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A DIGITAL TWIN FRAMEWORK FOR REAL-TIME ANALYSIS AND FEEDBACK OF REPETITIVE WORK IN THE MANUAL MATERIAL HANDLING INDUSTRY

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ABSTRACT

This research presents a digital twin concept and prototype to represent human operators in the material handling industry. To construct the digital twin, we use a simulation-based framework for data collection and analysis. The framework consists of three modules: Data Collection Module, Operator Analysis and Feedback Module and Digital Twin Module. A motion capture system assists in the development of the digital twin, which captures simulated material handling activities, similar to those which take place in an actual environment. This paper outlines the processes involved in the development of the digital twin and summarizes the results of pilot experiments to analyze the operator's fatigue as the operator completes repetitive motions associated with lifting tasks. Fatigue, in this study, is a function of change in joint angles. The digital-twin based tool provides feedback to the operator in real-time to enable correction of those factors which potentially cause injuries to the operator.

1 INTRODUCTION

Digital twins (DT) are virtual and exact representations of physical objects or systems over their life cycle (Mikell and Clark 2018). The main characteristics of DT include scalability (analyze varying information), interoperability (track multiple variables real-time), expansibility (ability to extend on the go), and fidelity (similarity to the real physical system). DTs add real-time capabilities for visualization, analysis, prediction, and optimization (Schleich et al. 2017).

Some practitioners have used digital twins and simulation interchangeably. However, we point out the following differences between simulation and digital twins. Simulation provides an understanding of a physical system using numbers. It leads to time and cost advantages by helping developers to better understand real-world product behavior and elevating product lifecycle management (ABB 2019).

While a simulation provides static information like design elements, materials, and operating conditions, starting its life as a static model, a DT simulation becomes active. Its ability to change with the flow of data dynamically, yields more valuable information which is not generated by a traditional simulation (Maloney 2019). A simulation model does not tend to involve the other parts of business beyond research & development whereas the continuous flow of data with a DT keeps the business provider in perfect synchronicity with the business operations. To summarize, the use of DTs allow the developers, supply chain managers, and customers, to 'drive' and experience the product in real-time, as it grows.

Expected challenges in the development of a DT include data analysis, enhanced manufacturing process and effectiveness of predictive analysis (Howard 2019). The economic value of DTs vary widely based on factors like development, implementation, and maintenance costs. The abstraction level of DTs range from the lowest component (data received & analyzed from an individual part), to asset (data from a machine e.g. tool life for predictive maintenance), to system or unit (production line in a facility) and the highest component, process (business-level view) (Woods 2018).

Digital Twin (DT) technology is increasingly penetrating the manufacturing and logistics sectors. Providing a digital representation of the material handling facility and supply chain system or finding the optimal conditions for enhanced performance, DT is beneficial to the researchers and technology companies (Jimenez 2020). Estimating the response of the real system to identify the factors affecting its environment and allowing communication and collaboration between other simulation models and digital twins, companies such as TESLA, GE, DHL have been working towards building digital twin versions for vehicles, engines and warehouses respectively (Schleich et al. 2017) (DHL Press releases 2019).

In 2017, The global DT market size was valued at USD 2.26 billion, with an estimated compound annual growth rate of 38.2% from 2018 to 2025 (Grand View Research 2018). International Data Corporation (IDC) anticipate 70% of manufacturers will use DT technology to conduct simulations and scenario evaluations by 2022. 1% to 3% increase in productivity was achieved by Unilever in Brazil, by using DT to cut down its facility's energy use, as a result of which, it led to a savings of approximately $2.8 million (Smith 2019).

Besides the use of DT technology in 'Automotive & Transport' and 'Manufacturing' industries, scarce research has been done to develop DTs for human manufacturing operators. Collecting data since 1972, the 'Injuries, Illnesses, and Fatalities' program of the U.S. Bureau of Labor Statistics shows that injuries and fatalities incurred by workers has decreased (Reeve et al. 2019). However, the results show that there is still a need for research to make workers safe on the job.

Alderson and Johnson (2016) build a personalized digital athlete as an approach to create a digital version of an on-field athletic performance (Alderson and Johnson 2016). The use of big data architectures allowed the creation of a personalized 'digital athlete'. On the basis of extensive datasets, missing individual data was estimated with the goal of reducing the use of traditional experimental designs to evaluate the ergonomics of humans in the sports biomechanics community. Researchers proposed the use of a Deep Learning Neural Network (DNN) scheme to estimate the missing data (ground reaction forces) using only motion capture trajectories as the input. Romero et al. (2016) introduced the concept of Operator 4.0, i.e. humans assisted by machines and technologies to enhance their physical, cognitive, and sensorial capabilities to perform their manufacturing tasks. Use of tools such as wearable tracking, Augmented Reality (AR), Virtual Reality (VR), robots, exoskeletons and data analytics were discussed, to enhance worker's capabilities. Jimenez (2020) explains the opportunities of building industrial digital twins of material handling operators. These include: 1) training based on digital copies of highly skilled operators, 2) real-time ergonomic evaluations and feedback, 3) workplace optimization and testing, 4) personalized health plans, and 5) communication between human-based and equipment-based digital twin agents. Sharotry et al. (2020) presents a framework to build digital twins' representations of manual and repetitive tasks in the material handling industry. Hernandez et al. (2019) proposed the use of Recurrent Neural Networks (RNN) to predict the motion of a human body which further can be used to predict fatigue in human operators for the specific material handling operation.

This paper is an extension of the research presented in Sharotry et al. (2020) to demonstrate the capabilities of the digital twin framework providing calculations and visualizations of real-time body kinematics of material handling workers. The body kinematic evaluations attempt to describe the worker's fatigue distribution as a function of the time elapsed as repetitive motions are completed as part of a 'lifting' exercise. This research article presents a comprehensive model for digital twin development of a human operator to analyze fatigue in MMH operations. Utilizing the real-time and predictive analysis component of a DT, we believe this research addresses the gap between conventional fatigue assessment methods and advanced industry 4.0 environments.

The remaining parts of this paper are organized as follows. In Section 2, the pre-existing ergonomic evaluation tools and their limitations are discussed briefly. Section 3 provides the process of conceptualizing a DT. Section 4 presents a case study, showcasing the application of proposed framework. Finally, a conclusion and an outlook are provided.

2 REAL-TIME ERGONOMIC EVALUATIONS AND FEEDBACK

A significant amount of manufacturing and material handling activities are highly manual (Visentin et al. 2018). Material handling is one of the most physically demanding tasks, and thus, can quickly become leading factors contributing to the operators' accumulation of both mental and physical fatigue (Visentin et al. 2018). According to the Bureau of Labor Statistics, 114 Million people were employed in the Warehousing and Storage Industry Group in 2018 (Data USA: Warehousing & storage 2018). These statistics show that 22% of the workforce are "Laborers & freight, stock & material movers, hand," and 17% work in stocking, order filling, or packaging by hand . According to Reeve et al. (2019), the industry sectors "Construction," "Transportation & Warehousing," and "Manufacturing" reported a cumulative total of 13,782; 10,952; and 5,177 fatalities from 2003 to 2016, respectively. The study also listed that 'Back – including spine – spinal cord' was the most frequently injured body part with 17% of cases involving days away from work and about 36% of cases involved sprains and strains. The study highlighted that human operators need a safer environment to work. The substantial reduction of fatalities over-time proves the use of safer practices but still corroborates the need for research in this field.

Factors such as personal characteristics, training, experience, and health conditions can influence the accumulation of fatigue in workers, which in turn impacts the performance of an activity (Visentin et al. 2018). While performing basic manual material handling tasks, workers experience physical fatigue, which occurs as a result of repetitive lifting/ loading and leads to high risk for low back, trunk, spine, hip, and knee injuries (Boocock et al. 2019).

Multiple tools have been introduced to measure fatigue in the workforce. Methods such as standard questionnaires after completing a job or using on-body sensors have been used in the past to analyze fatigue in construction workers (Yu et al. 2019). Despite their use, the on-body sensors tend to cause discomfort for the human workforce while performing tasks.

Various ergonomic assessment tools such as Rapid Upper Limb Assessment (RULA) and the job strain index method are commonly practiced in the industries to identify the repetitive movements (McAtamney and Corlett 1993) (Moore and Garg 1995). In order to identify strained postures, observational tools like Rapid Entire Body Assessment (REBA) and the Ovako Working Assessment System (OWAS) provide feedback based on an experienced user's scoring system (Hignett and McAtamney 2000) (B. Scott and R. Lambe 1996). The National Institute for Occupational Safety and Health's (NIOSH) lifting equations, Snook tables, and Liberty Mutual tables provide information on safe load capacity (TR et al. 1993) (Snook 1978). The commonly used Borg scale and Likert Scale assess fatigue by subjective worker feedback (Borg 1982). The majority of the methods described above require post experiment evaluation, resulting in an inability to provide real-time feedback to the operator.

Virtual human factor (VHF) tools such as virtual reality, digital human models, and discrete event simulation allow the user to perform an ergonomic assessment to the systems not yet constructed. A novel tool created by Greig et al. (2018) used methods like biomechanical regression modelling and Methods-Time Measurement to predict worker demand and element time, along with assisting the user in line layout and task balancing, although this tool possesses the limitation of being used only in the design stage of the process (Greig et al. 2018). The study was also restricted to light assembly work and considered loads at the shoulder joint. Research by Visentin et al. (2018) proposed the use of energy expenditure to measure the physical fatigue in manual material handling workers. The study induced a model for fatigue accumulation and rest allowance but was limited to less demanding activities. Activities, where high energy expenditure rate is experienced due to repetitive movements of the operator, were regarded as a drawback to this methodology (Visentin et al. 2018).

Results from the study by Vignais et al. (2013) and Boocock et al. (2019) has proven the use of real-time feedback for ergonomic evaluations, to reduce the risk of musculoskeletal injuries (Vignais et al. 2013) (Boocock et al. 2019). It is clear that using sensors, auditory and visual feedback to the operator, reduces the risk of injury.

3 METHODS

The following sections describe the methodology used to conceptualize the proposed framework. The framework, shown in Figure 1, has the following modules: 1) Data Collection Module, 2) Operator Analysis & Feedback Module, and 3) Digital Twin Module.

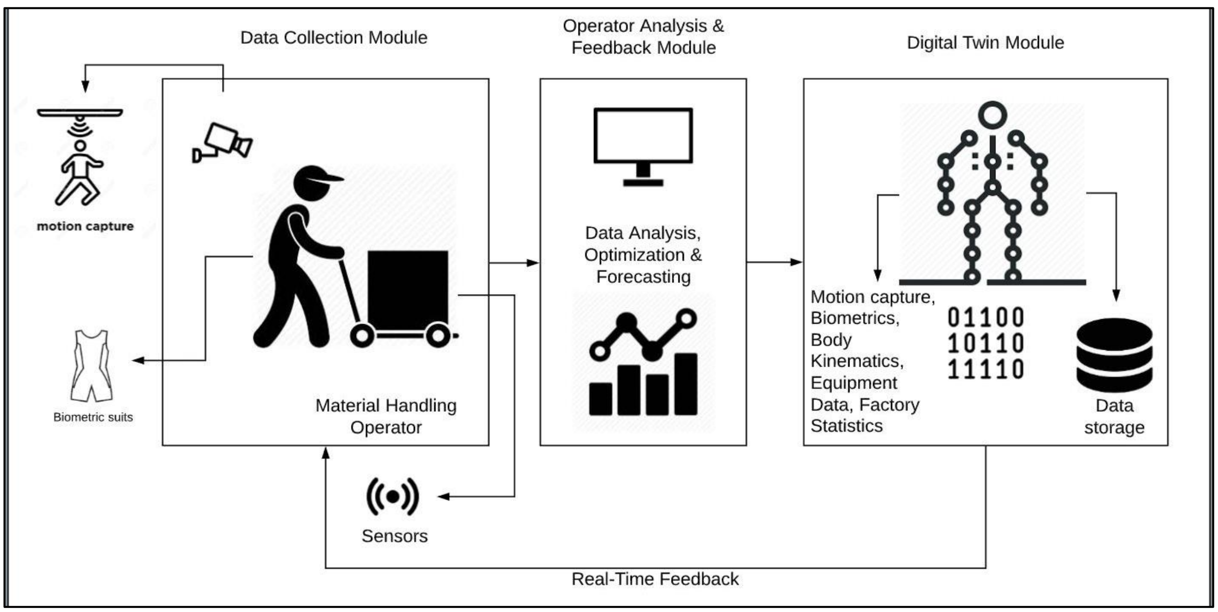

Figure 1: Framework of operator centric Industry 4.0 environment. Adapted from Digital Twin concept in Sharotry et al. 2020.

3.1 Data Collection Module

Digital twin development features advanced big data architectures, using passive & active imaging, multi-sensor integration, data mining, real-time image processing and non-linear data science analytics (Alderson and Johnson 2016). Conclusions have been made by researchers, regarding the lack of standard datasets in the field of material handling which acts as a barrier for validating operator behavior (Golan, Cohen and Singer 2019) (Peruzzini, Grandi and Pellicciari 2018). In Johnson et al. (2018), a significant number of data captures have been carried out for sport-specific applications, providing access to about 20,066 motion capture files (Johnson et al. 2018). The sports-specific exercises include walking & running trials, football kicking and baseball pitching; these exercises do not follow the motion patterns we find in industrial manual material handling applications. Hence, the data collection module is focused on creating structural databases and training sets for the development of a digital twin vision of an industrial manual material handler.

In order to accomplish the vision of a true DT of an operator, it is necessary to build specific datasets with required variables. We have identified the body kinematics and biometrics of the individual as important factors to determine body fatigue. Our novel approach tends to collect data specific to the motions carried out by a manual material handling operator while performing such tasks on the shop floor. Data collection simulates an actual manual material handling (MMH) operation in a controlled environment, collecting the motion and physiological data. Figure 2 shows the overall design of the study, including elements considered in development of this module.

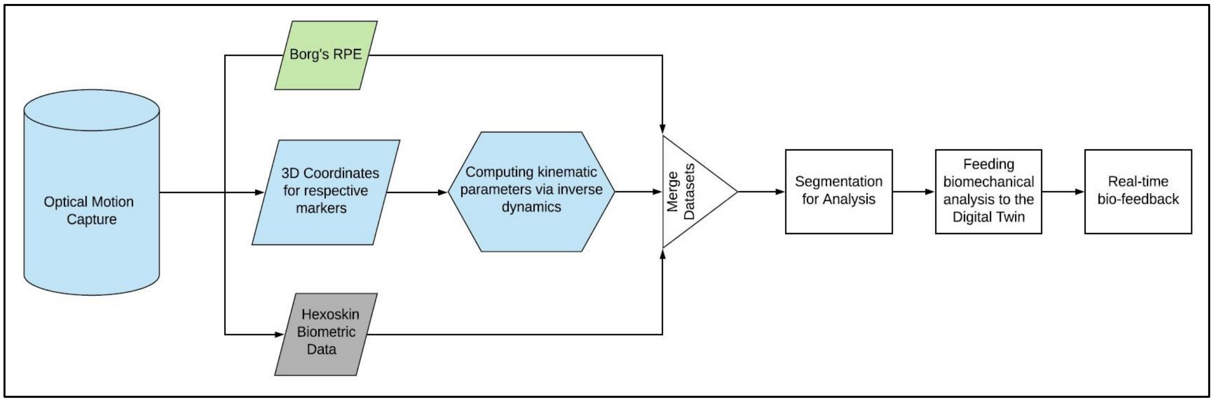

Figure 2: Overall design of the study.

Previous research by Karg et al. (2014) concluded that, as the humans accumulate fatigue, observable changes in joint kinematics such as range-of-motion (ROM), angular velocities, and angular acceleration can be observed (Karg et al. 2014). Hence, optical motion capture methodology with infrared cameras can be used to compute body kinematic parameters. Motion capture technologies provide more accurate measurements as compared to computer vision and inertial measurement units (IMU).

For the design of experiments to be performed by the human subjects performing 'lifting' task, a 2^k factorial design is created for 50% of the population for their factor levels, based on the Hazard Analysis Tool (Snook 1978). The factors determined for this study were: 'Gender of Subject', 'Height of lifting operation', 'Height of subject' and 'time interval of the experiment'. The factors and their respective levels are mentioned in Table 1. Based on gender, time interval and lift distance category of the subject, the weight of the box to be lifted was decided as per guidelines proposed by Snook (1978).

Table 1: Design of Experiment details.

Factor	**Levels**	**Number of Levels**
Gender of Subject	Male, Female	2
Height of Lifting operation (cm)	25, 51, 76	3
Height of Subject	Short, Medium, Tall	3
Interval of Experiment (seconds)	9, 14	2

The proposed framework (Figure 2) uses optical motion capture technology to record the motion of different segments of the body, to which retro-reflective markers are attached. Biometrics of the subject performing experiments are monitored for the physiological datasets via a smart suit. The motion capture provides the x-y-z coordinates of the segment, which are then analyzed for body kinematic parameters such as joint angle, angular velocity and angular acceleration using inverse kinematics (Qualisys AB n.d.). The biometric suit provides physiological data such as the electrocardiogram (ECG), heart rate, breathing rate, and heart rate variability, among other variables, which helps to monitor and characterize the impact of the material handling exercise on the subject. Along with the above discussed data, the human subject's Borg Scale of Perceived Exertion (RPE) is also measured (Borg 1982). The conducted experiments lead to datasets with respective motion capture, biometrics, RPE and activity metrics of the subject performing the MMH activity. These datasets are then merged to create a single dataset of an individual for further analysis, which will be discussed in the next section.

3.2 Operator Analysis & Feedback Module

This module of the DT framework conceptualizes the data analysis, optimization, and forecasting based on real-time data collection in the first module (Figure 1). Industries have identified human involvement, as an essential factor in the productivity of the system. MMH task risks are associated with the nature of the load, type of task, work environment and the operator (Workplace Safety & Prevention Services 2011). Characteristics of the operator include physical factors like the height of the human, reach, flexibility, musculoskeletal health history, and physiological factors, among many others. Environmental conditions like temperature, relative humidity, lighting, noise levels, time constraints, and physical conditions are some of the other factors affecting human operator productivity. Among the above listed factors, task conditions like repetitions, job time, resting period, hazardous postures, handles, and weight of the load are a few conditions recently researched as leading to creating a safe environment for the operator.

The proposed framework currently aims to incorporate real-time fatigue evaluation based on changes in joint angles. Body joints of concern were identified as: Left Elbow, Right Elbow, Left Knee, Right Knee and Back. The marker data collected in real-time via optical motion capture technology (Section 3.1) were analyzed to measure the change in these joint angles as the subject accumulates fatigue. This fatigue accumulation influences the postural control and movement coordination of the subject (Karg et al. 2014). Hence, the change in joint kinematics such as range-of-motion (ROM), joint angles, angular velocities, and angular acceleration reflect body fatigue. To analyze the selected joint angles while the person performs a 'lifting' task, we divide the activity based on 'Motion with Load' and 'Motion without Load'. 'Motion with Load' is the activity carried out by the subject as he/she grabs the lifting container and then lifts it to its location of placement at the required height (Table 1). This 'Motion with Load' is identified as a 'segment'.

A segmenting filter developed for the application, identifies and splits the motion capture data for real-time analysis into the desired segments. The collected data is also stored in a local database after merging the collected x-y-z marker data, biometrics and RPE data in segments (Figure 2). This complete dataset with all the required data points then can be utilized for further in-detail analysis of the motion performed by the subject.

Apart from the analysis of operator fatigue, we believe that this module can support the incorporation of additional operator centric statistics such as worker scheduling, rest interval, guidelines for safe practices, emergency contact, etc.

3.3 Digital Twin Module

Researchers in the field of ergonomics, Body-in-White production systems, and hybrid production systems have been developing frameworks for digital twins (Caputo et al. 2019) (Kousia et al. 2019) (Biesinger et al. 2018). The research is being done to develop real-time ergonomic assessment tools to ensure operator safety. To the best of the authors' knowledge, despite above mentioned developments, the application of DT technology within the field of MMH is scarce.

This module of the framework bridges the gap between the conventional workplace and an advanced interconnected factory floor. In order to be a true digital twin, we believe this component of the framework should be connected to the 'Operator Analysis & Feedback Module'. The fatigue analysis from the previous module will serve as a real-time assistant for the manual material handler. The operator fatigue determined as a change of joint angles in the previous module shall act as the input to the digital twin component. The future implementation of this component is aimed at the development of a machine learning model for understanding the implications of the entire workspace of an operator.

A series of experiments were carried out, to demonstrate the practicality of this proposed framework. It summarizes the use of methodologies discussed in Section 3. The digital twin module for this study has been showcased as a real-time feedback to the human subject on the correct method of performing the 'lifting' task.

4 CASE STUDY

The test environment is located in the Center for High Performance Systems (CHiPS) laboratory at the Ingram School of Engineering at Texas State University, San Marcos, Texas, USA. For the pilot experiment, subjects were recruited from the university student population. Participants with any muscular injury or primary treatment were excluded from the study. Ethical approval for this study was obtained from Texas State University's Institutional Review Board (IRB). To the best of authors' knowledge, the student participants were neither skilled in MMH activities nor performed manual material handling in their routine work. Participants performed a prescribed 'lifting' task to induce muscular fatigue (Boocock et al. 2019). As discussed earlier in Section 3.1, the optical motion capture methodology was used for data collection.

A fleet of twelve Qualisys cameras sampling at 100 Hz tracked forty-four reflective markers, attached to the human subject (Qualisys AB n.d.). The position of reflective markers was based on recommendations by Color Atlas of Skeletal Landmark Definitions (Sint Jan 2007). For physiological data, each subject concurrently wore a smart suit, Hexoskin® Shirt, which contains body sensors within the suit, and is paired with a Hexoskin® Smart Device for monitoring the biometrics of the subject at 60Hz (Hexoskin Health Sensors & AI n.d.). The data analysis of the operator's biometrics is not part of the scope of this study. As per the design of experiments, the subject was asked to perform a lifting activity. An audible cue was provided to the subjects, in order to initiate each lifting task in the loop at the selected time interval (9 seconds or 14 seconds). Additionally, at intervals of one minute, the subjects were asked to provide info on their rate of perceived exertion (RPE) using the 20-point Borg Scale of Perceived Exertion (Borg 1982). The subjects were asked to continue the 'lifting' task until they sensed exhaustion (fatigue) or they informed the value of 20 on the Borg Scale. Researchers ensured the use of the proper procedure for calibration and subject setup as recommended by the manufacturer of the equipment in the laboratory.

Figure 3 shows the laboratory environment of a male subject performing the lifting task at a floor – knuckle range of 25 cm.

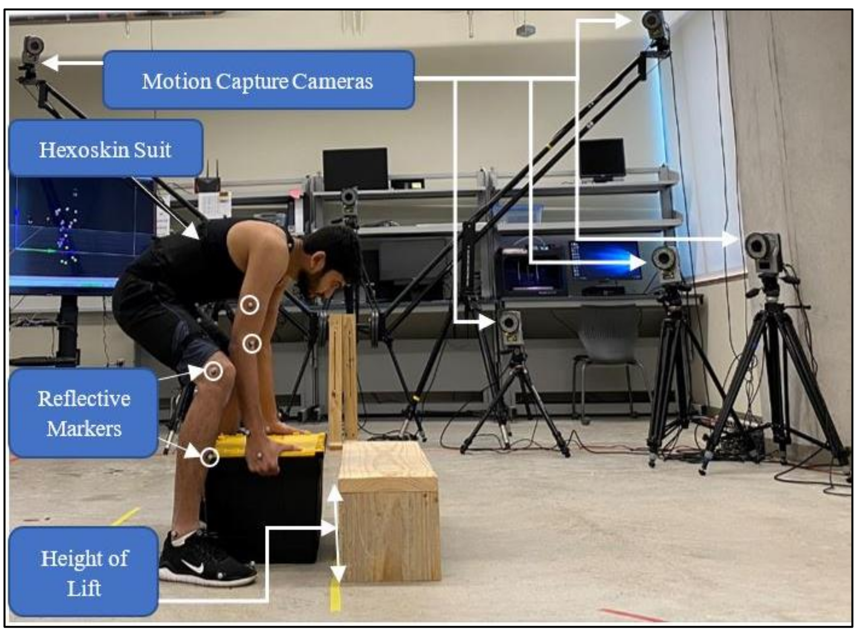

Figure 3: A subject performing the lifting task.

3D coordinate marker data along with biometrics data collected by the Hexoskin® Shirt was stored in a database for further analysis.

For the subject's fatigue analysis, an evaluation of change in selected joint angles and range of motion (ROM) was carried out. The angles were computed using inverse kinematics from the 3D motion capture data (Yu et al. 2019). Figure 4 shows the change of the Left Elbow joint angle in degrees when taking the whole set of motion into consideration. A segment in Figure 4 ranges from frame number 2749 – 2885. It is further displayed as 'Seg2' in Figure 5. Segmented data (Motion with Load), results for ten individual segments, extracted from the original complete motion file, are shown in Figure 5. The solid lines depict the change in angles during the first five segments (first five iterations of the activity) and the dotted lines show the last five segments (last five iterations of the activity) of the recorded activity. It can be seen that a substantial change in angle is observed as well as the duration of each lift also varies. At the beginning of the lifting experiment, the subject's elbow joint angle varies between 116° and 129.3° whereas at the end of the experiment, the same angle lies between 87.22° and 105.41° (towards 180° = elbow extension; towards 0° = elbow flexion). As a result of this change in joint angle, we deduce that in the initial five lifts (Seg1 – Seg5), the individual started with their elbows more extended and moved through a greater ROM. Whereas, towards the end of the activity (Seg65 – Seg69), the elbow extension reduces towards the beginning of 'lift', but the elbow flexion remains almost similar. Overall, the ROM was less when the subject was fatigued.

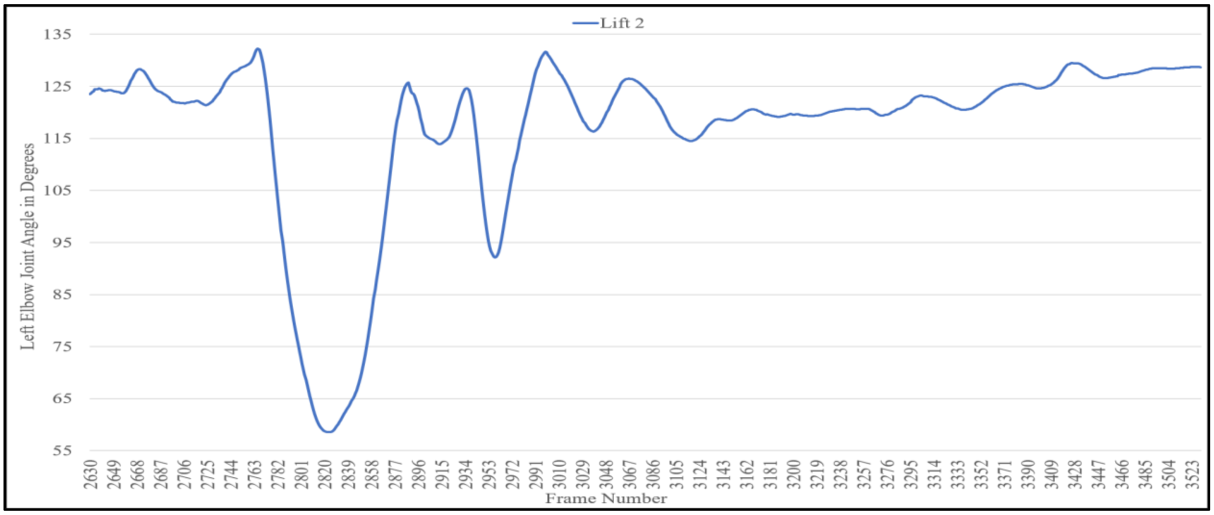

Figure 4: Change in left elbow joint angle segments with time.

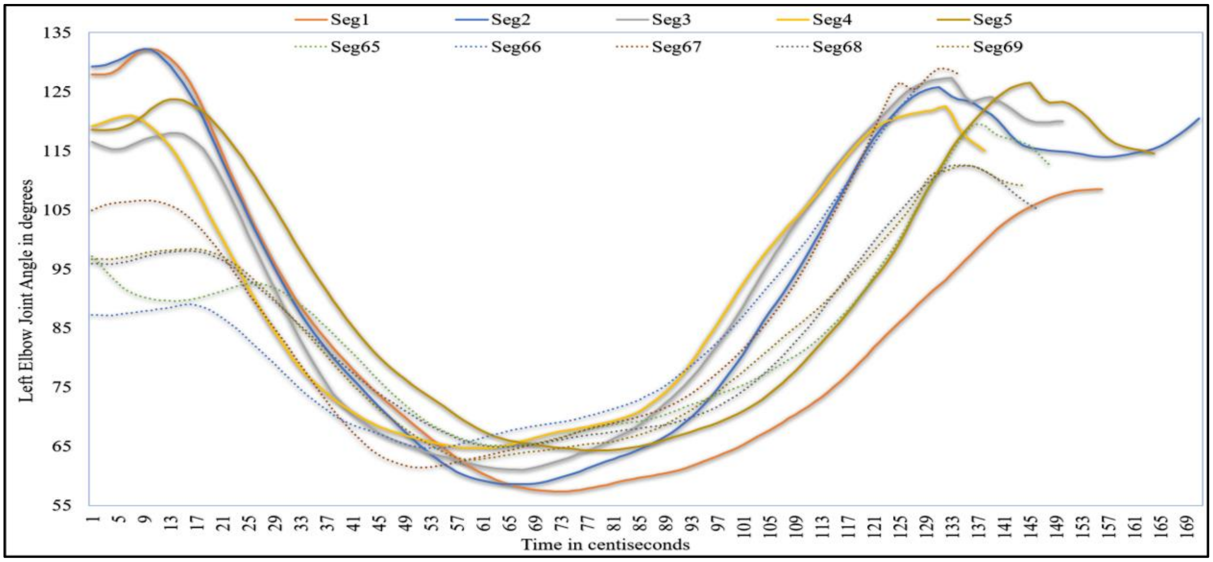

Figure 5: Change in left elbow joint angle segments with time.

For the real-time proof of concept, data collected during the experiment was further used for creating a digital twin of the operator using a software development kit (SDK), an interface between the Qualisys and Unity software (Qualisys AB n.d.) (Unity n.d.). The flowchart in Figure 6 displays the schematics for this DT development.

3D coordinate data collected real-time in Qualisys is used for avatar development. As per the U.S. National Library of Medicine, in order to prevent back injury while lifting, bending the knees is considered a vital point. This allows the weight to act on the thighs and hips instead of the spine (MedlinePlus n.d.).

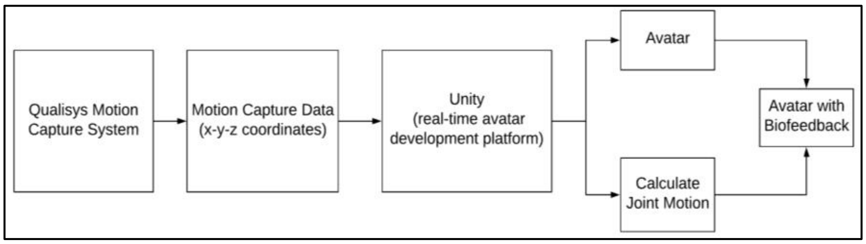

Figure 6: Digital Twin data flow.

Hence, the right and left knee joint was taken into consideration for the biofeedback trigger point. As the human subject performed the ‘lifting’ task without bending the knees (Right & Left), a red beacon and buzzer sound was activated in the avatar environment, providing an audio-visual cue. Rotation of the thigh bone was analyzed to determine the logic of this cue. Joint rotation values (in degrees) were evaluated at each frame in Unity for the ongoing lifting task during the Motion with Load. The threshold for joint rotation was measured before the lifting task by the research group for individual subject (θ = 345°). Figure 7a shows the side view of the subject in the original position before beginning the task. Figure 7b shows the correct and incorrect lifts performed by the subject in real-time.

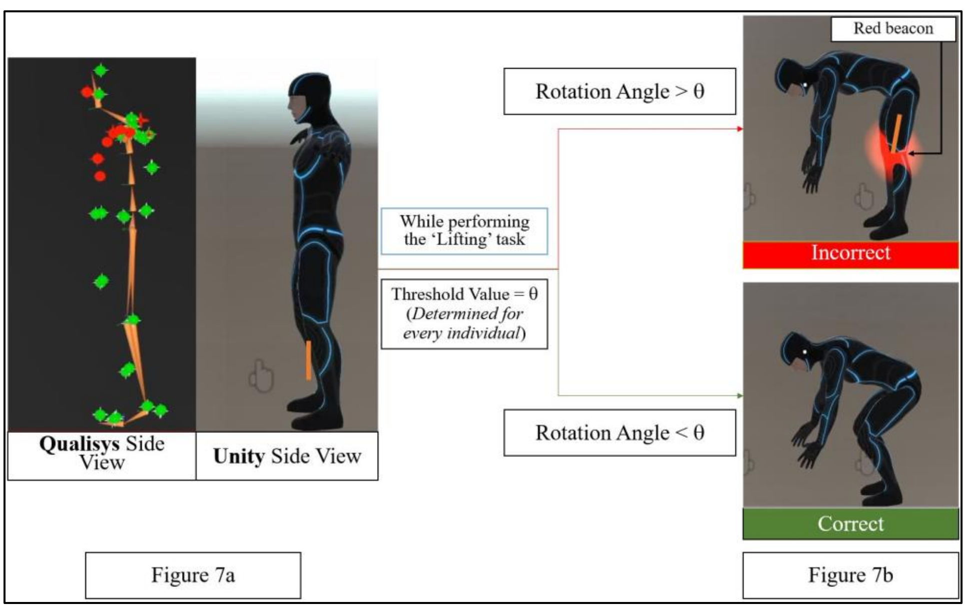

Figure 7: Real-time biofeedback.

5 LESSONS LEARNED

The proposed framework methodology, tends to fulfill the four dimensions of a true digital twin (DT), as concluded by Shao et al. i.e. connectivity, analyzability, visibility and granularity (Shao et al. 2019).

The first component, ‘Connectivity’ deals with the DT being a copy of the real system. In the framework, the Data Collection Module helps document the actual moves done by the operator in everyday work. The real-time data collection of the operator on the factory floor with technologies like Inertial Motion capture Units (IMU) & 3D vision shall allow on-site implementation of the concept.

The second dimension ‘Analyzability’ assists the DT in decision making, assisting the human operator in real-time. Evaluating the motion data as discussed in the Operator Analysis & Feedback module allows fulfillment of this component of the true DT development. The current use case focuses on the evaluation of joint angles for fatigue evaluation. Upon further development, the predictions can be made based on analysis of motion data (Hernandez et al. 2020). The application of this approach is not limited to operator fatigue but can also be used in making real-time decisions such as optimized scheduling, allocation of human resources, operator specific job tasks, and training new workforce.

With the real-time demo, the ‘Visibility’ element of this DT development was demonstrated. With advanced tools and dedicated SDKs dashboard development can be customized on-demand. The framework integrated Qualisys and Unity software to represent a futuristic avatar of the operator with real-time diagnosis of a ‘lifting’ motion (Qualisys AB n.d.) (Unity n.d.).

The discussed framework is a conceptual model with a high abstraction level, taking minimum details of the system into consideration with regard to the development of a true DT. Whereas, the fatigue analysis of the operator sits at a lower abstraction level, considering the very specifics of the operator body fatigue based on body joint movements. Hence, fulfilling the initial requirement of the fourth dimension of DT development i.e. ‘Granularity’.

6 CONCLUSIONS AND FUTURE RESEARCH

This study presented a digital twin framework for a manual material handling operator with a real-time proof of concept. Three modules of development were presented to achieve the goal of real-time analysis of an operator. In the Data Collection Module, a motion capture system was used to collect the precise positional data of the subject performing ‘lifting’ tasks along with worker fatigue measurements. The Operator Analysis and Feedback Module compared change in joint angles for all the repetitions of the lifting experiment as compared to the fatigue measures. In the Digital Twin Module, a real-time application displayed a real-time audio-visual cue to the operator on the basis of their knee joint movement. This real-time tool demonstrates a process to evaluate the risk of musculoskeletal disorders in a manual material handler by providing real-time feedback on proper lifting motions.

Future research will develop a predictive analysis tool and providing real-time feedback on operator fatigue levels on the basis of change in joint angles. Evaluating additional parameters such as forces acting on different body joints, heart rate and breathing rate can be included to study their effect on operator fatigue in real-time scenarios. Economic impact due to introduction of Digital Twins of operator in the workplace is also identified as a scope of future study.

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