

MARKER-LESS BASED DETECTION OF REPETITIVE AWKWARD POSTURES FOR CONSTRUCTION WORKERS

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ABSTRACT

The construction industry has been a major source of work related injuries. According to the U.S. Bureau of Labor Statics, Musculoskeletal Disorders (MSDs) are the single largest category of workplace injuries and are responsible for almost 30% of all workers' compensation costs. MSDs are injuries and disorders that affect the human body's movement or musculoskeletal system such as muscles, tendons, nerves, and discs. Risk factors that lead to MSDs can be broken into two categories: work-related (or ergonomic) risk factors (e.g., force, repetition, posture) and individual-related risk factors (e.g., poor fitness). Awkward postures place excessive force on joints and overload the muscles and tendons around the effected joint, and thus increase the risk of MSDs.

This research develops a marker-less tracking system for assessing construction worker's postures for the risk exposed to MSDs. The Posture Assessment System (PAS) uses Microsoft Kinet for capturing and tracking human skeleton, and then analyzes the MSDs risk exposure based on the categorization of Ovako Working posture Assessment System. An experiment involving fifteen graduate students performing four typical construction activities (e.g., materials handling, moving, hammering, and tiling) in simulated indoor environment were conducted to evaluate the accuracy of the system in terms of posture identification and OWAS categorization. The results are satisfactory and it appears promising to use the system to help professionals diagnose awkward work postures of construction workers. The posture identification accuracies were above 91.6% for all tasks except for hammering where accuracy dropped to 69.4%. The categorization accuracies were also above 85.4% for all tasks except for hammering where accuracy dropped to 48.4%.

Keywords □ Posture, Assessment, Construction

I. INTRODUCTION

The construction industry has been a major source of work related injuries. Most research and workplace guidelines have been focusing on mitigation of specific event-based or accidental injuries. Cumulative injuries caused due to prolonged adoption of stressful positions, occur in considerable measure and warrant an equal attention on development of solutions for helping in reduction of their occurrences. Based on the U.S. Bureau of Labor Statics [21], Musculoskeletal Disorders (MSDs) are the single largest category of

workplace injuries and are responsible for almost 30% of all workers' compensation costs. The average MSD requires a direct cost of almost \$15,000. In the Web-based program provided by OSHA [25] to project the total cost of company's occupational injury and illness, the associated indirect costs can be up to five times the direct costs of MSDs. Statistics also indicate that MSDs accounted for 24% of nonfatal occupational injuries and illnesses in U.S. construction workers in 2011 [21]. Schneider [13] also reported that construction workers are at about a 50% higher risk of work-related MSDs than those in other industries.

Injury prevention professional, government agencies and researchers may use different terms for MSDs such as repetitive motion injury, repetitive stress injury, ergonomic injury, cumulative trauma disorder, and overuse syndrome. Middlesworth [24] defined MSDs as injuries and disorders that affect the human body's movement or musculoskeletal system such as muscles, tendons, nerves, and discs. He also argues that, unlike other terms that implicate only a singular cause for damage to the musculoskeletal system, i.e., repetition and stress, the term "MSDs" more accurately describes the problem. Repetitive motion and stress is certainly a major risk factor to MSDs. However, in reality, there are many causative risk factors leading to MSDs. Risk factors that lead to MSDs can be broken into two categories: work-related (or ergonomic) risk factors (e.g., repetitive or sustained awkward postures, high task repetition, and forceful exertions) and individual-related risk factors (e.g., poor work practices, overall health habits, rest and recovery, nutrition, fitness and hydration).

This research focuses only on the risk factor of repetitive awkward postures, and aims to develop a computer system that can automatically track and detect postures of a construction worker, and objectively assess their risk of MSDs. In general, such a system requires a tracking mechanism that captures human body movements, transform the captured data into skeletal structure or a hierarchy of joints with information about its three dimensional coordinates of joints, and assess the corresponding risk levels for each of associated postures worthy of attention.

II. RELATED WORKS

2.1 Observation Methods for Assessing Postural Stress

Kee and Karwowski [12] divided the research methods that quantify postural stress into two categories: observational and instrument-based methods. The observational methods visually inspect the angular deviation of a body segment from its neutral position while the instrument-based method continuously records a body posture by attaching sensors to target subject. The observational methods are more widely used in industry because of its nature of noninterference with job processes, low cost, and use ease [6]. There are several observational models available in industry that aim to objectively analyze a subject's posture by quantifying awkward postures that may easily lead to the development of MSDs. These models include OWAS (Ovako working posture analysis system) [1], RULA [4], REBA [11], LUBA (Loading on the Upper Body Assessment) [12], TRAC [3], PATH [8], and PLAS [14], as well as the subjective Nordic Musculoskeletal Questionnaire developed by Nordic Council of Ministries [2]. Among these methods, OWAS, RULA, and REBA have been widely used and been developed for different purposes under a variety of workplace conditions [7]. Each of the three methods has its own posture classification scheme, and produces different recommended levels of required actions. Note that different methods may result in assignment of different recommended actions or postural stress scores for a given posture. Kee and Karwowski [12] compared these three methods based on 301 different postures sampled from the steel, electronics, automotive, and chemical industries, and a general hospital. The result shows the correlations among the three methods even though OWAS and REBA generally suggest lower level of stress scores compared to RULA. This research adopts OWAS's classification scheme to evaluate awkward postures that contribute to MSDs.

2.2 OWAS (*Ovako Working Posture Analysis System*)

The OWAS is a postural observational method commonly used to identify poor postures that cause discomfort and are detrimental to workers' health at a worksite. The OWAS evaluation is based on sampling from typical working postures of major body parts including back, forearms, and legs, and the information about the force exerted or load carried during work upon the observed subject.

OWAS uses a four-digit code to describe various postures and weight combinations. Except for the five neck postures that are considered only for reference and not actually used during the postural assessment of OWAS, the rest of the codes were used in this study. The codes include four back postures (i.e., "straight", "straight and bent", "straight and twisted", and "bent and twisted"), three upper limbs postures (i.e., "both limbs on or below shoulder level", "one limb on or above shoulder level", and "both limbs above shoulder levels"), seven lower limbs postures (i.e., "loading on both limbs, straight", "loading on one limb, straight", "loading on both limbs, bent", "loading on one limb, bent", "loading on one limb, kneeling", "body is moved by the limbs", and "both limbs hanging free"), and three levels of exerted force (i.e., "< 5 Kg", "5~10 Kg", and "> 10 Kg"). The OWAS then categorizes the total number of 252 (i.e., 4x3x7x3) possible combinations of the four digits into four levels of action categories (AC) according to their risk of injuries as follows.

- AC1: postures are normal and natural with no particular harmful effect on the musculoskeletal system, no action is required;
- AC 2: postures have some harmful effect on the musculoskeletal system, corrective actions are required in the near future;
- AC3: postures have a distinctly harmful effect on the musculoskeletal system, corrective actions should be done as soon as possible;
- AC4: postures have an extremely harmful effect on the musculoskeletal system, immediate corrective actions for improvement are required.

OWAS has been widely used in several industries for postural analysis, e.g., the works done by Engels et al. [5], Wright and Haslam [10], Scott and Lambe [9], and Gilkey et al. [15], and also in the construction industry. The OWAS evaluation is based on sampling from typical working postures of major body parts including back, forearms, and legs, and the information about the force exerted or load carried during work upon the observed subject.

Despite the advantages of being inexpensive and practical, OWAS still faces the problem of lacking precision and being time-consuming because it relies solely on human observations. To overcome the limitation of observational approaches, recent computer vision techniques have shown great potential for automated and real-time ergonomic analysis in construction (e.g., [16][17]). For example, Seo et al. [19] developed a computer vision-based posture classification that can automate existing observation-based postural evaluation methods according to predefined ergonomic checklists using shape- and radial histogram-based features from video sequences.

2.3 Motion Capture of Human Skeletal Structure

The implementation of an automatic system for detecting awkward postures of a construction worker faces several technique challenges, i.e., to collect accurate motion data without interfering with ongoing works, convert the data to a computerized skeletal structure, and categorizing the structure according to the adopted observational method. Motion capture has been widely used in a variety of industries such as cinema, entertainment, and computer games. Sharma et al. [18] reviewed several motion capture methodologies including marker-based motion capture (e.g., acoustical system, mechanical system, magnetic system, optical system) and marker-less motion capture such as video image recognition. Marker-based motion capture approaches usually cost more, require more setup, and also cause more interference to workers. Marker-less motion capture approaches on the other hand usually cost less, require less setup, and cause less interference

to workers. However, marker-less approach such as image recognition faces other challenges in a dynamic situation such as unpredicted human motions, only two-dimensional images available, changes of environment attributes (e.g., lighting), and blocking of camera's view of target human body parts. Seo et. al. [20] tackled the problems of vision-based motion capture by using silhouette images that are insensitive to color, texture, and contrast changes to increase the accuracy of human skeletal analysis.

Compared with an RGB image, a depth image contains data of the distance of pixels of three-dimensional objects surfaces from the camera. The tracking of human skeleton is one important feature provided by depth sensors. Microsoft's Kinect [23b] was originally developed for Xbox 360 video game console and Windows PC to support natural user interface that allows users to communicate with the system or the game using gesture without wearing any attachment or holding any controller. This research used Kinect as the required depth sensor because it is a low-cost motion-capture solution that may produce a three-dimensional human skeletal image and structure information. It does not require any special equipment attached to the observed subject either.

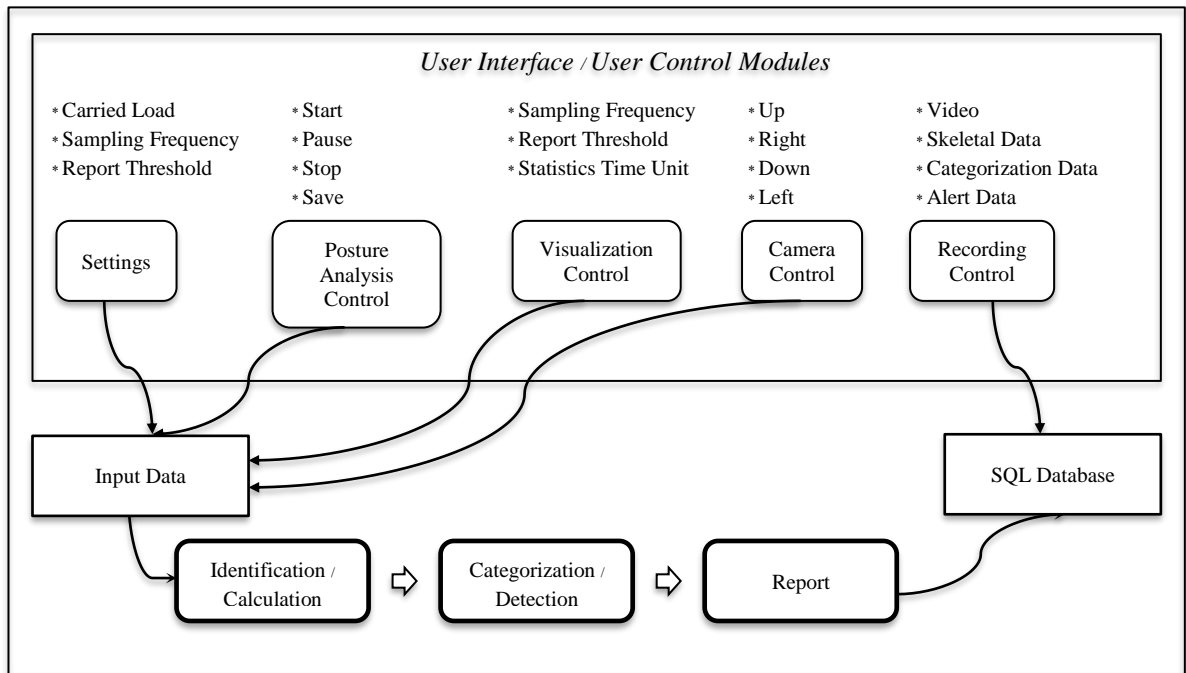
III. MODEL DESIGN

This study develops an automated system for detecting and analyzing awkward postures of a construction worker that may lead to work related MSDs. This section describes the architecture and the process of the proposed system. The hardware of the system should be composed of one or multiple motion sensing cameras and a computer for analyzing motion data. This study used three Microsoft Kinect cameras and a Windows PC. Each Kinect contains an RGB camera capturing a color image, an infrared emitter and an IR depth sensor capturing a depth image, a 3-axis accelerometer determining the current orientation of the Kinect, and a multi-array microphone capturing sound [23b].

Figure 1 shows the architecture and process of the proposed system. The system takes the input of processed video image via Kinect and parameters set by the user through the user interface, identifies and calculates positions of target skeletal joints, categorizes postures and detects awkward ones, and then reports or alerts according to user specifications. The input video image processed by Kinect SDK provides three-dimensional coordinates of 20 human skeletal joints of the observed subject, including "hip center", "spine", "shoulder center", "head", "shoulder left", "elbow left", "wrist left", "hand left", "shoulder right", "elbow right", "wrist right", "hand right", "hip left", "knee left", "ankle left", "foot left", "hip right", "knee right", "ankle right", and "foot right".

The bottom of Figure 1 shows the process of the system. For each video image frame, the system first identifies the skeletal joints of interest and calculates their coordinate relationships such as connected joints and their corresponding angles for later OWAS evaluation. The next step is to categorize the postures of back, arm, and leg according to the classifications of OWAS, and detect the awkward postures that require alerts and remedy actions as suggested by OWAS. The results will then be reported visually on the computer screen or stored in the database.

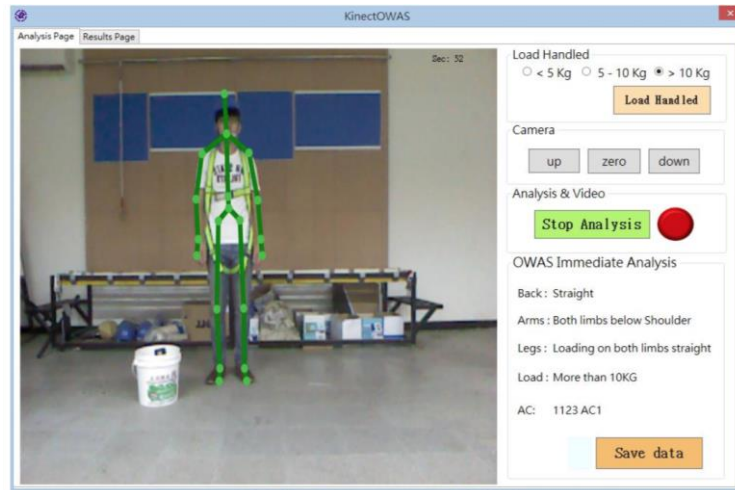
Figure 1
Architecture and Process of the System



The user interface includes several modules, including settings, posture analysis control, visualization control, camera control, and recording control. The setting module allows the user to specify the carried load of target subject and sampling frequency. The maximum carried load of the target subject needs to be specified manually by the user to avoid attachment of force sensor to the target subject. The sampling frequency determines the rate with which the system will capture from the original video images sent from Kinect when the posture analysis starts. For example, Kinect may offer 30 frames of video images per second but the user may only like to report one time of awkward posture if the target subject possesses an awkward posture continuously for that entire second. Figure 2 shows a captured screen of the prototype system.

The posture analysis model basically controls the execution of the posture analysis and saving of the execution data. The visualization control module determines how the computer screen presents the execution data, including the sampling rate of presented data from the captured image frames, the threshold for awkward postures to be alerted, and the unit of time period for presenting alerted postures statistically. For example, one may show the frequency of alerted awkward postures for every minute. The camera control module allows the user to select one from the installed Kinect cameras and adjust its angle. The recording control module determines what data will be saved when the posture analysis module saves data after an execution completes.

Figure 2 Interface of Prototype System



The prototype system was developed using Microsoft Visual Studio 2010 in C# language, and Kinect for Windows SDK [23a]. The system also uses SQLite Database, a popular public-domain database engine for local data storage, and EmguCV [22], a cross platform that allows Intel's OpenCV's image processing functions to be called from .NET compatible languages such as C# and Visual Basic.

The Kinect cameras can provide the position information about twenty joints of a human skeleton (e.g., head, hand right, wrist right, elbow left, hip center, knee left, ankle left, and foot right) in a three-dimension coordinate system. With this information, the relative distances, angles of the associated limbs or other body parts, and thus individual postures can be derived. The individual posture of back, arms, and legs need to be categorized first in order to determine the type of the entire body posture of each sampled video frame based on the OWAS.

For example, the OWAS categorizes the back posture into four types, i.e., "straight", "straight and bent", "straight and twisted", and "bent and twisted". The back posture will be identified as "straight" if the smaller angle between the vector (Vector1) passing through the spine and the shoulder center and the other vector (Vector2) passing through left hip and right hip is greater than or equal to 75° . The back posture will be identified as "straight and bent" if the smaller angle between Vector1 passing through the spine and the shoulder center and Vector2 passing through left hip and right hip is smaller than 75° . The back posture will be identified as "straight and twisted" if the angle measured in the X-Z plane, between the vectors normal to Vector1 passing through left shoulder and right shoulder and Vector2 passing through left hip and right hip is smaller than 15° . The back posture will be identified as "bent and twisted" if both "straight and bent" and "straight and twisted" conditions are met.

IV. EVALUATION

Fifteen graduate students from Civil Engineering Department of National Chiao Tung University, Taiwan, volunteered to participate in the evaluation of the prototype of the proposed system. The objective of the evaluation was to determine the accuracy of assigning observed postures into correct action levels as suggested based on the OWAS matrix. Three Kinect cameras (i.e., from the face/back, the side horizontally, and the 45° top angles) were set up to record each participant performing four tasks, including lifting and moving a bucket of sand, picking up tiles and put them into a paper box, hammering nails, and tiling magnet-glued tiles on a wall surface-mounted with steel board. Each task required four repetitions. All the tasks were performed on the same position except for the first task, for which the participant needed to lift the bucket and move for about three steps. Each participant was asked to perform the tasks naturally without any special constraints on body rotation or movement of body parts even they might block camera views. The task was designed to include common risk factors to MSDs such as unnatural work posture, repetitive

work, and exerted force, but not actually result in MSDs to the participants. Three experts, including a rehabilitation medical physician, a professor in physiotherapy, and a professor in medical engineering, also participated in assessing the accuracy of the detection of the system.

The evaluation resulted in 88.5%, 88.2%, 48.4%, and 85.4% accuracies of categorization of postures for the four tasks, respectively. Except for the third task, which was to hammer nails, the accuracies appeared to be satisfactory and thus demonstrated the feasibility and usefulness of the system in diagnosing awkward postures contributing to MSDs in a controlled environment.

Revisiting the miscategorized data and analyzing the causes to the categorization errors found a primary flaw in the design of tool for the task of hammering nails. As shown in Figure 3, a wooden box was specially made to allow a participant to hold the column inside the box while hammering the prefixed nails on the top surface of the box to avoid the participant's hand being injured by a hammer. The authors thought merely blocking of one hand should have only little effect on categorization accuracy because the OWAS matrix did not consider gesture of hands for the categorization analysis. However, it appeared that the box not only blocked each participant's hand but also blocked almost entire lower half of body parts because of requirement of squatting position to accomplish the task. This dramatically reduced Kinect's accuracy of identification of a skeletal joint structure where joints that were not blocked might be still identified but connected with wrongly associated joints. As a result, the accuracy of categorization of individual and body postures also dropped because the categorization highly depended upon an accurate skeletal joint structure. The authors believed the accuracy would increase fairly if the protection box was removed from or replaced with just a horizontal wooden board in the task just like in a regular working situation in the construction industry.

Figure 3 Protection box (left photo) for the task of hammering nails (right photo)



V. Conclusions and Future Work

Daily work activities of construction workers often involve sudden, repeated, or over-exertion that result in cumulative stress contributing to MSDs. This study proposes a computer system that uses Microsoft Kinect cameras and SDK to identify human skeletal structure and analyze and categorize the associated postures according to OWAS's assessment for postures of high risk to MSDs. A prototype system has been developed to evaluate the feasibility and usefulness of the system in assessing construction workers' awkward postures contributing to MSDs. The evaluation consists of four types of typical construction activities, and the system produces a satisfactory performance in all tasks with higher than 85% accuracy except for hammering nails. The accuracy of identification of skeletal structure of Kinect was dramatically affected because the associated protection wooden box blocked camera's view most of the time, and in turn affected the categorization accuracy of the proposed system. Due to this limitation, the system is not suitable to be directly used in general on a normal construction site to constantly monitor the postures of construction workers. The system is feasible and useful only in a situation where the body parts of a worker concerned by OWAS are not blocked most of the time.

Traditionally, a physical therapist evaluates a worker's risk to MSDs by visually observing and assessing how they perform their daily tasks. However, the assessment can be inaccurate for several reasons some of which are the inherent imprecision of measurement and low sampling rate of observation of human visual behavioral assessment. Thus, using the proposed system may provide the therapist with more accurate measurement and frequency estimation of postures. Considering the aforementioned limitation of the applicability of the prototype system, the future direction of this research will aim to extend the system so that it can be used to facilitate a therapist to diagnose awkward postures contributing to MSDs for construction workers or self-diagnosis and self-correction in a pre-arranged clinic room or a simulated virtual reality environment.

The other future direction for the proposed system is to extend its application to other industries where workers' risk to MSDs is also of concern. For example, MSDs are also one of major disease sources, along with others such as cardio-vascular disease and hand arm vibration syndrome, for causing seafarers to take longer breaks from sea life or even lead to disability. Thus, on a modern ship with gym facilities, it may be also feasible to equip such a system for self-diagnosis and improvement of postures.

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REFERENCES

- [1] O Karhu, P Kansi, & I Kuorinka (1977), "Correcting Working Postures in Industry: A Practical Method for Analysis", *Applied Ergonomics*, Vol. 8, No. 4, Pp.199-201.
- [2] I. Kuorinka, B. Jonsson, A. Kilbom, H. Vinterberg, F. Biering-Sorensen, G. Andersson, & K. Jorgensen (1987) "Standardised Nordic Questionnaires for the Analysis of Musculoskeletal Symptoms", *Applied Ergonomics*, Vol. 18, No. 3, pp. 233-237.
- [3] AJ van der Beek, LC van Gaalen, & MH FringsDresen (1992), "Working Postures and Activities of Lorry Drivers: a Reliability Study of on Site Observation and Recording on a Pocket Computer", *Applied Ergonomics*, Vol. 23, No. 5, Pp.331-336.
- [4] L McAtamney & EN Corlett (1993), "RULA: A Survey Method for the Investigation of Work-related Upper Limb Disorders", *Applied Ergonomics*, Vol. 24, No. 2, Pp. 91-99.
- [5] JA Engels, JA Landeweerd, & Y Kant (1994), "An OWAS-based Analysis of Nurses' Working Postures", *Ergonomics*, Vol. 37, No. 5, Pp.909-919.
- [6] AM Genaidy, AA Al-Shed, & W Karwowski (1994), "Postural Stress Analysis in Industry", *Applied Ergonomics*, Vol. 25, No. 2, Pp.77-87.
- [7] A Kilbom (1994), "Assessment of Physical Exposure in Relation to Work-Related Musculoskeletal Disorders-What Information Can Be Obtained from Systematic Observations?", *Scandinavian Journal of Work, Environment & Health*, Vol. 20, Pp. 30-45.
- [8] B Buchholz, V Paquet, L Punnett, D Lee, S Moir (1996), "PATH: a Work Sampling-Based Approach to Ergonomics Job Analysis for Construction and Other Non-repetitive Work", *Applied Ergonomics*, Vol. 27, No.3, Pp.177-187.
- [9] GB Scott & NR Lambe (1996), "Working Practices in a Perchery System, Using the OVAKO Working Posture Analysis System (OWAS)", *Applied Ergonomics*, Vol. 27, No.4, Pp. 281-284.
- [10] EJ Wright and RA Haslam (1999), "Manual Handling Risks and Controls in a Soft Drinks Distribution Centre", *Applied Ergonomics*, Vol. 30, No. 4, Pp. 311-318.

- [11] S Hignett & L McAtamney (2000), "Rapid Entire Body Assessment (REBA)", *Applied Ergonomics*, Vol. 31, No. 2, Pp.201-205.
- [12] D Kee & W Karwowski (2001), "LUBA: An Assessment Technique for Postural Loading on the Upper Body based on Joint Motion Discomfort and Maximum Holding Time", *Applied Ergonomics*, Vol. 32, No. 4, Pp. 357-366.
- [13] SP Schneider (2001), "Musculoskeletal Injuries in Construction: a Review of the Literature", *Applied Occupational and Environmental Hygiene*, Vol. 16, No. 11, Pp.1056-1064.
- [14] MK Chung, IS Lee, D Kee, & SH Kim (2002), "A Postural Workload Evaluation System Based on a Macro-postural Classification", *Human Factors and Ergonomics in Manufacturing & Service Industries*, Vol.12, No. 3, Pp:267-277.
- [15] DP Gilkey, TJ Keefe, PL Bigelow, RE Herron, K Duvall, et al. (2007), "Low Back Pain among Residential Carpenters: Ergonomic Evaluation Using OWAS and 2D Compression Estimation", *International Journal of Occupational Safety and Ergonomics*, Vol. 13, No. 3, Pp. 305-21.
- [16] SJ Ray & J Teizer (2012), "Real-time Construction Worker Posture Analysis for Ergonomics Training", *Advanced Engineering Informatics*, Vol. 26, Pp. 439-455.
- [17] S Han and S Lee (2013), "A Vision-based Motion Capture and Recognition Framework for Behavior-based Safety Management", *Automation in Construction*, Vol. 35, Pp. 131-141.
- [18] A. Sharma, M. Agarwal, A. Sharma, & P. Dhuria (2013), "Motion Capture Process, Techniques and Applications", *International Journal on Recent and Innovation Trends in Computing and Communication*, Vol. 1, No. 4, Pp.251-257.
- [19] J Seo, R Starbuck, S Han, S Lee, & T Armstrong (2015), "Motion Data- Driven Biomechanical Analysis during Construction Tasks on Sites", *Journal of Computing in Civil Engineering*, Vol. 29, No. 4, Pp. B4014005.
- [20] JO Seo, K Yin, & SH Lee (2016), "Automated Postural Ergonomic Assessment Using a Computer Vision-Based Posture Classification", *Proceedings of ASCE Construction Research Congress*, Pp. 809-818.
- [21] BLS (The U.S. Bureau of Labor Statistics) (2017), "Industry Injury and Illness Data", URL: <https://www.bls.gov/iif/oshsum.htm>.
- [22] Emgu CV (2017), Main page, URL: http://www.emgu.com/wiki/index.php/Main_Page.
- [23a] Microsoft (2017), "Download Center / Kinect for Windows SDK 2.0", URL: from: <https://www.microsoft.com/en-us/download/details.aspx?id=44561>
- [23b] Microsoft (2017), "Kinect for Windows Sensor Components and Specifications", URL: <https://msdn.microsoft.com/en-us/library/jj131033.aspx>.
- [24] M Middlesworth (2017), "The Definition and Causes of Musculoskeletal Disorders (MSDs)", *Ergonomics Plus*, URL: <http://ergo-plus.com/musculoskeletal-disorders-msd/>.
- [25] OSHA (Occupational Safety and Health Administration) (2017), "Estimated Costs of Occupational Injuries and Illnesses and Estimated Impact on a Company's Profitability Worksheet", URL: <https://www.osha.gov/dcsp/smallbusiness/safetypays/estimator.html>.