uploaded work task videos, which undergo processing and analysis by the cloud-based server. The server conducts posture analysis, behavior recognition, and posture risk assessment on the uploaded videos. Upon completion of data analysis, results are presented to users via graphical representations. Users can access posture data, joint angle measurements, behavior recognition outcomes, and C-REBA risk scores tailored to their specific requirements. The BAPAS system integrates algorithms for human posture recognition, behavior recognition, and C-REBA posture assessment. By simply uploading work videos, the system automatically decomposes them into frames and performs analysis on each frame.

In comparison to existing assessment systems, wearable devices have the potential to deliver enhanced precision in posture recognition. However, studies highlighted in the X-SENSE literature reveal that these devices are often perceived as cumbersome and disruptive by the individuals being tested. The act of wearing such devices can significantly interfere with normal work tasks, compromising the validity of the assessment. Moreover, certain studies aiming to achieve precise joint angle measurements resort to using accelerometers attached to multiple joints, leading to logistical challenges and high experimental costs, as stated in the accelerometer literature. In contrast, our proposed system presents a non-contact approach to behavior analysis and posture assessment. By eliminating the need for wearable devices or elaborate sensor setups, our system offers a user-friendly and practical solution. It effectively addresses the limitations associated with wearables and accelerometers, ensuring a smoother assessment experience for the individuals being tested. Additionally, our system exhibits the potential for seamless expansion to other assistive medical scenarios, contingent upon the availability of a larger dataset. Presently, the system has successfully been extended to applications in rehabilitation posture guidance and CPR posture assessment, displaying exceptional performance in posture recognition, evaluation, and guidance. This scalability enhances the system's applicability and significance across diverse healthcare contexts.

5.2 System design

5.2.1 System functional framework

The functional framework of the BAPAS system is illustrated in Figure 5.1, while the user login process (Figure 5.2) commences with user identity verification. Subsequently, the system proceeds to the homepage, where it verifies network connectivity, model API interfaces, camera connections, and storage memory availability (Figure 5.2). Following this, the system encompasses four functional partition modules, namely single data processing, batch data processing, real-time data processing, and extended applications. The single data processing function area is primarily composed of three modules: data upload and processing, result output, and data reset. Within the data upload and processing module, users can upload task videos for processing, which are then transmitted to the cloud server for human pose recognition, behavior identification, and C-REBA posture risk assessment. Upon completion of the processing, the results are returned to the user's end.

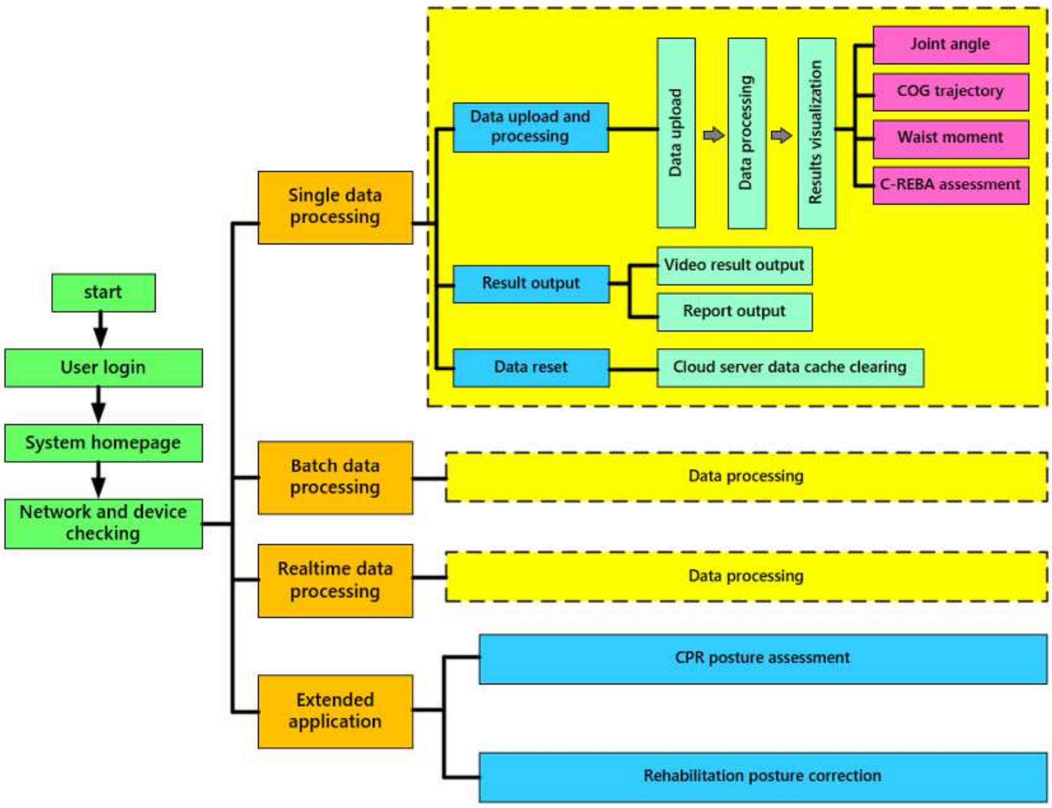

Figure 5.1 The functional framework of the BAPAS system.

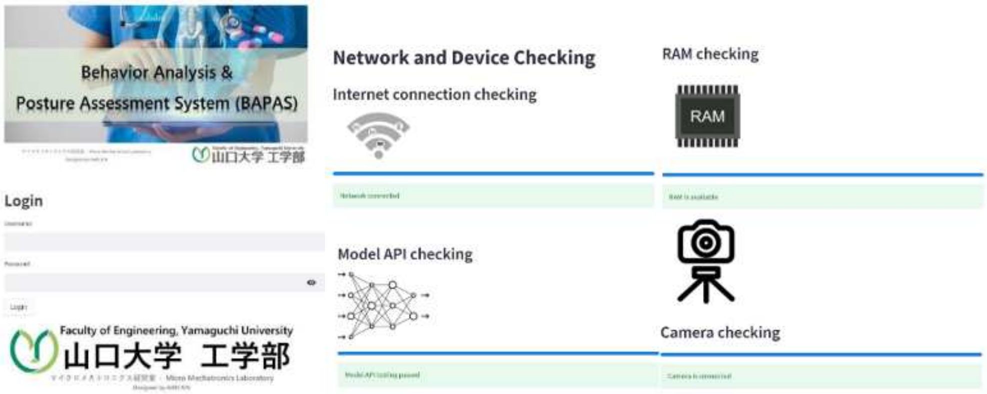

Figure 5.2 User login page and device check page.

The batch data processing function area operates similarly to the single data processing function, but with the capability to automatically process multiple datasets. The processing speed of this function area relies on the server's graphics memory. Meanwhile, the real-time data processing function area resembles the single data processing function, except for its automatic retrieval of video tasks from the camera for real-time processing. Due to the real-time video retrieval and background processing from the camera, the processing speed of this function area is relatively slower. The final function area pertains to the extension applications, which aims to broaden the system's capabilities. Currently, there are two primary directions for expansion. One direction focuses on the assessment of cardiopulmonary resuscitation (CPR) postures, as the accuracy of CPR postures is crucial for successful rescue operations, patient safety, and recovery. Our system provides correct posture guidance and evaluation for rescuers during CPR operations, ensuring effective chest compressions, airway clearance, and minimizing further injuries, thereby enhancing the success rate of CPR. The other direction involves rehabilitation posture correction, which plays a vital role in restoring functionality, alleviating pain, facilitating recovery, and preventing further damage. By improving posture and body alignment, rehabilitation posture correction aids patients in regaining normal physical function, improving their quality of life, and reducing the risk of future injuries. Our system monitors patients' daily rehabilitation postures, offering warnings and visualized skeletal alignment guidance for incorrect postures. The extended application functional area is continuously expanding to encompass more application scenarios, leveraging sufficient data to fine-tune the model and develop targeted posture assessment functions.

5.2.2 System visual feedback

The BAPAS system introduces a visually-oriented approach to ergonomic posture assessment and feedback, aiming to offer guidance to workers. By implementing appropriate ergonomic interventions, the system contributes to the reduction of musculoskeletal discomfort and injuries in caregiving contexts [1-3]. Among intervention methods, posture feedback has been identified as particularly effective [4]. Studies have shown that diversified posture feedback significantly lowers ergonomic risks for nurses [5]. Notably, relying solely on teaching and training for posture interventions has proven inadequate in effectively mitigating the risk of musculoskeletal discomfort and injuries. In contrast, interventions incorporating biofeedback, such as the visual feedback provided by the BAPAS system, have demonstrated greater effectiveness [6]. The visual biofeedback from the system encompasses joint angles, center of pressure trajectory, predicted lumbar moments, C-REBA posture assessment outcomes, and video feedback. Its purpose is to furnish risk assessment and guidance for work postures through visual biofeedback, thereby enhancing ergonomic practices.

The joint angle data encompasses major limb joints, including the neck, trunk, upper arm, lower arm, and legs, and is presented in chart format (Figure 5.3). Center of gravity trajectory data is generated at the image level using the previously described center of gravity calculation method, capturing the overall center of gravity trajectory, upper body center of gravity trajectory, and lower body center of gravity trajectory (Figure 5.3). The calculation of predicted waist torque is based on reference [7] and is presented in chart form, offering frame-by-frame feedback on waist torque. Higher waist torque indicates increased burden on the waist and a higher risk of injury. By analyzing the predicted values, workers can comprehend the level of waist load associated with different postures and reduce the frequency of high waist load postures (Figure 5.4). The feedback on C-REBA posture assessment data represents the risk level of musculoskeletal disorders associated with each posture, with higher scores indicating higher risks. This alerts workers to promptly modify high-risk postures. The data includes C-REBA scores for each joint and can be selectively viewed for specific joints. It is presented in both chart and video formats. Moreover, all the visualized data mentioned above incorporates statistically significant measures such as mean, standard deviation, maximum and minimum values, and quartiles. The video feedback is divided into four parts (Figure 5.5): the original video in the top left corner, posture recognition feedback video in the top right corner, real-time center of gravity trajectory video in the bottom left corner, and real-time C-REBA score video in the bottom right corner. In summary, the visual feedback provided by the system empowers workers to explore optimal force positions, maintain balance during lifting activities, and maximize strength output to prevent muscle injuries [8].

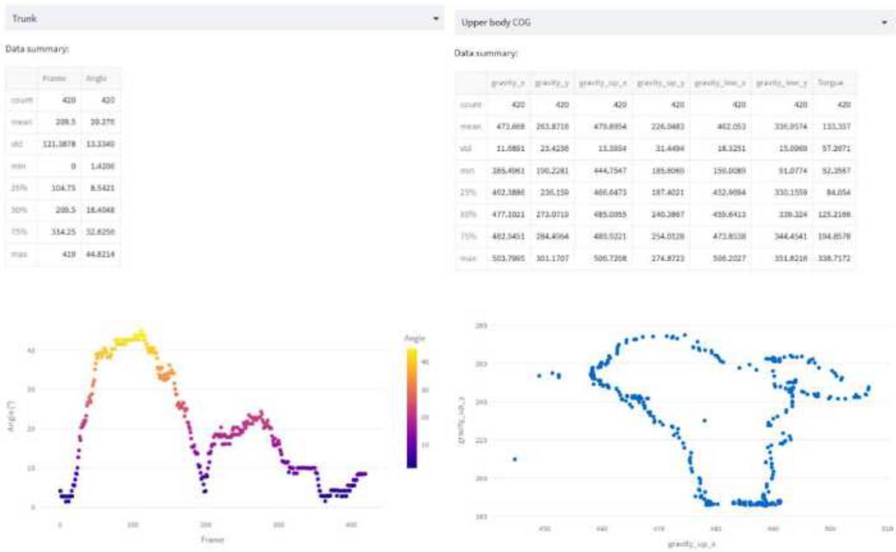

Figure 5.3 Joint angle and COG trajectory visualization function.

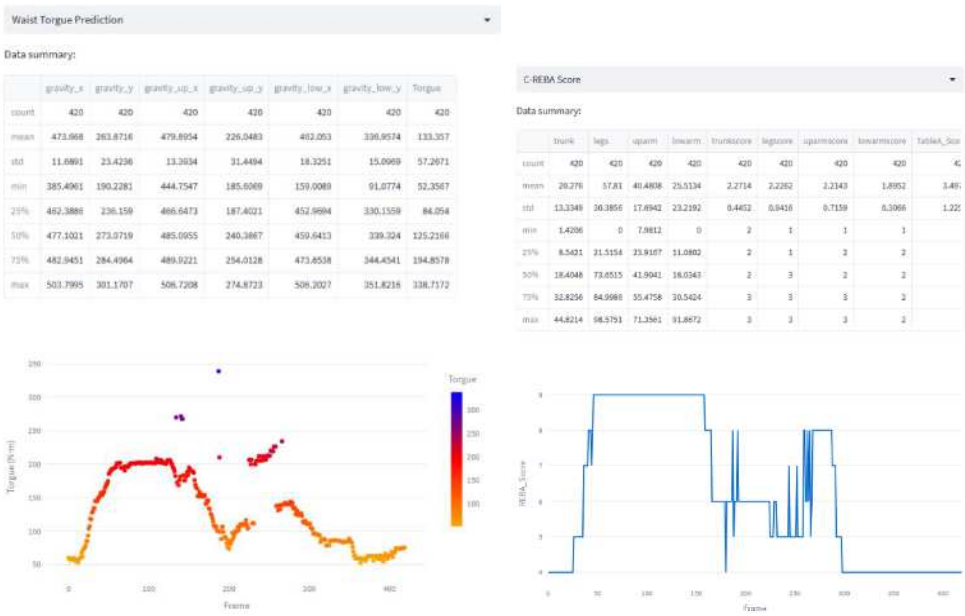

Figure 5.4 Waist moment prediction and C-REBA score visualization function.

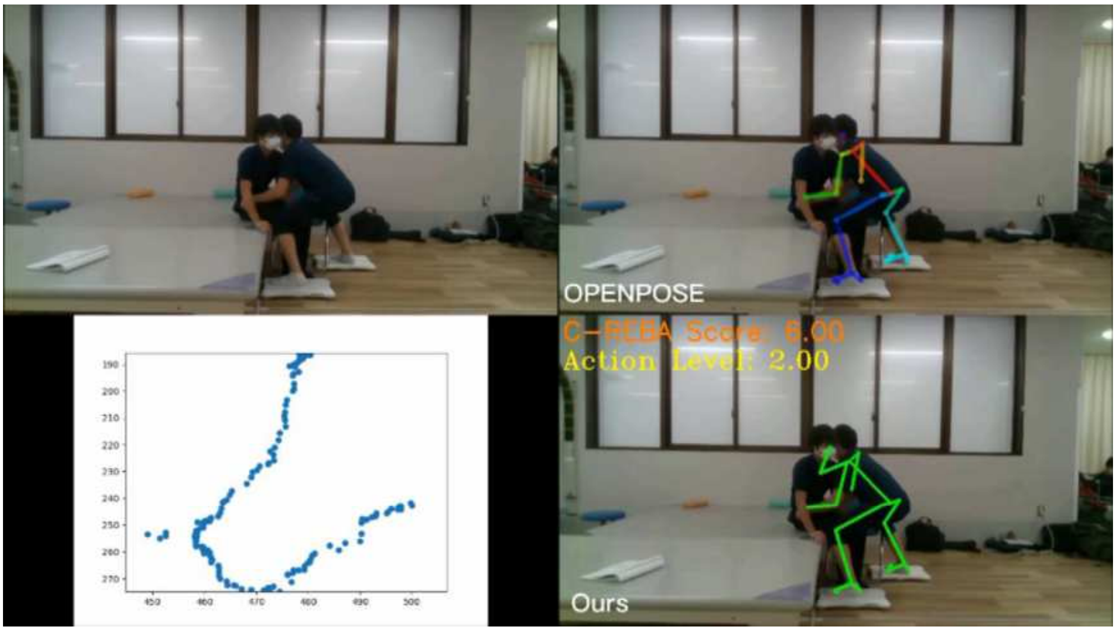

Figure 5.5 Multivariate data fusion outputs visual results.

5.2.3 System Configuration

The configuration of the BAPAS system encompasses software and hardware modules. The software modules comprise human pose recognition algorithms, behavior identification algorithms, and C-REBA posture assessment algorithms. For human pose recognition, we have employed the OpenPose open-source library, which has been shown by researchers in literature [1] to achieve superior joint detection accuracy compared to KinectV2 and exhibit enhanced robustness under non-ideal conditions. Utilizing OpenPose, we construct a human skeletal framework with 25 key joints covering major anatomical landmarks. This framework facilitates joint pose reconstruction and enables accurate pose scoring for the behavior identification and C-REBA posture assessment algorithms. Moving to the hardware configuration, the algorithm models are implemented in the PyTorch framework. Model training is conducted on a workstation equipped with an Intel Xeon CPU E5-1560 v4 @ 3.60 GHz and two Titan V devices. The workstation specifications include an AMD Ryzen 7 3800X 8-Core Processor x 16 @ 3.90GHz, 128 GB RAM, and a GeForce GTX1660Ti GPU. The entire software development process is carried out using the PyCharm 2020.3.2 platform, with Python 3.7 as the programming language.

5.3 System application extension

The field of healthcare encompasses a wide range of application scenarios that necessitate posture assessment and guidance. While the BAPAS system initially found its utility in caregiving scenarios like patient transfers, its applications extend to various medical assistance contexts.

Through the accumulation of posture data specific to medical assistance scenarios, the algorithm model can undergo fine-tuning to develop a dedicated posture assessment system tailored to specific medical assistance settings. Notably, the system has already demonstrated remarkable success in expanding its application to rehabilitation posture assessment and CPR posture assessment scenarios, achieving outstanding outcomes. These achievements underscore the immense potential of the BAPAS system in the realm of visualized posture assessment for medical assistance, paving the way for further advancements in this area.

5.3.1 Rehabilitation scenarios

In the realm of rehabilitation therapy, the correction of posture assumes a pivotal role in restoring muscle function, mitigating pain, fostering recovery, and preventing further injury. Maintaining proper posture is paramount for upholding normal body alignment and positioning. Inadequate or erroneous body posture can engender aberrant stress distribution on muscles and bones, resulting in pain, stiffness, and impairments in functionality. Through the implementation of rehabilitation posture correction, it becomes feasible to address postural issues, ameliorate body alignment, alleviate discomfort, and enhance overall functionality. Improper posture can induce muscle tension, heightened joint pressure, and nerve compression, consequently leading to pain and discomfort. The primary objective of rehabilitation posture correction is to alleviate these discomforts and pains, enabling patients to experience enhanced comfort and ease in their daily activities. Correct posture and body alignment can bolster muscle strength and coordination, amplify joint stability and flexibility, thereby facilitating the patient's functional recovery. By rectifying erroneous posture, specific regions of the body are relieved from undue pressure and stress, ultimately decreasing the risk of further injury. Rehabilitation posture correction aids in diminishing this excessive pressure and stress, thereby assisting patients in averting further harm and propelling the rehabilitation process forward.

To enhance engagement in rehabilitation training and optimize the efficacy of posture correction, the field of rehabilitation posture correction has witnessed notable advancements and research methodologies. Noteworthy studies [9-11] have introduced a sensor-based posture monitoring technique that employs inertial measurement units (IMUs) and pressure sensors for real-time monitoring and recording of patients' posture data. By capturing joint angles, body positions, and motion data, this approach generates comprehensive assessment reports on patient posture, providing real-time feedback and reference for rehabilitation therapists. However, the reliance on sensors in this method creates a substantial burden for patients and poses challenges in integrating the collected information. Wearable devices, including smart wristbands and smart garments, have emerged as promising tools in rehabilitation therapy, enabling posture and movement monitoring through embedded sensors [12-14]. These devices offer real-time feedback and suggestions. Nonetheless, the high cost associated with wearable integrated devices limits their widespread use among the general population. Virtual reality (VR) and augmented reality (AR) technologies have demonstrated immense potential in guiding rehabilitation posture by creating simulated environments. Through interaction with avatars or objects within virtual scenes, these technologies provide visual feedback and guidance, facilitating posture adjustment and improving rehabilitation outcomes [15-17]. Moreover, VR and AR technologies can offer personalized rehabilitation programs and gamified training, fostering patient engagement and motivation. Despite their promising effects, the high device costs and the need for specific models tailored to rehabilitation programs present substantial challenges to their applicability in rehabilitation posture correction. To address these challenges, we propose an innovative rehabilitation posture correction system, named BAPAS, which leverages deep learning frameworks and artificial intelligence technologies.

The BAPAS system represents a novel approach that integrates training algorithm models and a vast repository of posture data to automatically identify and evaluate patients' postures, thereby delivering personalized corrective suggestions. These technological advancements enable continuous optimization and adaptation of rehabilitation plans based on individual patient circumstances and progress, leading to improved efficacy in posture correction and rehabilitation outcomes. With a primary focus on patients' daily life postures during the rehabilitation process, the BAPAS system harnesses the power of computer vision technology. By leveraging camera surveillance connected to the Internet of Things, the BAPAS system can actively monitor patients' daily postures. In the event of incorrect postures, it promptly alerts patients and provides visual feedback through virtual skeletons displayed on a terminal. This feedback empowers patients to promptly rectify their postures, reducing the risk of injuries and facilitating the rehabilitation process.

To assess the efficacy of the BAPAS system in rehabilitating posture correction, a volunteer was recruited to emulate daily life postures, with particular emphasis on commonly adopted positions such as cleaning and lifting boxes, as depicted in Figure 5.6. Throughout the experiment, cloud-based servers were employed for data processing by the BAPAS system. Data collection from the user and feedback provision were facilitated using a laptop computer equipped with the following specifications: Microsoft Windows 10 operating system, Intel (R) Core (TM) i7-8750H 2.00 GHz CPU, 8 GB RAM, and Nvidia GeForce GTX 1050Ti GPU. To capture video clips of the volunteer executing tasks in various postures, an Intel RealSense depth camera D435 was utilized.

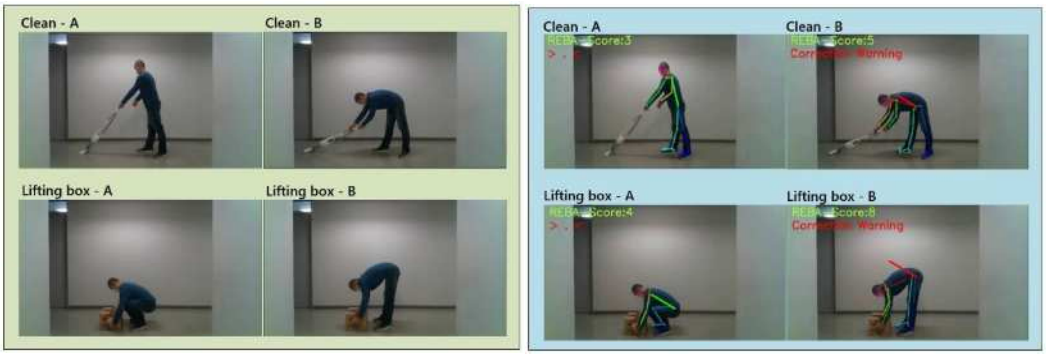

Figure 5.6 Visualization of inappropriate posture correction in Cleaning and Lifting tasks.

The obtained test results, illustrated in Figure 5.6, showcase the functionality of the BAPAS system in activating posture correction warnings and prompting patients to adjust their postures when the assessed posture risk surpasses the predetermined REBA score. The system visually presents virtual corrective skeleton positions on the display terminal. In the instances of Clean-B and Lifting box-B, where the REBA score exceeds the defined threshold, the system predicts skeleton positions based on low-risk postures and highlights them in red, compelling patients to swiftly align their postures with the indicated red virtual skeleton positions. Conversely, in Clean-A and Lifting box-A scenarios, where the posture risk remains below the specified REBA score, no posture correction warnings are triggered, and the skeleton color is displayed as green. Additionally, ethical considerations preclude the presentation of rehabilitation posture correction outcomes of the BAPAS system in this article, as patients were involved in the testing process. The comprehensive test outcomes collectively affirm the successful implementation of the BAPAS system in rehabilitation posture correction, with relatively affordable implementation costs. Moreover, as further rehabilitation posture data is accumulated, the accuracy and precision of the employed models can be enhanced, facilitating broader integration in diverse rehabilitation applications.

5.3.2 CPR scenarios

Cardiopulmonary Resuscitation (CPR) is a crucial emergency intervention aimed at restoring cardiac function and ensuring oxygenation. Among the key steps of CPR, chest compressions play a pivotal role and necessitate mastery by all emergency responders. By compressing the chest, these compressions facilitate effective circulation, ensuring proper blood flow to vital organs. Consequently, adopting the correct posture for chest compressions is of utmost importance in successfully executing CPR and enhancing patient survival rates. The appropriate posture enables rescuers to exert accurate and adequate force during compressions, ensuring optimal compression of the patient's sternum and sufficient blood flow to the heart. Furthermore, adhering to the correct posture minimizes the risk of harm to the patient. As society progresses, chest compression techniques are no longer confined to medical professionals and emergency responders alone, but are also being promoted at community and school levels. Traditional instruction by healthcare professionals remains a common approach for disseminating CPR chest compression techniques. However, post-training questionnaires reveal that individuals often struggle to comprehend and replicate these techniques, necessitating extensive training to attain proficiency in posture. Moreover, some individuals face difficulties in adjusting and rectifying their postures, and once incorrect chest compression habits are established, correcting them becomes challenging. Erroneous postures may become deeply ingrained in learners' muscle memory, posing challenges for healthcare professionals to consistently assess and rectify postures during prolonged and frequent intervals. These challenges pose significant obstacles to the promotion and instruction of this technique.

Ongoing research endeavors are dedicated to enhancing the quality and efficacy of chest compressions in cardiopulmonary resuscitation (CPR) through posture correction. Researchers are exploring real-time feedback mechanisms employing pressure sensors, accelerometers, and photodetectors to monitor and provide immediate feedback on the accuracy and quality of chest compression postures. These devices aid rescuers in optimizing hand placement, depth, and frequency to attain more favorable compression outcomes [18-19]. However, reliance on sensors and their incorporation in the process may potentially impact the effectiveness of chest compressions. In response, some researchers have employed virtual reality technology and simulation training devices to enable learners to practice chest compressions and rectify their postures through visual and tactile feedback. This training modality enhances learners' understanding and mastery of the correct compression postures while improving skill retention and application abilities [20-21]. Nonetheless, this approach entails high equipment costs and may not be suitable for widespread implementation in CPR training at societal and educational levels. Addressing these challenges, the BAPAS system presents a posture assessment approach based on neural network models, providing visual posture feedback to remind rescuers of posture intensity and correctness. With the support of this system, rescuers can undergo iterative training until they have achieved full mastery of the technique.

In order to refine the posture assessment capability of the BAPAS system specifically for chest compression, substantial adjustments were made to the evaluation criteria. Previously, the posture assessment scores represented the degree of musculoskeletal risk. However, for the assessment of chest compression postures, the scores now indicate the level of force that the compressor can exert on the patient. Professional input from emergency responders guided the division of chest compression force into four levels, as depicted in Figure 5.7. These levels include Level A (4-5), Level B (3), Level C (2), and Level D (1), with higher scores denoting superior force application capacity. Only postures reaching Level A are deemed optimal for CPR chest compressions, while postures at other levels are considered inadequate. Additionally, the system retained the function of assessing posture risk and integrated it into the posture correction process. When an incorrect chest compression posture is detected, a virtual skeleton prompt is displayed on the visual terminal to guide the compressor. To assess the effectiveness of the BAPAS system in evaluating and correcting CPR chest compression postures, three volunteers were recruited and received chest compression technique training under the guidance of a professional emergency care provider. Throughout the experiment, cloud-based servers were utilized for data processing by the BAPAS system. User data collection and feedback were facilitated using a laptop computer equipped with the following specifications: Microsoft Windows 10 operating system, Intel(R) Core (TM) i7-8750H 2.00 GHz CPU, 8 GB RAM, and Nvidia GeForce GTX 1050Ti GPU. Video clips of the task postures were captured using an Intel RealSense depth camera D435. All CPR data were downloaded from YouTube due to ethical consideration.

Figure 5.7 CPR chest compression position available force level.

The test findings, illustrated in Figure 5.8, reveal that the BAPAS system offers posture assessment scores corresponding to different chest compression postures, reflecting the level of force that can be exerted during compressions. Postures depicted in Figure 5.8b, Figure 5.8c, and Figure 5.8d exhibit incorrect chest compression postures, as evidenced by their low force application scores. Only postures achieving Level A are considered satisfactory. Moreover, for incorrect postures, the BAPAS system provides visual feedback for posture correction. Postures meeting Level A force application criteria receive no warnings and are annotated with green skeletal markers. However, postures falling short of Level A force application prompt posture correction alerts. The system predicts skeletal positions based on postures with high force application and marks them with red skeletal annotations, reminding compressors to promptly rectify their posture to align with the red virtual skeletal positions. Additionally, professional emergency responders were invited to participate in the testing process to evaluate the efficacy of the results. The outcomes demonstrate that the BAPAS system performs admirably in assessing and guiding CPR chest compression postures, while maintaining low implementation costs. It exhibits significant potential for application in other emergency posture guidance scenarios.

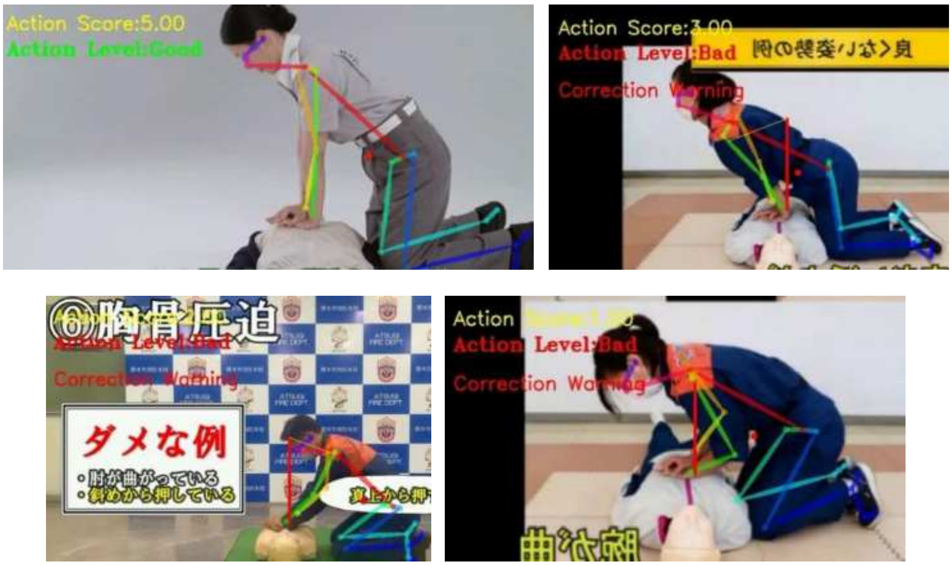

Figure 5.8 Visualization of available force levels scoring and postural correction for different chest compression techniques posture.

5.4 Discussion

The BAPAS system endeavors to assess work postures in assistive medical tasks, providing valuable insights into ergonomic risks and potential musculoskeletal disorders. Through the integration of posture recognition, behavior analysis, and risk assessment functionalities, the system offers visual feedback and guidance on biomechanical posture risks. Users can access posture data, joint angles, behavior recognition results, center of gravity trajectory, and C-REBA risk scores as per their requirements, enabling a comprehensive understanding of posture risk levels during task performance and facilitating adjustments to mitigate the occurrence of musculoskeletal disorders. The accuracy and performance of posture assessment within the system are contingent upon the size of the dataset, as it relies on deep neural network models. Currently undergoing testing, the system will incorporate additional posture training data in future iterations to enhance accuracy and generalizability.

Moreover, the BAPAS system exhibits considerable application prospects and potential. Through the integration of behavior analysis and posture assessment functionalities, the system holds the promise of significantly enhancing workflow efficiency and minimizing human errors in caregiver scenarios. Consequently, this advancement can elevate the quality of patient care and ameliorate the overall well-being of healthcare professionals. Notably, the system's successful expansion into rehabilitation posture assessment and guidance, as well as CPR chest compression posture assessment and guidance, underscores its versatility and adaptability in diverse healthcare environments. The versatility of the BAPAS system extends beyond its current applications, encompassing a wide range of medical procedures and tasks, such as surgical interventions, patient lifting in intensive care units, and ergonomic evaluations in clinical settings. By amassing additional data from various medical assistance contexts, the system can be further refined and tailored to address the specific posture assessment requirements of distinct medical scenarios. The ongoing development and refinement of the BAPAS system, coupled with the integration of domain-specific data, will augment its effectiveness and applicability across diverse medical assistance scenarios. Consequently, the potential impact of the BAPAS system in the realm of visualized posture assessment for medical assistance is substantial, providing invaluable support to healthcare professionals and fostering improved patient outcomes.

User feedback and acceptance hold paramount importance in the assessment of the system. The endorsement and positive feedback received from healthcare professionals and users underline the system's usability and effectiveness. To ensure seamless integration of the system into clinical practice, additional user training and support may be required. Furthermore, continuous user engagement and collaboration are essential to refine and optimize the system based on real-world user requirements and preferences. The issue of data security and privacy protection also necessitates attention. Strict adherence to robust data security protocols is vital to safeguard sensitive medical information. Measures such as secure data storage, encrypted transmission, and stringent access control must be implemented to preserve patient privacy and comply with relevant regulations and standards. Looking ahead, the future development of the BAPAS system should explore the integration of artificial intelligence technologies to enhance real-time posture guidance, thus further enhancing its usability and effectiveness. Additionally, integrating the system with other medical devices and systems can offer a more comprehensive and holistic approach to healthcare. Further research and development efforts should concentrate on these areas to augment the system's capabilities and broaden its potential applications.

5.5 Conclusion

The BAPAS system presents a comprehensive solution for the evaluation of job postures and the assessment of musculoskeletal disorder risks in assistive medical tasks. By harnessing advanced algorithms and a cloud-based server, this system enables the processing and analysis of work videos, generating valuable insights into posture data and risk assessment outcomes. Our non-contact behavior analysis and posture assessment approach, as exemplified in this system, effectively overcomes the limitations associated with wearable devices and accelerometer-based methods. With a strong emphasis on user-friendliness and practicality, our system provides an efficient and effective solution for assessing job postures in assistive medical tasks. Moreover, the system holds substantial potential for expansion into other assistive medical scenarios. By aggregating additional posture data from diverse assistive medical contexts and refining the underlying model, a targeted posture assessment system can be developed to cater to specific scenarios. Notably, the system has already demonstrated exceptional performance in posture recognition, evaluation, and guidance, as evidenced by its successful application in rehabilitation posture guidance and CPR posture assessment. In summary, our system has the capacity to enhance workplace safety and improve the overall well-being of healthcare professionals.

Reference

[1] Kim, W., Sung, J., Saakes, D., Huang, C., & Xiong, S. (2021). Ergonomic postural assessment using a new open-source human pose estimation technology (OpenPose). International Journal of Industrial Ergonomics, 84, 103164. DOI: 10.1016/j.ergon.2021.103164.

[2] Chanchai, W., Songkham, W., Ketsomporn, P., Sappakitchanchai, P., Siriwong, W. & Robson, M. (2016). The Impact of an Ergonomics Intervention on Psychosocial Factors and Musculoskeletal Symptoms among Thai Hospital Orderlies. International Journal of Environmental Research and Public Health, 13(5), p.464. DOI: 10.3390/ijerph13050464.

[3] Hoe, V.C., Urquhart, D.M., Kelsall, H.L., Zamri, E.N. & Sim, M.R. (2018). Ergonomic interventions for preventing work-related musculoskeletal disorders of the upper limb and neck among office workers. Cochrane Database of Systematic Reviews, 10(10). DOI: 10.1002/14651858.cd008570.pub3.

[4] Ziam, S., Lakhal, S., Laroche, E., Lane, J., Alderson, M. & Gagné, C. (2023). Musculoskeletal disorder (MSD) prevention practices by nurses working in health care settings: Facilitators and barriers to implementation. Applied Ergonomics, 106, p.103895. DOI: 10.1016/j.apergo.2022.103895.

[5] Oliver Hernández, C.; Li, S.; Merino Rivera, M.D. & Mateo Rodríguez, I. (2022). Does Postural Feedback Reduce Musculoskeletal Risk?: A Randomized Controlled Trial. Sustainability, 14(1), pp.583. DOI:10.3390/su14010583.

[6] Owlia, M., Kamachi, M. & Dutta, T. (2020). Reducing lumbar spine flexion using real-time biofeedback during patient handling tasks. Work, 66(1), pp.41–51. DOI: 10.3233/wor-203149.

[7] Miyajima S, Tanaka T, Imamura Y, et al. Lumbar joint torque estimation based on simplified motion measurement using multiple inertial sensors[C]//2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2015: 6716-6719.

[8] Ferland, P. M., & Comtois, A. S. (2019). Classic powerlifting performance: A systematic review. The Journal of Strength & Conditioning Research, 33, S194-S201. DOI: 10.1519/JSC.0000000000003099.

[9] Cha Y, Nam K, Kim D. Patient posture monitoring system based on flexible sensors[J]. Sensors, 2017, 17(3): 584.

[10] Ran X, Wang C, Xiao Y, et al. A portable sitting posture monitoring system based on a pressure sensor array and machine learning[J]. Sensors and Actuators A: Physical, 2021, 331: 112900.

[11] Lei H, Xiao J, Chen Y, et al. Bamboo-inspired self-powered triboelectric sensor for touch sensing and sitting posture monitoring[J]. Nano Energy, 2022, 91: 106670.

[12] Bowman T, Gervasoni E, Arienti C, et al. Wearable devices for biofeedback rehabilitation: a systematic review and meta-analysis to design application rules and estimate the effectiveness on balance and gait outcomes in neurological diseases[J]. Sensors, 2021, 21(10): 3444.

[13] Park Y S, An C S, Lim C G. Effects of a rehabilitation program using a wearable device on the upper limb function, performance of activities of daily living, and rehabilitation participation in patients with acute stroke[J]. International journal of environmental research and public health, 2021, 18(11): 5524.

[14] de Fátima Domingues M, Rosa V, Nepomuceno A C, et al. Wearable devices for remote physical rehabilitation using a Fabry-Perot optical fiber sensor: ankle joint kinematic[J]. IEEE Access, 2020, 8: 109866-109875.

[15] Nam Y G, Park S Y, Kwon B S. Rehabilitation Exercise Using a Smart-Bar Device with Augmented Reality Guide Function[J]. International Journal of Precision Engineering and Manufacturing, 2023: 1-8.

[16] Wang K, Tan D, Li Z, et al. Supporting Tremor Rehabilitation Using Optical See-Through Augmented Reality Technology[J]. Sensors, 2023, 23(8): 3924.

[17] Gatica-Rojas V, Cartes-Velásquez R. Telerehabilitation in Low-Resource Settings to Improve Postural Balance in Older Adults: A Non-Inferiority Randomised Controlled Clinical Trial Protocol[J]. International Journal of Environmental Research and Public Health, 2023, 20(18): 6726.

[18] Xie J, Wu Q. Design and Evaluation of CPR Emergency Equipment for Non-Professionals[J]. Sensors, 2023, 23(13): 5948.

[19] Oh J H, Noh H, Lee J G, et al. Effects of vertical compression during pediatric cardiopulmonary resuscitation using the one-handed chest compression technique[J]. The American Journal of Emergency Medicine, 2022, 59: 24-29.

[20] Allan K S, O'Neil E, Currie M M, et al. Responding to cardiac arrest in the community in the digital age[J]. Canadian Journal of Cardiology, 2022, 38(4): 491-501.

[21] Stumpf E, Ambati R T, Shekhar R, et al. A Smartphone application to provide real-time cardiopulmonary resuscitation quality feedback[J]. The American Journal of Emergency Medicine, 2022, 60: 34-39.

Chapter 6

Conclusion and prospect

6.1 Conclusion

As the global aging problem worsens, the demand for nursing care is on the rise, placing substantial mental and physical strain on both formal and informal caregivers. Particularly, informal caregivers, lacking professional nursing training, face an elevated risk of musculoskeletal disorders. In light of this, our study aims to address the risk of musculoskeletal disorders among caregivers and offer posture guidance to informal caregivers through the proposal of a visual posture assessment and feedback algorithm based on ergonomic posture risk assessment methods. Furthermore, we have developed a system for assistive healthcare behavior analysis and posture risk assessment that can be seamlessly integrated into mobile devices. The key components of our work encompass the following three main aspects:

(1) Enhancing skeleton recognition accuracy in complex nursing tasks.

Pose recognition methods play a pivotal role in visual-based posture risk assessment research. Among these methods, OpenPose stands out as one of the leading algorithms for pose recognition. However, it encounters challenges in complex scenarios that involve multiple interactions and occlusions, resulting in the misidentification and missing of skeletons. To address this issue, we propose a skeleton reconstruction method based on ST-GCN. Our method leverages behavioral features as crucial indicators and utilizes temporal inference to reconstruct missing skeletons. For misidentified skeletons, we employ the weights of behavioral features to identify abnormal behaviors and reconstruct the skeletons based on similar behavioral features as references. We validate our approach from three dimensions: joint angles, REBA scores, and accuracy. Through comprehensive experiments on joint angles, REBA scores, and accuracy, our results demonstrate that our method achieves joint angles and REBA scores that are not significantly different from ground truth values, surpassing the challenges of skeleton missing and misidentification in nursing tasks and thereby enhancing the accuracy of joint angles and REBA scores. Notably, our method outperforms other skeleton correction methods in terms of REBA score accuracy for nursing task postures, achieving an impressive accuracy of 87.34%. By optimizing skeleton tracking accuracy in nursing tasks, our method enhances the efficiency and accuracy of posture risk assessment, ultimately contributing to the health and safety of healthcare workers.

(2) A C-REBA scoring method for nursing scenarios was proposed.

REBA, an ergonomics-based method for assessing posture risk, plays a crucial role in mitigating the risk of musculoskeletal disorders in nursing tasks. Despite demonstrating favorable evaluation performance across various industries, further investigation is required to compare its evaluation results with actual risks in different scenarios. Our application of the REBA method to nursing tasks revealed an overestimation of the risk level associated with nursing postures and provided identical evaluation results for both experienced and inexperienced caregivers, failing to offer posture risk guidance and references for the latter. To address this limitation, we have developed the C-REBA method, which incorporates nursing task-specific parameters such as center of gravity (COG) trajectory, load duration, and asymmetric load. Experimental findings demonstrate that C-REBA effectively discriminates between experienced and inexperienced caregivers, particularly in nursing task stages 2-4, where it provides posture risk guidance for inexperienced caregivers. As this method evolves, by adjusting the parameters based on data collected from diverse medical scenarios, it can be extended to posture risk assessment in other healthcare settings, thereby enhancing the generalizability of the REBA method.

(3) An assistive healthcare behavior analysis and posture risk assessment system was developed.

The behavior analysis and posture risk assessment system presented in this study offers a comprehensive solution for evaluating work postures and assessing the risk of musculoskeletal disorders in assistive healthcare tasks. Leveraging deep neural network algorithms and cloud-based servers, the system efficiently processes and analyzes work videos, yielding valuable insights into pose data and risk assessment outcomes. By employing non-contact-based behavior analysis and posture assessment methods, our system overcomes the limitations associated with wearable devices and accelerometer-based approaches. Prioritizing user-friendliness and practicality, our solution provides an effective and efficient means of evaluating work postures in assistive healthcare tasks. Moreover, the system holds significant potential for expansion to other assistive healthcare scenarios. By gathering additional posture data from diverse assistive healthcare environments and refining the underlying models, targeted posture assessment systems can be tailored for specific contexts. Currently, the system has successfully extended to applications such as rehabilitation posture guidance and cardiopulmonary resuscitation posture assessment, showcasing exceptional performance in pose recognition, assessment, and guidance. With its potential to enhance workplace safety and improve the overall well-being of healthcare professionals, our system represents a promising advancement in the field of assistive healthcare technology.

6.2 Prospect

While this paper has made notable research advances, there are still limitations and opportunities for further improvement. Thus, we outline the following prospects and future research directions.

Firstly, the current adoption of a 2D-based pose recognition algorithm restricts the calculation of 3D spatial characteristics of pose skeletons, which presents challenges in scoring rotational movements and capturing rotational behavioral features. Our next research focus involves exploring 3D pose recognition methods to enhance skeleton recognition accuracy and enable automated REBA posture risk assessment. Secondly, occlusion during nursing work remains a primary factor contributing to inaccurate EPRA. However, most fixed surveillance cameras utilized for evaluation in elderly care facilities lack the flexibility to adjust angles and mitigate occlusion. To address this issue, we propose leveraging frame interpolation techniques using traditional statistical methods (e.g., linear, cubic spline, Lagrange, Newton polynomial interpolation, and low-rank matrix completion) to compensate for data loss resulting from short-term occlusion. For time intervals exceeding 1 second, machine learning approaches are required to comprehend object motion patterns. In computer vision, various algorithms and methods have been proposed for estimating poses under occlusion, such as masking specific modules during training through data augmentation or employing deep generative motion fillers. These approaches have demonstrated effectiveness in scenarios involving severe and prolonged occlusions, finding applications in rehabilitation and entertainment. However, their adoption in human pose risk assessment remains limited. Future research should explore modifications or adaptations of these algorithms to improve the evaluation of caregiver posture risk.

The pose recognition algorithm exhibits limitations in detecting human skeletons and assessing posture risk under low light or low-resolution conditions. The fusion of caregiver hair color with clothing color further hinders human detection. Previous studies have reported decreased accuracy in low-resolution images. While heatmap filtering adjustments can identify more potential low-confidence targets, unintended targets may be included. Super-resolution algorithms have shown potential in enhancing video quality and image resolution, which can improve the success rate of human detection, but their practical effectiveness requires validation. Furthermore, current research predominantly focuses on posture assessment and guidance for caregivers, neglecting the impact of patient posture and movements on assistive healthcare effectiveness. Future investigations should incorporate patient posture considerations and develop methods for patient posture assessment and guidance to provide a more comprehensive care solution. Lastly, despite the system's favorable performance in laboratory settings, its deployment and application face challenges. Further research is needed to address system usability, user-friendliness, and privacy protection concerns. Future studies should encompass real healthcare environments for long-term field testing and evaluation.

In conclusion, the research presented in this paper offers significant contributions in the advancement of an assistive healthcare posture assessment and behavior analysis system. This work serves as a valuable exploration and showcases innovative approaches in the field. Moving forward, future research endeavors will focus on refining and expanding this area of study to augment the effectiveness of assistive healthcare practices. By doing so, we can strive to provide enhanced health management and care services for both caregivers and patients, fostering improved outcomes in the field of assistive healthcare.

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