공학석사 학위논문

Development of a Video-based Work Pose Entry System for Ergonomic Postural Assessment

인간공학적 자세 평가를 위한 비디오 기반의 작업 자세 입력 시스템 개발

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이 논문을 공학석사 학위논문으로 제출함

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산업공학 전공

김 경 빈

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Abstract

Development of a Video-based Work Pose Entry System for Ergonomic Postural Assessment

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Work-related musculoskeletal disorders are a crucial problem for the worker's safety and productivity of the workplace. The purpose of this study is to propose and develop a video-based work pose entry system for ergonomic postural assessment methods, Rapid Upper Limb Assessment(RULA) and Rapid Entire Body Assessment(REBA). This study developed a work pose entry system using the YOLOv3 algorithm for human tracking and the SPIN approach for 3D human pose estimation. The work pose entry system takes in a 2D video and scores of few evaluation items as input and outputs a final RULA or REBA score and the corresponding action level. An experiment for validation was conducted to 20 evaluators which were classified into two groups, experienced and novice, based on their level of knowledge or experience on ergonomics and musculoskeletal disorders.

Participants were asked to manually evaluate working postures of 20 working videos taken at an automobile assembly plant, recording their scores on an Excel worksheet. Scores were generated by the work pose entry system based on individual items that need to be inputted, and the results of manual evaluation and results from the work pose entry system were compared. Descriptive statistics and Mann-Whitney U test showed that using the proposed work pose entry system decreased the difference and standard deviation between the groups. Also, findings showed that experienced evaluators tend to score higher than novice evaluators. Fisher's exact test was also conducted on evaluation items that are inputted into the work pose entry system, and results have shown that some items that may seem apparent can be perceived differently between groups as well. The work pose entry system developed in this study can contribute to increasing consistency of ergonomic risk assessment and reducing time and effort of ergonomic practitioners during the process. Directions for future research on developing work pose entry systems for ergonomic posture assessment using computer vision are also suggested in the current study.

Keywords: Work-related musculoskeletal disorders, Rapid Upper Limb Assessment, Rapid Entire Body Assessment, Computer vision, Semi-automated posture assessment
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Chapter 1

Introduction

1.1 Background

Musculoskeletal disorders are injuries or disorders of the muscles, nerves, tendons, joints, cartilage, and spinal discs(CDC, 2020). According to CDC, when work environment and performance of work contribute significantly to the condition or the condition is made worse or persists longer due to work conditions, the disorder is referred to as a work-related musculoskeletal disorder (WMSD). As WMSDs occur from accumulated load from repetitive inappropriate postures and movements, it is important to assess the posture and movements of workers to prevent and decrease the risk of WMSDs. Some of the working conditions that may lead to WMSDS are routine lifting of heavy objects, daily exposure to whole-body vibration, routine overhead work, work with the neck in a chronic flexion position, or performing repetitive forceful tasks(Bernard & Putz-Anderson, 1997). Different body parts can suffer from WMSDs depending on the type of task performed. For example, pain is likely to occur in the upper arm, lower arm, wrists, shoulders, and neck, when the task is mostly performed using the upper body.

WMSDs are a serious problem in terms of workers' safety and the productivity of the workplace. In the United States, there were 247,620 cases of WMSDs in private industries in the year of 2020, involving a median of 14 days away from work(U.S.

Bureau of Labor Statistics, 2020). It is also estimated that the annual direct cost of workers' compensation with MSDs is approximately $20 billion(Kang et al., 2014). Moreover, indirect costs, which involve costs related to hiring and training replacement workers were as 5 times the direct cost(Kang et al., 2014). WMSDs were ranked second worldwide in shortening people's working years(Sebbag et al., 2019). The situation is not much different in South Korea. According to the Korea Occupational Safety and Health Agency(KOSHA), 87.4% of all work-related diseases in South Korea were WMSDs as of 2021. As shown in Figure 1, the number of work-related musculoskeletal diseases has kept increasing for the past 10 years. Therefore, there is no doubt that ergonomic risk assessment is necessary to prevent WMSDs.

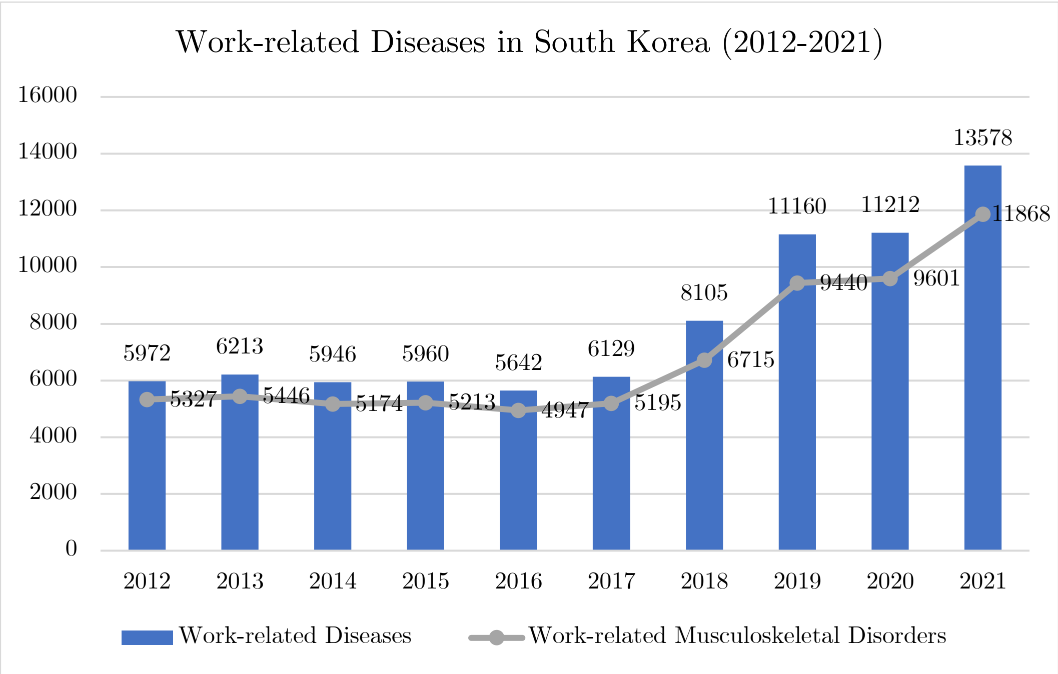

Figure 1 Work-related Diseases in South Korea (2012-2021)

Various methods have been proposed and design for postural evaluation in the workplace. These techniques can be classified as the following: self-reports, observational methods, direct methods(David, 2005; Vignais et al., 2017).

Self-reports methods include worker diaries, interview, questionnaires and are useful when data of large population is needed in short time. However, a major drawback of self-reports is that the data can lack reliability since the data relies on the subjective difficulty of the worker. Also, interpretation of the requires certain skills, which can result in costs relevant to analysis. Observational methods require an ergonomic expert evaluator to manually partition body parts and evaluate the posture of the worker being observed on different risk factors which include repetitive movements, duration, and muscle force (Andrews et al 2012). Several observational tools have been proposed by previous studies, including Rapid Upper Limb Assessment (RULA), Rapid Entire Body Assessment (REBA), and Ovako Working Postures Analysis System (OWAS). These methods differ in the scales the posture is measured with and the body segments being measured. The main drawback of observational methods is that the assessment process is time-consuming and depends on the proficiency and viewing angle of the evaluator, leading to intra- and inter-evaluator variability. Moreover, these techniques require a trained evaluator to perform the assessment, making the method costly. These methods are also suitable for static postures only. Lastly, the direct methods aim to assess postural risk by using advanced technologies such as the inertial measurement units (IMU) and Kinect-based depth cameras. Direct methods are useful for gathering large amount of data and has the advantage of not requiring the manual segmentation of body parts. However, as attaching sensors to the body of workers is not always possible, this may not be an appropriate method to use in the real workplace environment. These techniques also require high initial cost for purchasing the equipment, as these anthropometric devices are quite expensive.

The worksheet-based human observation posture assessment system is cumbersome and prone to human error. Additionally, this process focuses only on a single posture image chosen by the evaluator, which may be insufficient to include the all movements occurring in the working cycle of a certain task. The proposed method aims to address these issues by developing a video-based work pose entry system for ergonomic postural assessment, which can be used by any evaluator regardless of the amount of knowledge or experience with RULA or REBA with videos taken in the real workplace by a single-camera. The work pose entry system generates postural evaluation results based on a video, which evaluates all possible postures taken in a single work cycle.

1.2 Research Objectives

The purpose of this study is to develop a video-based work pose entry system for ergonomic postural assessment to evaluate postures based on the RULA and REBA assessment tool. To be more specific, this study is about developing a system that can generate scores from the videos of workers in real workplace conditions performing occupational tasks. The proposed work pose entry system generates RULA/REBA scores with little input required from the investigator and the Euler angle of each relevant joint, which is automatically computed by computer vision algorithms. The reliability of the proposed tool is validated by comparing manual evaluation results and results from the proposed system between two groups with different experience or knowledge on ergonomic posture analysis. This method is expected to reduce time and effort of ergonomic analysts in RULA, REBA evaluation as only little manual input is required, which are easy to determine.

1.3 Organization of the Thesis

The thesis is composed of 5 chapters. In Chapter 2, we review literatures and important concepts related to the present study. Chapter 3 contains the design of the proposed work pose entry system developed in the current study. Chapter 4 presents the methodology and results of the validation experiment. Chapter 5 contains a discussion of the results of the experiment. Finally, in Chapter 6, we give concluding remarks and possible future research directions of this thesis.

Chapter 2

Literature Review

2.1 Overview

This chapter provides concepts, definitions, and important findings from previous research that relates to the scope of this research. As the main goal of this study is to develop a video-based work pose entry system for RULA and REBA, basic concepts and research regarding work-related musculoskeletal disorders and ergonomic posture assessment are discussed first. After that, definitions and various methods relevant to 3D human pose estimation are presented.

2.2 Work-related Musculoskeletal Disorders

Musculoskeletal diseases(MSD) are injuries or pain that affects the body's joints, ligaments, muscles, nerves, tendons, and structures that support limbs, neck, and back(Hadler, 2005). MSDs can occur from many reasons, examples of which are awkward working posture, repetitive tasks, insufficient recovery time, excessive force exertion, and vibration. Not only can MSDs undermine the performance of the worker, they can also inflict permanent disability. In cases where MSDs are induced or aggravated by working conditions in a workplace, they are referred to as work-related musculoskeletal disorder(Schneider et al., 2010). Some examples of WMSDs are low back pain, carpal tunnel syndrome, tendinitis, and epicondylitis(Da Costa & Vieira, 2010).

2.3 Ergonomic Posture Analysis

According to International Ergonomics Association, ergonomics is the scientific discipline concerned with the understanding of interactions among human and other elements of a system, and the profession that applies theory, principles, data, and methods to design in order to optimize human well-being and overall system performance(IEA). Techniques for ergonomics posture analysis can be classified into self-reports, observational methods, direct methods, and vision-based methods.

2.3.1 Self-reports

Self-report methods collect data by using worker diaries, interview, and questionnaires. These methods have the advantage of being able to be applied in a wide range of context, and useful for surveying a large population. However, a major drawback of these methods is that the perceptions of workers have been found to be imprecise and unreliable(David, 2005). Moreover, the problem of there being different levels of understanding of the job being done may increase the difficulty of using such methods(Spielholz et al., 2001).

2.3.2 Observational Methods

Human-observation risk assessment methods require investigators to assess the working posture of workers in real-time or by videos containing the work-cycle of a certain job. Investigators manually segment each body part and assign the score based on the worksheet of a postural assessment tool. Various postural assessment tools have been developed, such as the Ovako Working Posture Analysis System (OWAS), Rapid Upper Limb Assessment (RULA), and Rapid Entire Body

Assessment (REBA). These tools differ in purpose, relevant body parts, input needed for scoring, and the output generated by the method.

Ovako Working Posture Analyzing System (OWAS)

Developed in 1973 in the steel industry OVAKO OY(Helsinki, Finland), the OWAS method analyzes work postures by observing the frequency and duration of each posture in a single work-cycle(Karhu et al., 1977). Each posture is described by a three-digit code and is classified into one of the 252 possible combinations of the back, upper limb, and lower limb, and the weight of load or amount of force exerted. Four postures of the back, 3 postures of the upper limbs, and 7 postures for the lower limbs are identified, and the load or force is classified into 3 categories(Figure 2).

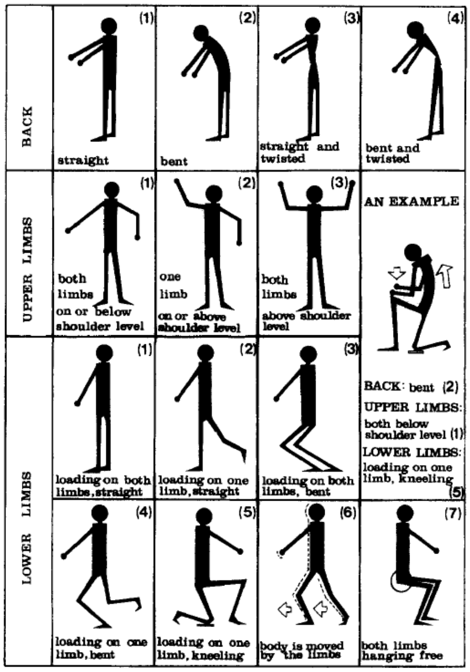

Figure 2 List of items classified by OWAS (Source: Karhu et al., 1977)

The classified posture is then re-classified into 4 categories, which were named operative classes. The larger the number of the class, the more uncomfortable the posture is. Each class indicates the severity of injury and action needed to be taken(Table 1).

Table 1 Operative class of OWAS

Operative class	Implication
Class 1	Normal postures which do not need any special attention, except in some special cases
Class 2	Postures must be considered during the next regular check of working methods
Class 3	Postures need consideration in the near future
Class 4	Postures need immediate consideration

As OWAS is relatively easy to use and is applicable in a wide range of occupations, OWAS has been used in different industries, such as manufacturing, healthcare, and agriculture(Brandl et al., 2017; Herzog et al., 2015; Sakamoto et al., 2017). However, a major limitation of the OWAS method is that it only includes the posture evaluation of the back, upper limb, and lower limb, and that the repetition or duration information is not included.

Rapid Upper Limb Assessment (RULA)

RULA is a survey-based ergonomic risk assessment tool developed to investigate work-related upper limb disorders(McAtamney & Corlett, 1993). This tool has the advantage of requiring no special equipment in providing a quick assessment of postures of the neck, trunk, and upper limbs along with muscle function and external loads.

When using RULA, the investigator must segment the relevant body parts. The relevant body parts are divided into two groups, where Group A consists of upper arm, lower arm, and wrist, and Group B includes the neck, trunk, and legs. The investigator first assigns position scores for each relevant body part. After that, the Muscle Use score, which concerns whether the posture is static or repeated, and Load/Force score, which concerns how much load is exerted on the body, is added to the position scores of each group. Lastly, the combination of each group's score decides the grand score, which is then categorized into 4 action levels(Table 2). The action levels indicate what level of investigation and modification is needed in the observed operations. The scoring methodology of RULA is shown in Figure 3.

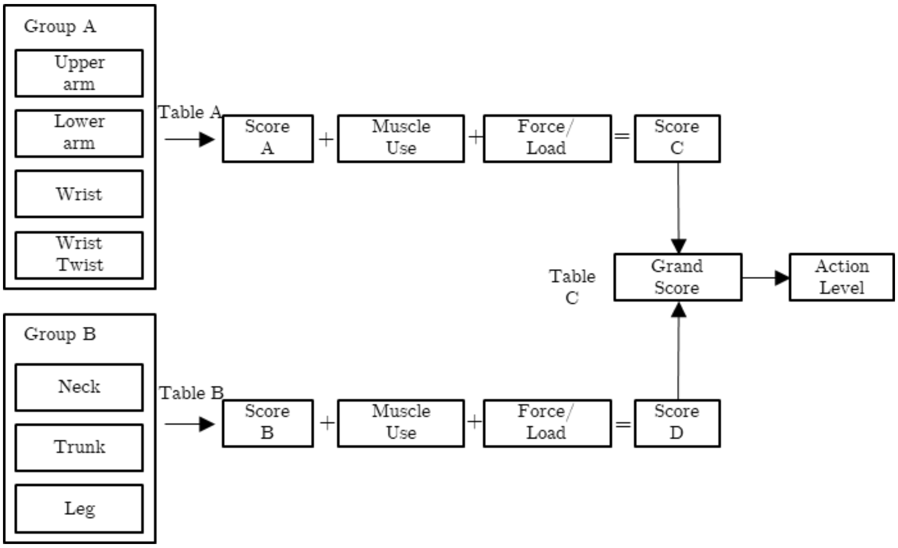

Figure 3 Scoring methodology of RULA

Table 2 Action Levels of RULA

Action Level	Score range	Implication
1	1-2	The posture is acceptable if it is not maintained or repeated for long periods.
2	3-4	Further investigation is needed and changes may be required.
3	5-6	Investigation and changes are required soon.
4	7+	Investigation and changes are required immediately.

As RULA is simple to use and applicable in many different areas where repetitive tasks using the upper limbs take place, it has been used in a variety of domains in previous studies (Azizi et al., 2019; Ekinci et al., 2019; Li et al., 2019; Ratzlaff et al., 2019; Tang & Webb, 2018).In fact, total of 19 categories were found to have been using RULA in a study, where the field of manufacturing had the most studies, total of 74(Gómez-Galán et al., 2020). It was followed by 38 studies on human health and social work activities.

Kee (2020) conducted a study to compare three observational techniques, OWAS, RULA, and Rapid Entire Body Assessment(REBA). The author conducted an experiment with 15 participants to measure discomfort, where hand height, hand distance, and external load were used as independent variables. Load scores for 48 postures by the three assessment methods were generated, and the significance and effects of the independent variables were investigated. Results showed that the RULA grand score reflected the effects of the independent variables. Moreover, the score was the most linearly proportional to the whole-body comfort, which is a measure of postural loads.

However, the RULA method has some limitations as well. First, only the left or right side is assessed at a time. The observer may assess the other side when undecided, but the fundamental process of RULA only takes one side into account(McAtamney & Corlett, 1993). Also, it does not consider how much time it takes for the worker to complete the task(Takala et al., 2010).

Rapid Entire Body Assessment (REBA)

REBA is a survey-based postural analysis system developed to be sensitive to unpredictable working postures found in health care and other service industries(Hignett & McAtamney, 2000). This tool has the advantage of being cost-effective and easy to apply, requiring only pen and paper for collecting data. REBA differs from other methods in that it considers the lower extremities of the body.

Like RULA, REBA requires the investigator to divide the body in to segments to be coded individually, with reference to movement planes. The relevant body parts are divided into two groups, where Group A consists of the trunk, neck, and legs, and Group B includes the upper arms, lower arms, and wrist. The investigator first assigns position scores for each relevant body part. After that, the Load/Force score, which concerns how much load is exerted on the body, is added to scores of Group A, and the coupling score is added to scores of Group B. Activity Scores are also adjusted based on muscle activity. Score C is then calculated based on Score A and Score B, and the final score results to sum of Score C and Activity Score. At last, action level indicating risk level and urgency is provided(Table 3). Figure 4 shows the scoring methodology of REBA.

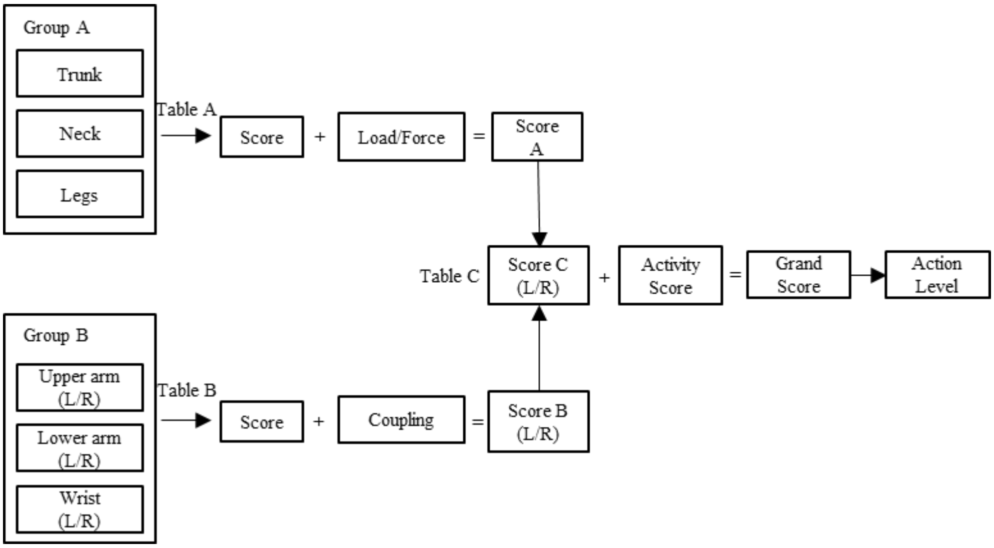

Figure 4 Scoring methodology of REBA

Table 3 Action Levels of REBA

Action Level	Score range	Risk level	Action
0	1	Negligible	None necessary
1	2-3	Low	May be necessary
2	4-7	Medium	Necessary
3	8-10	High	Necessary soon
4	11-15	Very high	Necessary NOW

As REBA is cost-effective and easy to apply, it has been used in many areas, such as manufacturing(Abaraogu et al., 2016; Boulila et al., 2018; Gönen et al., 2018; Yoon et al., 2016) and agriculture(Das & Gangopadhyay, 2015; Das et al., 2013; Houshyar & Kim, 2018). The method has been mainly used for analysis of forced postures rather than repetitive movements(Hita-Gutiérrez et al., 2020).

The main limitation of REBA, however, is that the method does not consider the duration of tasks or the repetition of certain postures. Moreover, like RULA, separate assessment of the left and right sides is required for the investigator. REBA was also shown to underestimate postural loads in a study comparing OWAS, RULA, and REBA (Kee et al. 2020).

2.3.3 Direct Methods

Direct methods are useful and convenient in that they do not require the investigator to manually segment and perform evaluation on each relevant body part. In addition, compared to the observational methods, direct methods are more likely to excel in terms of speed and accuracy. Previous studies on direct methods can be classified into wearable device-based studies and Kinect-based studies.

Peppoloni et al. (2016) proposed a wearable wireless system for assessing muscular efforts and postures of the upper limb, using surface EMG sensors and inertial measurement units (IMUs). The method scores for ergonomic risk according to RULA and Strain Index (SI). For application and testing the accuracy of the system, data is collected from supermarket cashiers performing real-life operations and compared with the results of two human investigators' results. A major limitation of this study is, however, that the positions of the neck, trunk, and leg were considered to be constant throughout each work cycle. Vignais et al. (2017) performed ergonomic analysis of a filter cleaning task by combining subtask video analysis and RULA score calculation using a motion capture system which consists of IMU and electro goniometers. IMUs were used to collect data of the upper arm, forearm, head, trunk, pelvis, and the electro goniometers were used to record wrist angles. Maurer-Grubinger et al. (2021) conducted analysis on two work routines in dentistry using kinematic data recorded from using inertial sensors. RULA scores were analyzed in terms of RULA score, relative RULA score distribution, RULA steps score, relative RULA steps score occurrence, and relative angle distribution. Subjects had to wear a measuring suit, with 17 sensors attached. A major limitation of a wearable device-based assessment is, however, that having to attach body sensors on a worker's body or having the workers wear a certain measuring suit may be difficult and intrusive to implement in real workplace environment in many domains(Abobakr et al., 2017).

Another direct method involves using the Microsoft Kinect. Manghisi et al. (2017) presented a semi-automatic RULA evaluation software based on the Microsoft Kinect v2 depth camera. The system was validated by conducting two experiments. In the first experiment, RULA scores of 15 static postures generated by the proposed system were compared with those obtained from a reference optical motion capture system, and in the second experiment, the scores were compared by the scores of a RULA expert evaluator. Plantard et al. (2017) proposed and evaluated Kinect-based RULA assessment method in real work conditions. As occlusions were the main problem of the Kinect-based methods, different levels of occlusions were tested by using a box. In addition, the proposed method was evaluated within a real workplace, at a car manufacturer factory. Results showed that the method accurately calculates the RULA score in various environments. The drawback of the Kinect-based assessment is that it may suffer from noisy information of the hand joints. In fact, wrist and neck related information needed to be manually set(Manghisi et al., 2017; Plantard et al., 2017). Another drawback concerns light condition. As the Kinect is based on infrared technology, accuracy can be unstable depending on the light conditions of the environment(Humadi et al., 2021; Plantard et al., 2017).

2.3.4 Vision-based Methods

Computer vision-based approaches have been made to generate ergonomic postural analysis scores from images. Yan et al. (2017) developed an ergonomic posture classification system based on OWAS and 2D human pose estimation framework. Three classifiers in terms of arms, back, and legs were trained using different machine learning algorithms. Similarly, Zhang et al. (2018) proposed a method using 3D view-invariant features from a single 2D camera for recognition of hazardous postures at the workplace, where classifiers were trained using machine learning models as well. However, the limitation of these studies is that recognition of postures is not sufficient for ergonomic posture assessment.

Li et al. (2020) explored a deep learning-based algorithm for RULA, which takes normal RGB images as inputs and outputs the RULA action level. It consists of a 2D pose detector built on OpenPose(Cao et al., 2017), a popular open-source technology for 2D human pose estimation, and a RULA estimator which infers action level from 3D joint coordinates by a second deep neural network. For training and evaluation, posture data from Human 3.6 dataset and lifting postures collected in laboratory were used. RULA scores were obtained from manual evaluation of two experimenters with experiences in ergonomics risk assessment. An accuracy of 93% was achieved. A limitation of this study was that wrist score, muscle use, and workload were assumed uniform. Moreover, only static postures were examined, not considering body movement frequency and level of muscle use. In similar fashion, MassirisFernández et al. (2020) presented an OpenPose-based system for computing RULA. Given an input image, workers' skeletons are detected, body-joint positions are inferred, and RULA scores are computed. Drawbacks of this study were that as angles were calculated from 2D projections, projective distortions may occur, and that wrist scores were manually set. Kim et al. (2021) also proposed an OpenPose-based system for computing joint angles and RULA/REBA scores and validated against the reference motion capture system, and compared its performance to the Kinect-based system. Results showed that OpenPose-based method shows good performance at conditions with intended occlusions or tracked from non-frontal views, but a limitation of this study was that manual scoring was given for upper arm rotation, wrist twisting, and neck twisting due to lack of body keypoints for calculating joint angles.

Recently, Nayak and Kim (2021) developed an automated RULA-based posture assessment system using a CNN-based neural model, DeepPose(Toshev & Szegedy, 2014) to estimate RULA scores, including scores for wrist posture. For training and validation, Whole-Body Human Pose Estimation in the Wild dataset was used. Images in the dataset were of people in various postures in common, real-life activities. Validation of the system were done on common occupational workplace posture images that have been manually evaluated by two ergonomic experts.

Drawbacks of this study are that shoulder raising score was fixed at 0, and that joint angles were calculated from 2D joint locations, which can result in projective distortions. Moreover, the reliability of the algorithm depends on the recordings of the postures. Also, the process of validating the method against scores of ergonomic analysts is questionable.

2.4 3D Human Pose Estimation

Human pose estimation refers to the process of estimating the configuration of the body from a single, typically monocular image or video(Sigal, 2020). As it can be applied in various fields including motion analysis, action detection, human-computer interaction, and extended reality, the field of human pose estimation has been receiving significant attention from the scientific community especially in the past decade. With the advancement of Convolutional Neural Networks(CNN) and popular human pose datasets such as Microsoft Common Objects in Context(COCO)(Lin et al., 2014), MPII human Pose dataset(Rohrbach et al., 2015), and Human 3.6M(Ionescu et al., 2013), the field has progressed dramatically. Human pose estimation can be classified as 2D Pose estimation and 3D pose estimation, which is based on whether the location of body keypoints are predicted in 2D space or 3D space.

3D human pose estimation can be classified into model-free approaches and model-based approaches. A model-free approach is a method of directly estimating the location of each vertex. On the other hand, the model-based approach is a method of estimating the parameters of the human model from input images or videos instead of estimating the location of each vertex.

In this thesis, we focus on the various methods and studies on the Skinned Multi-Person Linear(SMPL) model, which is widely used in recent 3D human pose estimation and used in the system proposed in the current study. The SMPL model is a skin vertex-based model trained in thousands of 3D scans, which allows accurate representation of various body joints and shapes in natural poses(Loper et al., 2015).

2.4.1 Model-free Approaches

Model-free approach for pose estimation was first introduced through GraphCMR, which was proposed by Kolotouros, Pavlakos and Daniilidis (2019). In this approach, the feature extracted from the input image is embedded in the graph network to estimate 3D coordinates of the human mesh. Here, the number of nodes in the graph is equal to the number of vertices of the human mesh model. Moon and Lee (2020) proposed I2LMeshNet, which consists of Posture Network (PoseNet) and MeshNet. PoseNet estimates a three-dimensional Gaussian heat map of a single RGB image, representing a three-dimensional joint position. The output of the algorithm is the final human mesh, which is acquired by receiving the features extracted from the first part of PoseNet and the last estimated three-dimensional Gaussian heat map as input. Recently, Lin et al. (2021) proposed a method for restoring human meshes using a self-attention transformer-based encoder network called METRO, which extracts features from a given single RGB image using CNN. The extracted image features are merged with the three-dimensional joint and vertex coordinates of the SMPL human template, and generate joint queries and vertex queries to be processed in the transformer. The transformer encoder network then receives joint queries and vertex queries and outputs three-dimensional joint coordinates and vertex coordinates in parallel.

2.4.2 Model-based Approaches

The model-based approach refers to the process of estimating posture and shape parameters of the human model without directly estimating the location of each vertex. These approaches have been used in numerous recent studies(Biggs et al., 2020; Bogo et al., 2016; Kolotouros, Pavlakos, Black, et al., 2019; Li et al., 2021; Pavlakos et al., 2018). Model-based approaches have shown remarkable results and can be reclassified into direct and indirect estimation methods.

Indirect pose estimation

In this approach, input images are converted to keypoints, human mask, or Gaussian heat maps before estimating SMPL parameters. Bogo et al. (2016) proposed SMPLify, in which DeepCut(Pishchulin et al., 2016) takes in an image to estimate a two-dimensional posture. The estimated two-dimensional posture is then used as an input to a fitting algorithm, where posture and shape parameters of SMPL are fitted to the 2D posture estimated by DeepCut by minimizing errors in the projected joints, postures, and features in the SMPL model. The error function is minimized through repetitive methods by the fitting algorithm.

Pavlakos et al. (2018) proposed a CNN-based method for estimating SMPL parameters from a single image, which is composed of an initialization module, a feature module, and a posture module. The initialization module simultaneously estimates a two-dimensional thermal map and a silhouette from the input image based on the multi-task learning paradigm. After that, a two-dimensional heat map is entered into the posture module to estimate the posture parameters, and the silhouette is used to estimate the shape parameters in the shape module.

Direct pose estimation

Direct pose estimation methods estimate SMPL parameters directly from the input image. Kanazawa et al. (2018) proposed human mesh recovery (HMR). Instead of using a single CNN network, HMR used Generative Adversarial Networks (GANs) to design the network. The generation network estimates the SMPL parameters from a single image by using a discriminator to determine whether the estimated human mesh is real or fake to prevent the creation of unreliable human meshes.

Kolotouros, Pavlakos, Black, et al. (2019) proposed SMPL oPtimization IN the loop (SPIN), a mixture of CNN-based and optimization-based methods. In general, CNN-based methods show fast and satisfactory performance in estimating mesh, but do not perform well compared to well-designed optimization-based methods. On the other hand, the optimization-based method shows good fitting performance, but its performance depends a lot on the initial prediction value and is very slow. The main idea of SPIN is to input images into CNN networks to estimate the initial SMPL parameters. The initial parameters typically exhibit about half the performance of the result of the SPIN model. The optimization technique performs repetitive fitting using parameters estimated by CNN as a starting point for optimization. This allows the SPIN to significantly reduce the time required for optimization

Chapter 3

Proposed System Design

3.1 Overview

This chapter discusses the architecture and details of the work pose entry system proposed in the current study. The structure of the work pose entry system is depicted in the figure below(Figure 5).

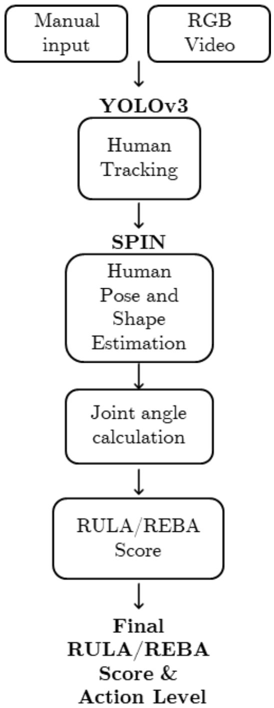

Figure 5 Overview of the proposed work pose entry system

3.2 Human Tracking

The first step of the proposed system involves tracking the worker of interest in the video. This process is necessary as most videos taken in the real workplace context would typically capture multiple workers simultaneously. Yet, ergonomic posture assessment is designed for one worker at a time. The human tracking process therefore gets rid of needless background information and other workers that aren't targeted for analysis.

This system employs the convolutional neural network(CNN)-based algorithm YOLOv3(You Only Look Once, Version3) for tracking, as it has balanced performance in terms of detection speed and accuracy(Redmon & Farhadi, 2018). The core of YOLOv3 algorithm is to reconstruct object detection as a logistic regression problem. The input image is divided into a w*k grid and for each part of the grid some number of bounding boxes around objects are predicted. Using logistic regression, the algorithm predicts whether the objects is in the box. The proposed system defines the worker for assessment as one with the largest bounding box that exists in more than $1/3$ of the input video.

3.3 3D Human Pose Estimation

This step concerns reconstructing the 3D human body from the 2D input video to identify and classify the joints. This tool adopts the SPIN(SMPL oPtimization IN the loop) approach. which is based on the SMPL model(Loper et al., 2015). The SMPL is a skinned vertex-based model learned from thousands of 3D body scans, which can thus represent a wide variety of body joints and shapes. It represents the human skeleton by a hierarchy of 24 joints (Ha, 2018). The hierarchy is defined by a kinematic tree based on relative rotations from parent joints. Originally, rotation is encoded by an axis-angle representation of 3 scalar values, but to reflect the scoring criteria of RULA and REBA, angle representation is converted to Euler angles.

The SPIN approach uses a collaboration of a regression method and an optimization-based method for training deep network for 3D human pose and shape estimation. When an input image with a person is given, CNN regresses the full 3D shape of the person. Then iterative optimization is done to fit the body to 2D joints in the training loop. Therefore, a self-improving cycle is made, resulting in low recognition error(Kolotouros, Pavlakos, Black, et al., 2019)(Figure 6). The approach has been shown to have low mean per joint position error(MPJPE) compared to the state-of-the-art.

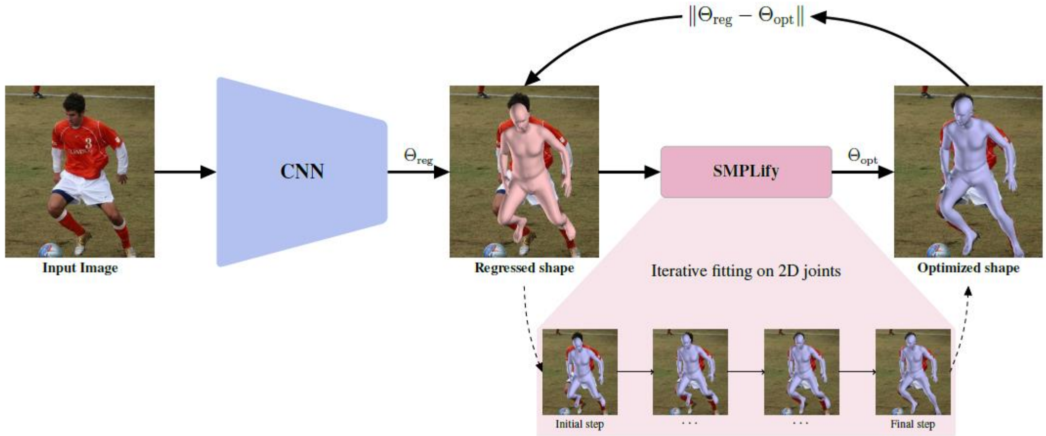

Figure 6 Overview of SPIN (Source: Kolotouros, Pavlakos, Black, et al., 2019)

3.4 Score Calculation

3.4.1 Posture Score Calculation

After the joints are detected from pose estimation, the rotation angle of targeted joints for each assessment tool is calculated. In this study, θx, θy, θz defines the rotation angle with respect to the x-axis, y-axis, z-axis as shown in Figure 7.

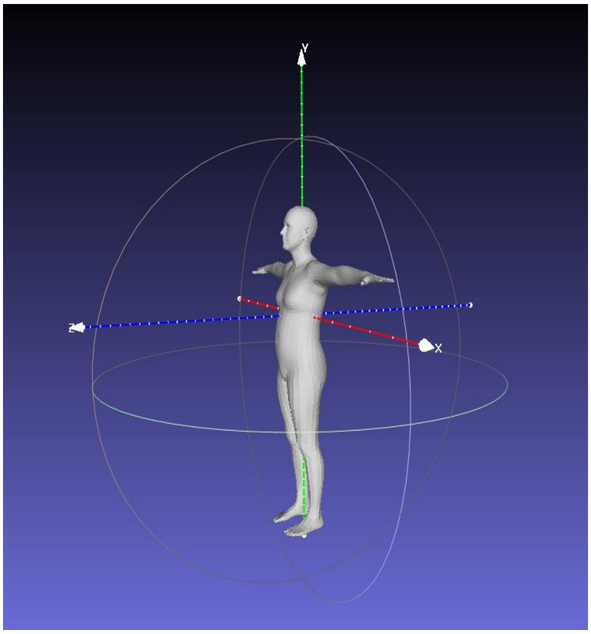

Figure 7 Location of the x,y,z-axis for calculating Euler angles

Thresholds were quantified as defined in previous studies(Nayak & Kim, 2021; Vignais et al., 2017) or newly quantified where it was necessary. The following evaluation items are automatically calculated by the proposed tool, and example images of each item is shown also(Figure 8,Figure 9,Figure 10,Figure 11,Figure 12).

Upper arm position(flexion/extension): θy of the shoulder joint was used to calculate upper arm flexion/extension angles.

Upper arm abduction: θz of shoulder joint was used to calculate upper arm abduction. The upper arm was considered to be abducted when θz was above 45 °.

Upper arm rotation: θx of shoulder joint was used to calculate upper arm abduction. The upper arm was considered to be abducted when θx of the shoulder was above 10 °.

Raised Shoulder: θz of the thorax joint was used to calculate raised shoulder. The shoulder was considered to be raised if θz was above 10°.

Lower arm position: θy and θz of the elbow joint was used to calculate lower arm position. Score was given depending on the larger value between the two rotation angles.

Lower arm across the midline/bent out to side: θx of the thorax joint was used to calculate whether the lower arm is across the midline or bent out to the side.

Wrist position(flexion/extension): θx of the wrist joint was used to calculate wrist flexion/extension.

Wrist side-bending(radial/ulnar deviation): θx of the wrist joint was used to calculate wrist side-bending. The wrist was considered side-bent when the rotation angle is larger than 10°.

Wrist twist(pronation/supination): θx of the wrist joint was used to calculate wrist twist.

Neck position(flexion/extension): θx of the neck joint was used to calculate neck flexion/extension.

Neck side-bending: θz of the neck joint was used to calculate neck side-bending. The neck was considered side-bent when the rotation angle is larger than 10°.

Neck twist: θy of the neck joint was used to calculate neck twist. The neck was considered twisted when the rotation angle is larger than 10°.

Trunk position(flexion/extension): θx of the torso joint was used to calculate trunk flexion/extension.

Trunk side-bending: θz of the torso joint was used to calculate trunk side-bending. The trunk was considered side-bent when the rotation angle is larger than 10°.

Trunk twist: θy of the torso joint was used to calculate trunk twist. The trunk was considered twisted when the rotation angle is larger than 10°.

Leg angle: θy of the knee joint was used to calculate leg bending angle

The rest of the evaluation items require input information from the evaluator:

RULA:

- Group A: Muscle Use(L), Muscle Use(R), Arm support(L), Arm support(R), Load/Force(L), Load/Force(R)
- Group B: Load/Force, Muscle Use, Legs posture scores

REBA:

- Group A: Load/Force, Legs posture scores, Sitting
- Group B: Arm support(L), Arm support(R), Coupling
- Activity Score

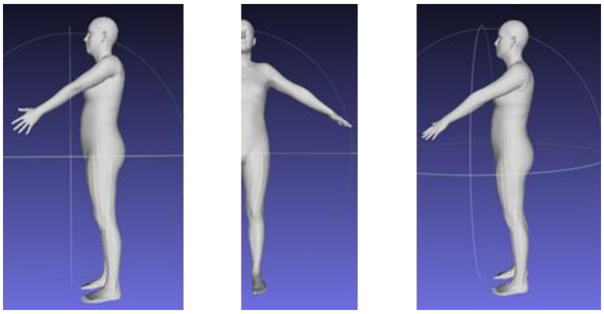

Figure 8 Example images of Upper Arm Bending, Upper Arm Abduction, Upper Arm Rotation

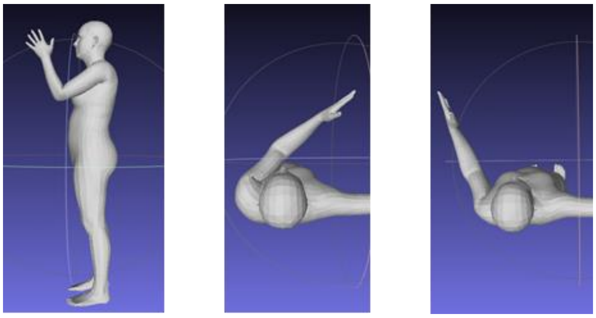

Figure 9 Example images of Lower arm bending, Lower arm across the midline, Lower arm bent to side

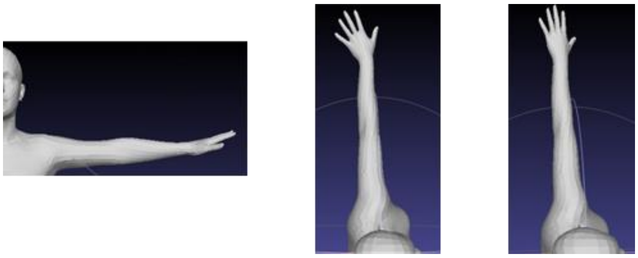

Figure 10 Example images of Wrist flexion, Wrist side-bending, Wrist twist

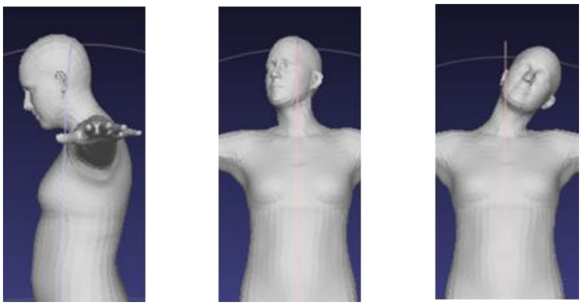

Figure 11 Example images of Neck flexion, Neck twist, Neck side-bending

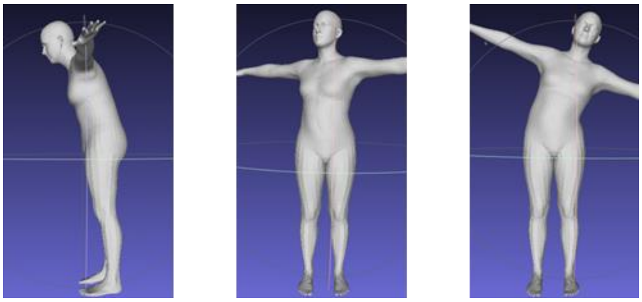

Figure 12 Example images of Trunk flexion, Trunk twist, Trunk side-bending

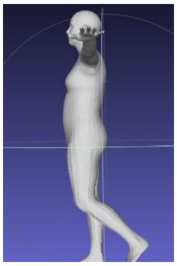

Figure 13 Example image of bent leg

3.4.2 Output of the Proposed System

The output of the proposed system is a video showing score for each joint and RULA or REBA score for each frame. In addition, the final RULA/REBA score, which is the highest score calculated in the video, and the corresponding action level and action is outputted in a text file(Figure 14).

Frame #59

Frame #253

Frame #665

```
1 AVG Score: 10.669
2 %50 Score: 11.858
3 %10 Score: 13.0
4 MAX Score: 13
5 MODE Score: 11
6 Action level: 5
7 Action: Very high risk. Implement change
```

Figure 14 Example of the output of the system

Chapter 4

Validation Experiment

4.1 Hypotheses

An experiment for validation of the proposed system was conducted based on the following hypotheses:

1) The difference in evaluation scores between two groups with different level of knowledge or experience with ergonomic posture assessment should decrease by the proposed system.
2) Items for manual input should not be different between groups with different level of knowledge or experience with ergonomic posture assessment.

4.2 Methods

4.2.1 Participants

A total of 20 evaluators, 11 males and 9 females were recruited to participate in an ergonomic posture assessment experiment. The average age of the participants was approximately 28(min=24, max=35). The participants were classified into experienced group and novice group based on their experience or level of knowledge on ergonomic posture assessment. Participants were considered as experienced evaluators if they are currently a Ph.D student majoring in ergonomics or have prior experience in conducting RULA or REBA, and were considered novice evaluators if they have successfully completed the ergonomics course on a graduate level or is currently a Master's student majoring in ergonomics. As a result, 15 participants were classified as novice evaluators and 5 participants were classified as experienced evaluators.

4.2.2 Apparatus

A worksheet was made with Microsoft Excel to make simultaneous evaluation using both tools possible(Figure 15). Since RULA and REBA share many evaluation items, the worksheet was made to require input for only one tool when the evaluation item exits in both tools. As the experiment was conducted remotely, participants used their own personal computer where they can watch videos and use Microsoft Excel to record scores for each video.

4.2.3 Procedure

An online survey using Google Forms was conducted to investigate the level of knowledge or experience the participant has on ergonomic posture analysis. Each participant was instructed to watch a 30-minute introductory video on RULA and REBA on YouTube. After that, participants conducted ergonomic posture analysis for 20 videos of automobile assembly plant workers using RULA and REBA. Participants were instructed to conduct evaluation on what they consider the most dangerous posture in the video, and to record scores for both left and the right side of the body where required. Weight information of the load in each video were given. The example image of each video is in Figure 16 and Figure 17.

흰 색의 입력칸에만 입력하세요. 회색 칸의 경우 RULA 항목과 완전히 동일하여 입력 필요 없음. 검정색 칸의 경우 해당 평가 방법에는 속하지 않는 항목이라 입력 하지 않습니다.

평가자 이름						
		※기입 방법※	RULA(L)	RULA(R)	REBA(L)	REBA(R)
Neck	목 위치	드롭다운 목록에서 선택	0-10도 굽힘		0-20도 굽힘	
	비틀림	0:해당 없음 1:해당	0		0	
	옆으로 구부림	0:해당 없음 1:해당	0		0	
	Neck score		**1**		**1**	
Trunk	허리 위치	드롭다운 목록에서 선택	0-20도 굽힘		0-20도 굽힘	
	앉은 자세 여부	0:해당 없음 1:해당	0			
	(앉은 자세의 경우에만 기입) 허리 지지 여부	0:지지가 잘됨 1:지지가 잘				
	비틀림	0:해당 없음 1:해당	0		0	
	옆으로 구부림	0:해당 없음 1:해당	0		0	
	Trunk score		**2**		**2**	
Leg	두 다리가 안정적으로 지지됨	0:해당 없음 1:해당	1		1	
	무릎이 굽혀진 정도(곧게 뻗은 상태가 0도)	드롭다운 목록에서 선택				
	앉은 자세 여부	0:해당 없음 1:해당			0	
	걷기 여부 (=걸으면서 하는 작업)	0:해당 없음 1:해당			0	
	Leg score		**2**		**#N/A**	
Force/Load	중량물 무게 ※(NECK, TRUNK, 또는 LEG에 가해지는)	드롭다운 목록에서 선택	2-10kg (정적 자세 또는 반복)		5-10kg	
	충격 또는 갑작스러운 힘	0:해당 없음 1:해당	0		0	
정적 자세/반복 여부	1분 이상 한 자세를 유지	0:해당 없음 1:해당	1		1	
	분당 4회 이상 반복 (걷기는 고려 하지 않음)	0:해당 없음 1:해당	1		1	
	자세에 갑작스러운 큰 변화 발생/불안정한 기반	0:해당 없음 1:해당			0	

			RULA(L)	RULA(R)	REBA(L)	REBA(R)
Upper Arm	윗팔 위치	드롭다운 목록에서 선택	45-90도 앞으로	45-90도 앞으로	45-90도 앞으로	45-90도 앞으로
	옆으로 벌어짐	0:해당 없음 1:해당	0	0	0	0
	윗팔 회전	0:해당 없음 1:해당			1	1
	어깨 들림	0:해당 없음 1:해당	1	1	1	1
	팔이 어딘가 기대있거나 지지되어 있는 상태	0:해당 없음 1:해당	1	1	1	1
	Upper arm score		**3**	**3**	**4**	**4**
Lower Arm	아래팔 위치	드롭다운 목록에서 선택	60-100도 굽힘	60-100도 굽힘	60-100도 굽힘	60-100도 굽힘
	팔이 몸 안쪽을 교차하여 작업	0:해당 없음 1:해당	0	0		
	팔이 몸통을 벗어나 작업	0:해당 없음 1:해당	0	0		
	Lower arm score		**1**	**1**	**1**	**1**
Wrist	손목 각도	드롭다운 목록에서 선택	15도 이상 들림/꺾임	15도 이상 들림/꺾임	15도 이상 들림/꺾임	15도 이상 들림/꺾임
	손목이 옆으로 굽혀짐	0:해당 없음 1:해당	1	1	1	1
	손목 비틀림	0:해당 없음 1:해당	0	0	0	0
	Wrist score		**5**	**5**	**3**	**3**
Force/Load	중량물 무게	드롭다운 목록에서 선택	-10kg (정적 자세 또는 반복	0kg (정적 자세 또는 반	5-10kg	
	충격 또는 갑작스러운 힘	0:해당 없음 1:해당	0	0	0	
정적 자세/반복 여부	1분 이상 한 자세를 유지	0:해당 없음 1:해당	0	0	0	
	분당 4회 이상 반복 (걷기는 고려 하지 않음)	0:해당 없음 1:해당	1	1	1	
	자세에 갑작스러운 큰 변화 발생/불안정한 기반	0:해당 없음 1:해당			0	
손잡이 분류	좋음, 보통, 나쁨, 부적절	좋음:0 보통:1 나쁨:2 부적			1	

RULA

Score A		Muscle		Force		Score C	
L	R	L	R	L	R	L	R
5	5	1	1	2	2	8	8

Score B	Muscle	Force	Score D
1	1	3	5

Grand Score	
L	R
7	7

REBA

Group A	Force
3	1

Score A
4

Score C	Activity Score
6	2

Grand Score
8

Group B		Coupling	Score B
L	R	1	6
5	5		

Figure 15 Excel worksheet for manual evaluation

Video 1

Video 2

Video 3

Video 4

Video 5

Video 6

Video 7

Video 8

Video 9

Video 10

Figure 16 Example images of videos evaluated in the experiment

Video 11

Video 12

Video 13

Video 14

Video 15

Video 16

Video 17

Video 18

Video 19

Video 20

Figure 17 Example images of videos evaluated in the experiment (Cont.)

4.2.4 Data Analysis

Data were analyzed using the Statistical Package for Social Sciences (SPSS Inc., Chicago, IL). Between-group differences were analyzed in Grand Scores and Action Levels using Mann-Whitney U Test due to the small sample size and the normality of the data did not appear. In addition, Fisher's exact test was conducted to determine if there was significant association between level of experience and the evaluation items that require input from the investigator while using the proposed system.

4.3 Results

4.3.1 RULA

Grand score

Table 4 Descriptive statistics of RULA Grand Scores (Mean(SD))

Vid	Manual			System		
.	Novice	Expert	All	Novice	Expert	All
1	6.27(±0.88)	6.8(±0.45)	6.4(±0.82)	6.93(±0.26)	7(±0)	6.85(±0.22)
2	5.4(±1.45)	6.6(±0.55)	5.7(±1.38)	6.67(±0.49)	6.6(±0.55)	6.8(±0.49)
3	5.67(±1.23)	5.8(±0.84)	5.7(±1.13)	6.27(±0.46)	6.2(±0.45)	6.7(±0.44)
4	6.33(±1.11)	7(±0)	6.5(±1)	6.93(±0.26)	7(±0)	6.85(±0.22)
5	4.93(±1.28)	6.6(±0.55)	5.35(±1.35)	7(±0)	7(±0)	6.8(±0)
6	4.8(±1.66)	5.2(±1.64)	4.9(±1.62)	7(±0)	7(±0)	6.7(±0)
7	5.73(±1.44)	6.8(±0.45)	6(±1.34)	6.33(±0.49)	6.8(±0.45)	6.9(±0.51)
8	6.53(±0.83)	7(±0)	6.65(±0.75)	6.73(±0.46)	7(±0)	6.9(±0.41)
9	3.87(±1.19)	5.4(±1.34)	4.25(±1.37)	6.73(±0.46)	6.6(±0.55)	6.8(±0.47)
10	3.93(±1.28)	5.2(±1.3)	4.25(±1.37)	6.53(±0.52)	6.2(±0.45)	6.9(±0.51)
11	4.4(±1.5)	5.2(±1.79)	4.6(±1.57)	7(±0)	7(±0)	6.8(±0)
12	6(±1.2)	7(±0)	6.25(±1.12)	6.8(±0.41)	7(±0)	6.55(±0.37)
13	5.27(±1.33)	5.8(±1.3)	5.4(±1.31)	7(±0)	7(±0)	6.9(±0)
14	4.6(±1.3)	5.4(±1.34)	4.8(±1.32)	6.27(±0.46)	6.6(±0.55)	6.85(±0.49)
15	4.73(±1.58)	6.2(±0.45)	5.1(±1.52)	6.87(±0.35)	7(±0)	6.85(±0.31)
16	6.53(±1.06)	7(±0)	6.65(±0.93)	7(±0)	7(±0)	6.9(±0)
17	6(±1.25)	6.8(±0.45)	6.2(±1.15)	7(±0)	7(±0)	6.7(±0)
18	6.47(±0.83)	6.6(±0.89)	6.5(±0.83)	7(±0)	7(±0)	6.75(±0)
19	6.47(±0.92)	6.4(±0.89)	6.45(±0.89)	7(±0)	7(±0)	6.9(±0)
20	5.53(±1.3)	6.2(±1.3)	5.7(±1.3)	7(±0)	7(±0)	6.9(±0)

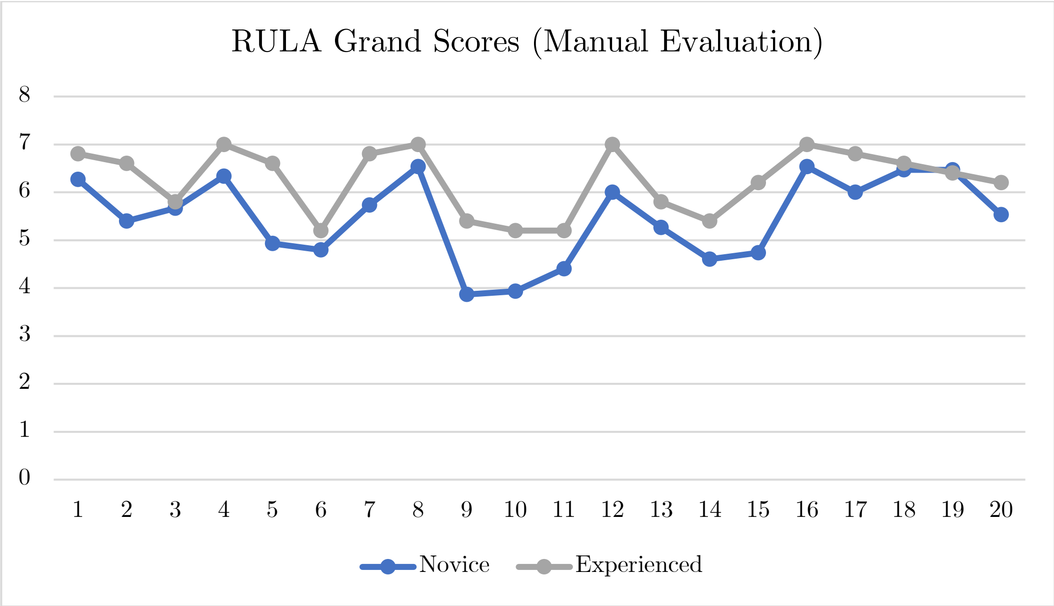

Figure 18 Mean of RULA Grand Scores (Manual Evaluation)

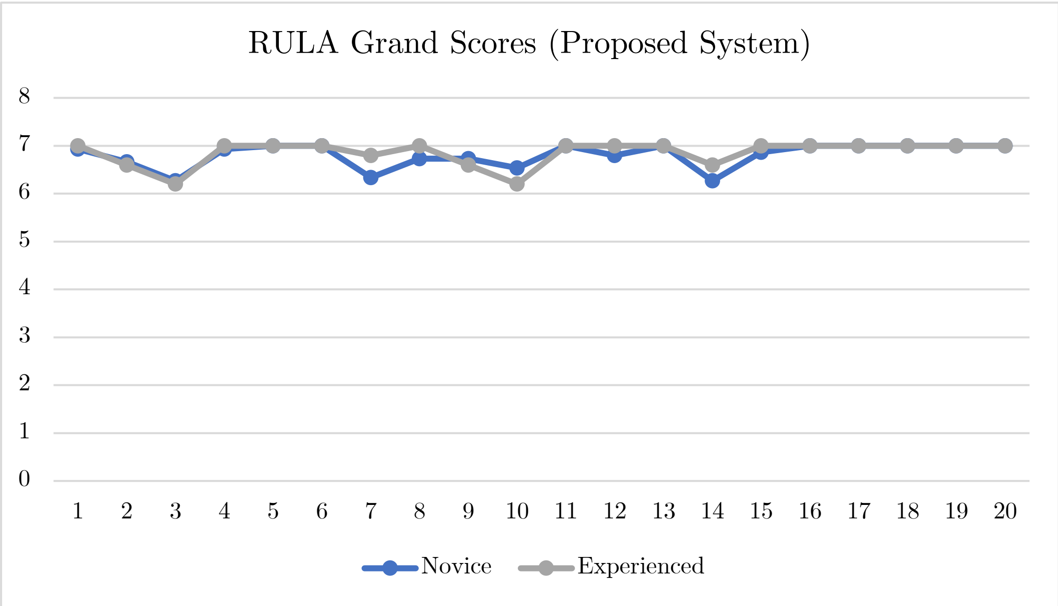

Figure 19 Mean of RULA Grand Scores (Proposed System)

Table 5 Results of Mann-Whitney U Test for difference in RULA Grand Scores between novice and experienced evaluators

Vid.	Sig.	
	Manual	System
1	0.186	0.564
2	0.076	0.564
3	0.926	0.564
4	0.104	0.564
5	0.016*	1.000
6	0.417	1.000
7	0.099	0.077
8	0.149	0.208
9	0.048*	0.583
10	0.065	0.206
11	0.342	1.000
12	0.047*	0.290
13	0.447	1.000
14	0.233	0.187
15	0.063	0.402
16	0.210	1.000
17	0.162	1.000
18	0.569	1.000
19	0.797	1.000
20	0.200	1.000

* $p<.05$

Significant differences between groups in RULA Grand Scores were found in video 5,9,12 when evaluation was done manually(Table 4). There was also a general trend that experienced evaluators had higher mean RULA Grand Scores compared to the novice evaluators(Figure 18). For data generated by the proposed system, there were no significant differences between groups within each video(Table 5). Standard deviation of all evaluators for RULA scores decreased with the proposed system compared to manually generated scores.

Action Level

Table 6 Descriptive statistics of RULA Action Levels (Mean(SD))

Vid.	Manual			System		
	Novice	Expert	All	Novice	Expert	All
1	3.4(±0.63)	3.8(±0.45)	3.5(±0.61)	3.93(±0.26)	4(±0)	3.95(±0.22)
2	3.07(±0.7)	3.6(±0.55)	3.2(±0.7)	3.67(±0.49)	3.6(±0.55)	3.65(±0.49)
3	3.07(±0.7)	3.2(±0.45)	3.1(±0.64)	3.27(±0.46)	3.2(±0.45)	3.25(±0.44)
4	3.53(±0.64)	4(±0)	3.65(±0.59)	3.93(±0.26)	4(±0)	3.95(±0.22)
5	2.6(±0.74)	3.6(±0.55)	2.85(±0.81)	4(±0)	4(±0)	4(±0)
6	2.67(±0.82)	2.8(±1.1)	2.7(±0.86)	4(±0)	4(±0)	4(±0)
7	3.2(±0.77)	3.8(±0.45)	3.35(±0.75)	3.33(±0.49)	3.8(±0.45)	3.45(±0.51)
8	3.6(±0.63)	4(±0)	3.7(±0.57)	3.73(±0.46)	4(±0)	3.8(±0.41)
9	2.2(±0.68)	2.8(±0.45)	2.35(±0.67)	3.73(±0.46)	3.6(±0.55)	3.7(±0.47)
10	2.2(±0.56)	2.8(±0.84)	2.35(±0.67)	3.53(±0.52)	3.2(±0.45)	3.45(±0.51)
11	2.53(±0.83)	3(±1)	2.65(±0.88)	4(±0)	4(±0)	4(±0)
12	3.27(±0.8)	4(±0)	3.45(±0.76)	3.8(±0.41)	4(±0)	3.85(±0.37)
13	2.93(±0.7)	3.2(±0.84)	3(±0.73)	4(±0)	4(±0)	4(±0)
14	2.47(±0.64)	2.8(±0.84)	2.55(±0.69)	3.27(±0.46)	3.6(±0.55)	3.35(±0.49)
15	2.6(±0.83)	3.2(±0.45)	2.75(±0.79)	3.87(±0.35)	4(±0)	3.9(±0.31)
16	3.67(±0.62)	4(±0)	3.75(±0.55)	4(±0)	4(±0)	4(±0)
17	3.33(±0.72)	3.8(±0.45)	3.45(±0.69)	4(±0)	4(±0)	4(±0)
18	3.53(±0.64)	3.8(±0.45)	3.6(±0.6)	4(±0)	4(±0)	4(±0)
19	3.6(±0.63)	3.6(±0.55)	3.6(±0.6)	4(±0)	4(±0)	4(±0)
20	3(±0.65)	3.4(±0.89)	3.1(±0.72)	4(±0)	4(±0)	4(±0)

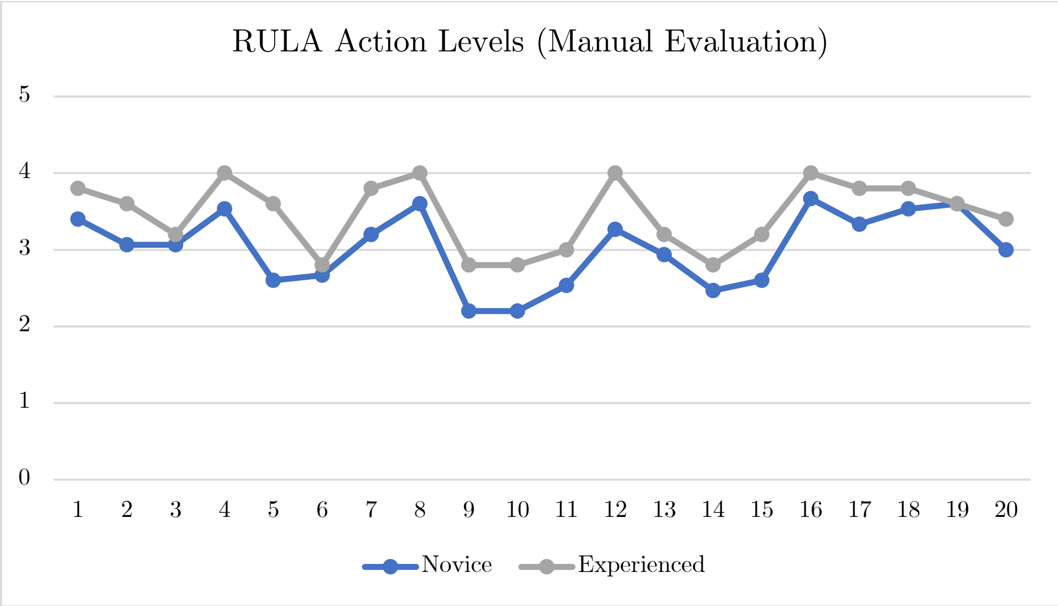

Figure 20 Mean of RULA Action Levels (Manual Evaluation)

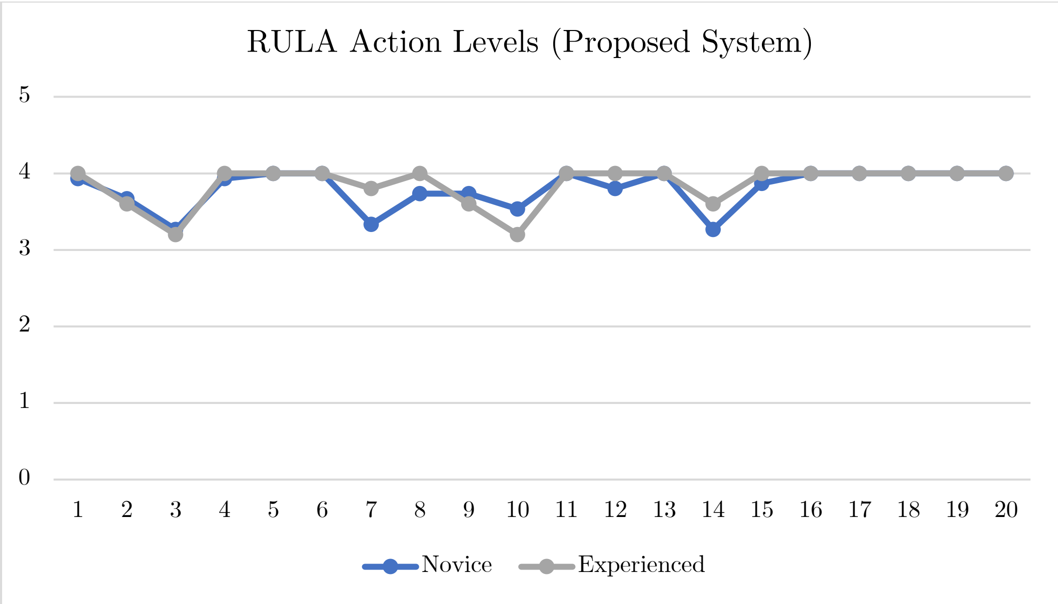

Figure 21 Mean of RULA Action Levels (Proposed System)

Table 7 Results of Mann-Whitney U Test for difference in RULA Action Levels between novice and experienced evaluators

Vid.	Sig.	
	Manual	System
1	0.196	0.564
2	0.138	0.792
3	0.817	0.771
4	0.102	0.564
5	0.018*	1.000
6	0.884	1.000
7	0.114	0.077
8	0.149	0.208
9	0.035*	0.583
10	0.120	0.206
11	0.295	1.000
12	0.046*	0.290
13	0.477	1.000
14	0.377	0.187
15	0.118	0.402
16	0.210	1.000
17	0.185	1.000
18	0.404	1.000
19	0.876	1.000
20	0.254	1.000

* $p<.05$

Significant differences between groups in RULA Action Levels were found in video 5,9,12 when evaluation was done manually(Table 7). There was a general trend that experienced evaluators had higher mean RULA Action Levels compared to the novice evaluators(Figure 20). For data generated by the proposed system, there were no significant differences between groups within each video(Table 7). Standard deviation of all evaluators for RULA Action Levels decreased with the proposed system compared to manually generated scores(Table 6, Figure 21).

4.3.2 REBA

Grand scores

Table 8 Descriptive statistics of REBA Grand Scores (Mean(SD))

Vid.	Manual			System		
	Novice	Expert	All	Novice	Expert	All
1	8.13(±2.1)	9.6(±2.79)	8.5(±2.31)	12(±1.22)	10.6(±1.24)	10.95(±1.36)
2	7.2(±2.83)	9.8(±2.49)	7.85(±2.92)	10.6(±1.34)	9.53(±1.19)	9.8(±1.28)
3	8.27(±2.31)	9(±1.22)	8.45(±2.09)	8.8(±0.84)	8.33(±1.18)	8.45(±1.1)
4	8.33(±2.26)	11(±1)	9(±2.32)	10(±1)	9.27(±0.59)	9.45(±0.76)
5	5.07(±1.79)	7.6(±2.07)	5.7(±2.13)	11.4(±0.89)	9.6(±1.06)	10.05(±1.28)
6	5.13(±2.42)	7.2(±3.49)	5.65(±2.78)	9.8(±1.92)	8.8(±1.01)	9.05(±1.32)
7	7.13(±2.42)	10.6(±2.07)	8(±2.75)	10(±0.71)	8.13(±1.25)	8.6(±1.39)
8	9.87(±3.07)	10.8(±2.28)	10.1(±2.86)	11.2(±1.1)	10.87(±1.06)	10.95(±1.05)
9	3.73(±1.71)	6.4(±1.95)	4.4(±2.09)	8.2(±1.48)	7.8(±1.37)	7.9(±1.37)
10	4.93(±1.79)	7.4(±2.07)	5.55(±2.11)	9.4(±1.34)	8.67(±0.62)	8.85(±0.88)
11	7.47(±2.72)	9.2(±1.79)	7.9(±2.59)	11(±1)	11.6(±1.12)	11.45(±1.1)
12	8.13(±2.75)	10(±1.58)	8.6(±2.6)	9.2(±1.3)	9.07(±0.96)	9.1(±1.02)
13	6(±2.54)	8.4(±1.52)	6.6(±2.52)	9.2(±0.84)	8.8(±0.77)	8.9(±0.79)
14	5.93(±2.71)	7.6(±0.89)	6.35(±2.48)	8.2(±0.45)	7.87(±0.83)	7.95(±0.76)
15	5(±2.33)	7.8(±1.79)	5.7(±2.49)	9.4(±0.55)	8.93(±1.1)	9.05(±1)
16	9(±2.54)	12(±2.65)	9.75(±2.83)	13(±1.22)	11.6(±0.91)	11.95(±1.15)
17	7.93(±2.58)	7.8(±2.39)	7.9(±2.47)	11(±0.71)	10.33(±0.9)	10.5(±0.89)
18	9.67(±2.38)	11.4(±2.3)	10.1(±2.43)	12(±0.71)	12.13(±0.92)	12.1(±0.85)
19	11(±2.45)	10(±3.16)	10.75(±2.59)	11.2(±2.05)	11.67(±1.18)	11.55(±1.39)
20	10.07(±1.87)	10.8(±2.77)	10.25(±2.07)	12.2(±0.84)	11.93(±1.03)	12(±0.97)

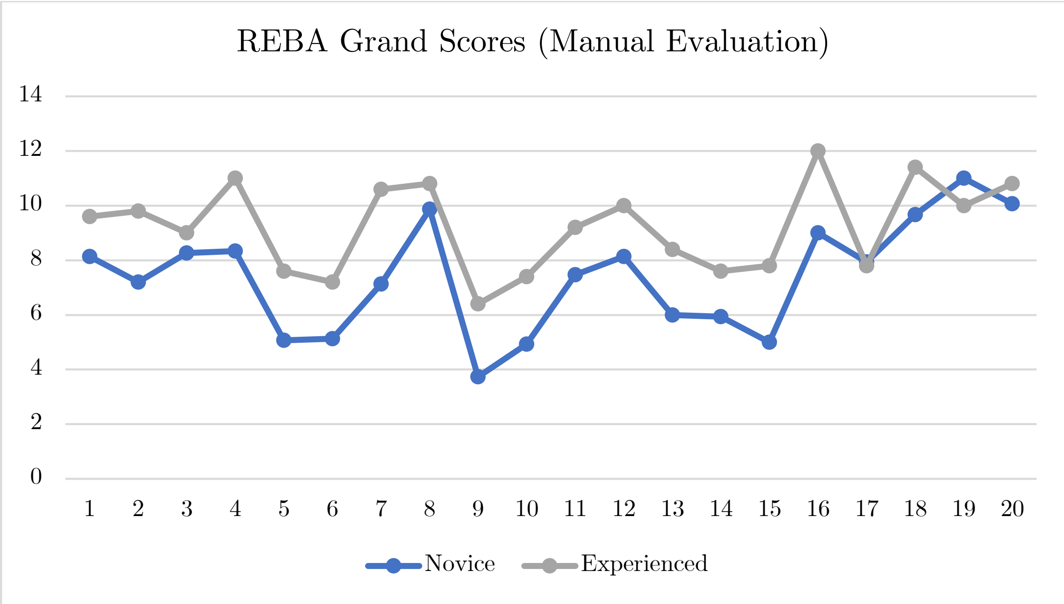

Figure 22 Mean of REBA Grand Scores (Manual Evaluation)

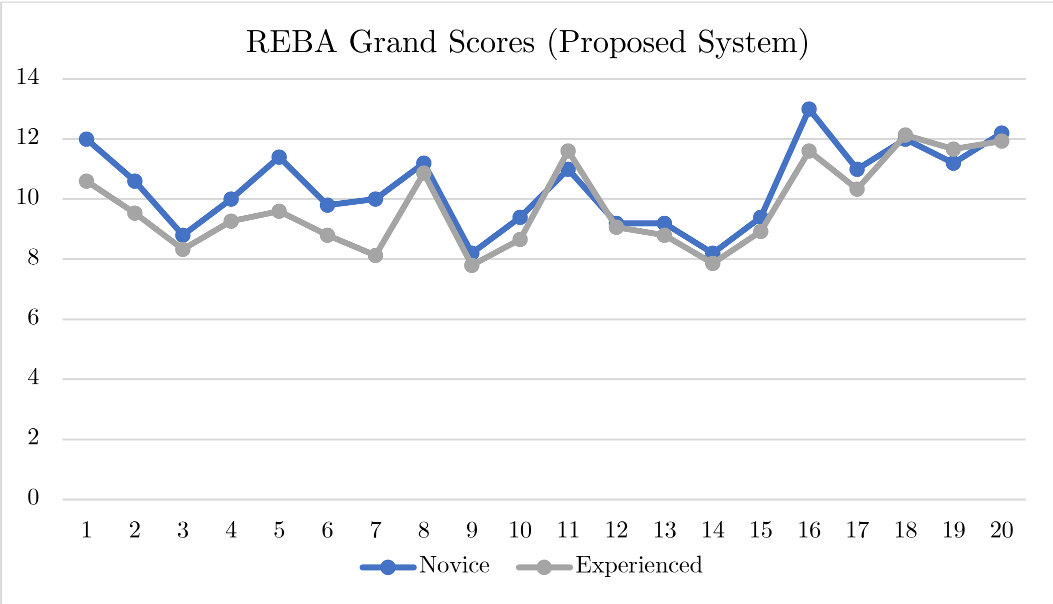

Figure 23 Mean of REBA Grand Scores (Proposed System)

Table 9 Results of Mann-Whitney U Test for difference in REBA Grand Scores between novice and experienced evaluators

Vid.	Sig.	
	Manual	System
1	0.402	0.049*
2	0.071	0.089
3	0.859	0.494
4	0.014*	0.120
5	0.030*	0.007*
6	0.181	0.272
7	0.017*	0.009*
8	0.568	0.582
9	0.036*	0.621
10	0.033*	0.242
11	0.124	0.300
12	0.217	0.963
13	0.070	0.328
14	0.186	0.374
15	0.027*	0.488
16	0.033*	0.024*
17	0.965	0.149
18	0.166	0.816
19	0.564	0.719
20	0.215	0.677

* $p<.05$

Significant differences between groups in REBA Grand Scores were found in video 4,5,7,9,10,15,16 when evaluation was done manually(Table 8). For data generated by the proposed system, significant difference between groups were found only in video 1,5,7,16(Table 9). Standard deviation of all evaluators for REBA scores decreased with the proposed system compared to manually generated scores(Table 8, Figure 23).

Action Level

Table 10 Descriptive statistics of REBA Action Levels (Mean(SD))

Vid.	Manual			System		
	Novice	Expert	All	Novice	Expert	All
1	2.73(±0.59)	3(±1)	2.8(±0.7)	3.53(±0.52)	3.8(±0.45)	3.6(±0.5)
2	2.6(±0.83)	3.2(±0.84)	2.75(±0.85)	3.27(±0.46)	3.4(±0.55)	3.3(±0.47)
3	2.73(±0.7)	3.2(±0.45)	2.85(±0.67)	2.73(±0.46)	3(±0)	2.8(±0.41)
4	2.8(±0.86)	3.6(±0.55)	3(±0.86)	3(±0)	3.4(±0.55)	3.1(±0.31)
5	1.93(±0.59)	2.6(±0.55)	2.1(±0.64)	3.2(±0.41)	3.8(±0.45)	3.35(±0.49)
6	2(±0.85)	2.8(±1.1)	2.2(±0.95)	3(±0.38)	3.2(±0.45)	3.05(±0.39)
7	2.47(±0.74)	3.6(±0.55)	2.75(±0.85)	2.67(±0.62)	3.2(±0.45)	2.8(±0.62)
8	3.27(±0.8)	3.6(±0.55)	3.35(±0.75)	3.6(±0.51)	3.8(±0.45)	3.65(±0.49)
9	1.47(±0.83)	2(±0.71)	1.6(±0.82)	2.6(±0.51)	2.8(±0.45)	2.65(±0.49)
10	1.8(±0.68)	2.4(±0.55)	1.95(±0.69)	3(±0)	3.2(±0.45)	3.05(±0.22)
11	2.53(±0.74)	3.2(±0.84)	2.7(±0.8)	3.8(±0.41)	3.6(±0.55)	3.75(±0.44)
12	2.8(±0.77)	3.4(±0.55)	2.95(±0.76)	3(±0.38)	3.2(±0.45)	3.05(±0.39)
13	2.13(±0.74)	2.8(±0.45)	2.3(±0.73)	3(±0)	3(±0)	3(±0)
14	2.07(±0.8)	2.8(±0.45)	2.25(±0.79)	2.6(±0.51)	3(±0)	2.7(±0.47)
15	1.93(±0.8)	2.6(±0.55)	2.1(±0.79)	2.87(±0.35)	3(±0)	2.9(±0.31)
16	3(±0.85)	3.8(±0.45)	3.2(±0.83)	3.87(±0.35)	4(±0)	3.9(±0.31)
17	2.8(±0.68)	2.8(±0.84)	2.8(±0.7)	3.47(±0.52)	3.8(±0.45)	3.55(±0.51)
18	3.27(±0.8)	3.8(±0.45)	3.4(±0.75)	4(±0)	4(±0)	4(±0)
19	3.47(±0.64)	3.4(±0.89)	3.45(±0.69)	3.8(±0.41)	3.6(±0.55)	3.75(±0.44)
20	3.27(±0.59)	3.6(±0.89)	3.35(±0.67)	3.87(±0.35)	4(±0)	3.9(±0.31)

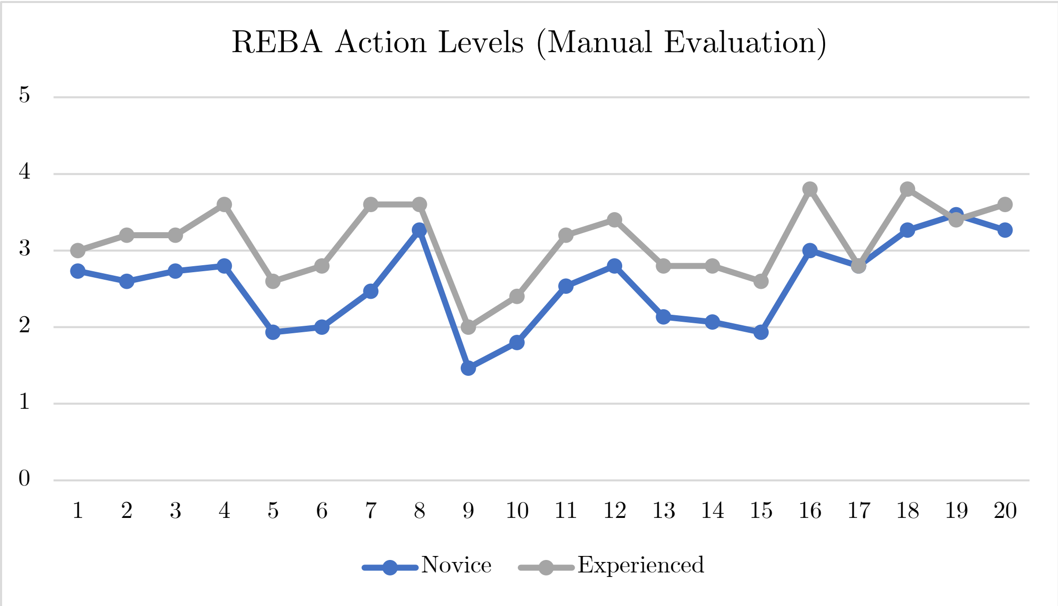

Figure 24 Mean of REBA Action Levels (Manual Evaluation)

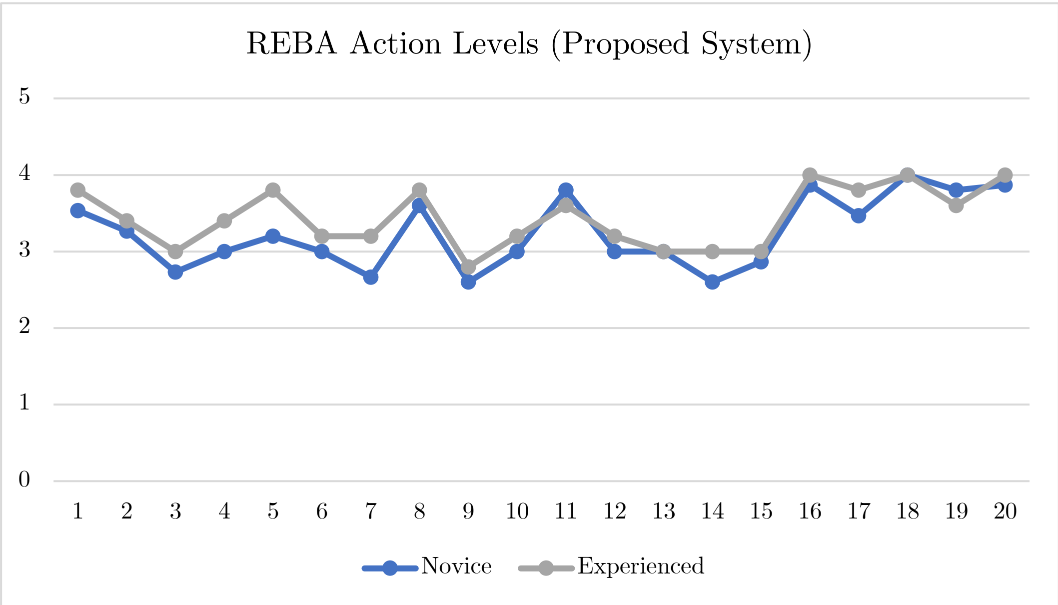

Figure 25 Mean of REBA Action Levels (Proposed System)

Table 11 Results of Mann-Whitney U Test for difference in REBA Action Levels between novice and experienced evaluators

Vid.	Sig.	
	Manual	System
1	0.566	0.304
2	0.179	0.583
3	0.161	0.208
4	0.062	0.012*
5	0.041*	0.018*
6	0.136	0.325
7	0.009*	0.088
8	0.444	0.429
9	0.218	0.429
10	0.090	0.083
11	0.106	0.383
12	0.122	0.325
13	0.071	1.000
14	0.042*	0.099
15	0.080	0.402
16	0.041*	0.402
17	0.962	0.206
18	0.173	1.000
19	1.000	0.383
20	0.210	0.402

* $p<.05$

Significant differences between groups in REBA Action Levels were found in video 5,7,14,16 when evaluation was done manually(Table 10). There was a general trend that experienced evaluators had higher mean REBA Action Levels compared to the novice evaluators(Figure 24). For data generated by the proposed system, significant difference between groups were found only in video 4,5. Standard deviation of all evaluators for REBA Action Levels decreased with the proposed system compared to manually generated scores(Table 10, Figure 25).

4.3.3 Evaluation Items for Manual Input

RULA

Group A:

- Muscle Use(L): There was not a statistically significant association between experience and muscle use(L) score in any videos.
- Muscle Use(R): Statistically significant association between experience and muscle use(R) score was found in video 9 (two-tailed $p=.038$).
- Arm support(L): There was not a statistically significant association between experience and arm support(L) score in any videos.
- Arm support(R): Statistically significant association between experience and arm support(R) score was found in video 8 (two-tailed $p=.038$).
- Load/Force(L): Statistically significant association between experience and load/force(L) score was found in video 1 (two-tailed $p=.006$).
- Load/Force(R): Statistically significant association between experience and load/force(R) score was found in video 7 (two-tailed $p=.032$).

Group B:

- Load/Force: Statistically significant association between experience and load/force score was found in video 1(two-tailed $p=.001$), video 5(two-tailed $p=.017$), video 9(two-tailed $p=.035$), and video 17(two-tailed $p=.032$).
- Muscle Use: There was not a statistically significant association between experience and muscle use score in any videos.
- Legs posture scores: Statistically significant association between experience and legs posture scores was found in video 15(two-tailed $p=.014$) and video 16(two-tailed $p=.005$).

REBA

Group A:

- Load/Force: Statistically significant association between experience and load/force score was found in video 1(two-tailed p=.032).
- Legs posture scores: Statistically significant association between experience and legs posture scores was found in video 15(two-tailed p=.014) and video 16(two-tailed p=.005).
- Sitting: There was not a statistically significant association between experience and sitting in any videos.

Group B:

- Arm support(L): There was not a statistically significant association between experience and arm support(L) score in any videos.
- Arm support(R): Statistically significant association between experience and arm support(R) score was found in video 8 (two-tailed p=.038).
- Coupling: Statistically significant association between experience and coupling scores was found in video 10(two-tailed p=.019) and video 13(two-tailed p=.018).

Activity Score: Statistically significant association between the experience and activity score was found in video 1(two-tailed p=.024) and video 10(two-tailed p=.029).

Chapter 5

Discussion

The goal of this study is to develop a video-based work pose entry system for RULA and REBA. To conduct validation on whether using the proposed work pose entry system yields consistent results regardless of the experience or knowledge the investigator has on ergonomic posture assessment, an experiment was conducted. 20 videos of jobs at an automobile assembly plant were evaluated by experienced and novice evaluators. As expected, results showed that the difference in scores between the two groups decreased when the proposed system was used compared to when evaluation was done manually. Furthermore, group difference in evaluation items for manual input when using the proposed system was explored as well. Details of the findings are discussed in the current chapter.

5.1 Group Difference

Results of the experiment conducted for validation revealed difference in how evaluators with different level of knowledge or experience with ergonomic posture assessment provide scoring when evaluation was manually done or scores are generated by the proposed system.

5.1.1 RULA

In terms of RULA Grand Scores, significant difference between the experienced group and novice group were found in 3 videos(Video 5,9,12) from manual evaluation. Although not all significantly different, a general trend showed that experienced evaluators scored higher than the novice evaluators. This finding goes in line with (Im et al., 2011). The reason may be that the experienced group is more familiar with musculoskeletal disease-related risk working postures covered by RULA or REBA than the novice group, so it is judged that the image containing the problematic risk working posture is selected well. When the score was generated by the proposed system, significant difference was not found in any videos.

Likewise, in terms of RULA Action Levels, significant difference between the two groups of evaluators occurred in 3 videos(Video 5,9,12). Action levels also showed a general trend where experienced evaluators scored higher than novice evaluators. This finding goes in line with (Cheon & Jung, 2020). Moreover, no significant difference between groups were found in scores by the proposed system.

5.1.2 REBA

Significant difference between the two groups in REBA Grand Scores were found in 7 of the 20 videos evaluated (Video 4,5,7,9,10,15,16) in manual evaluation. Experienced evaluators scored higher than the novice evaluators, except for Video 20. For scores generated by the proposed system, significant difference was found in 4 of the 20 videos (Video 1,5,7,16). Further investigation is needed on how significant different was shown while using the proposed system when difference wasn't shown in manual evaluation(Video 1). Another interesting finding was that the scores of novice evaluators when using the proposed system turned out to be higher than scores of experienced evaluators in videos where significant difference was found, while in manual evaluation, scores of experienced evaluators were higher. Further research should look into how and why individual scores of REBA occurs differently between each group while using the proposed system. In terms of action levels, significant difference between the two groups were found in 3 videos (Video 5,7,14,16). As for scores generated by the proposed system, significant difference was found only in video 4 and 5.

5.2 Evaluation Items for Manual Input

Evaluation items for manual input when using the proposed system were explored to determine how the scores of these items can contribute to outputting different scores.

Although the evaluators were given the same information on the weight of the load in each video, Load/Force scores were found to have significant relationship with experience in 4 videos in RULA, and 1 video in REBA. This result suggests that given the same load weight, evaluators can perceive differently about the physical load that may affect the work being performed.

In addition, in REBA, significant relationship with experience were found in 2 videos for Coupling, and 2 videos for Activity Score as well. It can be inferred that the appropriateness of coupling and the muscle activity of the worker can be perceived differently between evaluators with different experience. To the best of my knowledge, how coupling or activity scores vary between evaluators have not been explored yet and account for further analysis.

Moreover, cases where significant relationship with experience for leg postures were found in 2 videos also. This implies that in terms of ergonomic posture assessment, the effect of position of the legs on the working posture may also be perceived differently depending on the evaluator.

5.3 Proposed Work Pose Entry System

Compared to scores from manual evaluation, standard deviation of all evaluators for both RULA and REBA scores and action levels decreased when scores were generated with the proposed system. For RULA, while significant difference between the two groups of evaluators was found in 3 videos in manual evaluation, significant difference was not found in any videos when scores were generated by the proposed system. In the case of REBA grand scores, the number of videos showing significant difference decreased from 7(manual) to 4(proposed system). This implies that using the proposed system can be helpful in decreasing the difference between different evaluators and contribute to generating consistent results.

While previous studies used existing human posture dataset or used videos images taken for the purpose of experimenting, this study is meaningful in that validation was conducted with videos taken freely at a real workplace. Thus, interesting results and insights on areas with room for improvement were obtained.

First, after examining the output videos of the proposed system, it was observed that the proposed system can be useful for videos taken at a real workplace in the sense that most videos may include multiple workers. As can be seen in Figure 26, in most cases, the proposed system was able to detect the worker of interest while the video included more than 2 people. However, there was also a case(Video 7) where the system detected the wrong person for evaluation(Figure 27). Thus, further research seems to be needed for providing a guideline on recording videos at the workplace with multiple workers. Although guidelines to record postures in a workplace for better analysis is discussed in Lowe et al. (2014), specific details are not provided for taking recordings where recording cannot avoid including multiple workers.

Figure 26 Examples of videos where detection for worker of interest was successful (Left: Video 12, Right: Video 4)

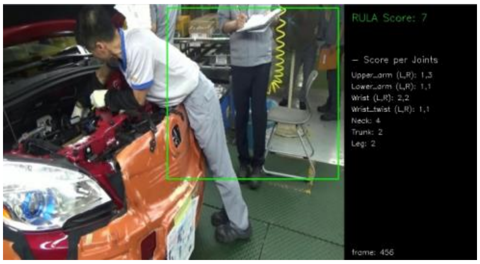

Figure 27 Example of video where detection for worker of interest failed

Figure 28 Examples of videos where workers wore certain headgear

Moreover, the proposed system has shown that it can be used in contexts where workers wear specific gear needed for the job being performed. In videos where the worker of interest wore headgear or a mask(Figure 28), problem for detection or generating posture scores has not occurred. Therefore, the proposed system can be used in various type of workplaces in natural context without being intrusive to the work being performed.

Chapter 6

Conclusion

6.1 Conclusion

This study discusses a computer vision-based method to assist ergonomic practitioners in generating ergonomic posture scores from 2D videos at occupational workplaces by receiving manual input of only few items that are rather easy to determine, and reconstructing the human body and identifying the relevant 3D joints. The work pose entry system reflects all movements occurring in a work cycle of a job, where the final score is defined as the highest score. To validate the proposed system in terms of consistency, an experiment was conducted where evaluators with different level of experience or knowledge performed ergonomic posture assessment on 20 videos taken at an automobile assembly plant. Scores were compared in terms of grand scores and action levels. In summary, it was found that the number of videos showing significant difference between the two groups decreased when using the proposed system compared to manually evaluation, for both RULA and REBA.

6.2 Limitation, Contribution, and Future Direction

The current study proposed a new method for ergonomic posture assessment. Moreover, it provides insight on how results of RULA and REBA can vary between evaluators with different experience or knowledge on work-related musculoskeletal disorders and ergonomic posture assessment, when it is done manually and when it is done with the proposed system.

However, the present research has some limitations. First, the accuracy of detecting and computing joint angles should be examined more thoroughly. Although the SPIN approach has been evaluated on different datasets and have been shown to outperform the state-of-the-art, future studies should compare the computed joint angles and scores with that of the reference motion capture system on occupational posture datasets, which can help validate the accuracy of the proposed work pose entry system. Another limitation of the current study is that although the experiment was conducted with evaluators with different experience or knowledge on ergonomic posture analysis, better insights may have been provided if an actual ergonomic practitioner was included in the experiment. Moreover, the small sample size and the unbalanced ratio of participants in each group are also limitations in this study. And lastly, future studies may include whether the scores generated by the proposed system is correlated to the subjective discomfort of the worker that is being investigated.

The current study contributes to research on ergonomic posture assessment and workplaces safety. The output of the proposed system can be used to assess various movements and postures involved in a work cycle, without the time-consuming process that includes the evaluator to manually segment each relevant body part and calculate each joint angle. This thus leads to decreasing the cognitive workload and time of the evaluator, requiring scoring for only few items that are relatively easy to determine. In addition, instead of just evaluating a single posture or image, the proposed work pose entry system outputs the final score based on the highest score, reflecting all postures and corresponding scores in the video. Moreover, as using this method decreases the difference in results between evaluators, the time and cost for training an ergonomic practitioner will be reduced as well. The last contribution of the study is that validation was conducted with videos taken at an actual, natural workplace environment, which can thus provide future research directions related to using computer vision techniques for ergonomic posture assessment with working images taken in relatively uncontrolled situations.

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국문초록

작업 관련 근골격계 질환은 근로자의 안전과 작업장의 생산성 향상에 중요한 문제다. 본 연구의 목적은 인간공학적 자세 분석에 사용되는 대표적인 방법인 Rapid Upper Limb Assessment(RULA) 및 Rapid Entire Body Assessment(REBA)를 위한 비디오 기반의 작업 자세 입력 시스템을 제안하는 것이다. 본 연구는 영상 내 사람 탐지 및 추적을 위한 YOLOv3 알고리즘과 3차원 사람 자세 추정을 위한 SPIN 접근법을 사용하는 시스템을 개발했다. 해당 작업 자세 입력 시스템은 2차원 영상과 몇 개의 평가 항목 점수를 입력으로 받아 최종 RULA 또는 REBA 점수와 해당 조치수준(Action level)을 출력한다. 본 연구에서 제안하는 작업 자세 입력 시스템이 일관적인 결과를 산출하는지 알아보기 위해 인간공학 및 근골격계 질환에 대한 지식이나 경험을 기준으로 숙련된 평가자와 초보 평가자의 두 그룹으로 분류된 평가자 20명을 대상으로 검증 실험을 진행했다. 참가자들은 국내 자동차 조립 공장에서 찍은 20개의 작업 영상의 작업 자세를 수동으로 평가하여 Excel 워크시트에 점수를 기록하였다. 시스템 사용 시 입력해야 하는 개별 항목을 기준으로 시스템을 통한 점수를 생성하고 기존의 전통적인 방법으로 평가한 결과와 시스템에서 얻은 결과를 비교하였으며, 기술 통계와 Mann-Whitney U test는 제안된 시스템을 사용하면 그룹 간의 차이와 표준 편차가 감소한다는 것을 보여주었다. 또한, 경험이 많은 평가자들이 초보 평가자들보다 더 높은 점수를 받는 경향이 있다는 것을 보여주었다. 시스템에 입력되는 평가 항목과 경험 정도와의 관계를 확인하기 위해 Fisher's exact test를

수행하였으며, 결과는 명백해 보일 수 있는 일부 항목도 그룹 간에 다르게 인식될 수 있음을 보여주었다. 이 도구에서 개발된 작업 자세 입력 시스템은 인간공학적 자세 평가의 일관성을 높이고 평가 과정 중 중에 인간공학적 평가자의 시간과 노력을 줄이는 데 기여할 수 있다. 또한 컴퓨터 비전을 활용한 인간공학적 자세 평가를 위한 작업 자세 입력 시스템 개발에 대한 향후 연구 방향도 이번 연구에서 제시된다.

주요어: 작업 관련 근골격계 질환, RULA, REBA, 컴퓨터 비전, 반자동 자세 평가

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