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Analysis of Biometric Sensor Data for Predicting Fatigue: A Framework Towards Reducing Work-Related Musculoskeletal Disorders in Aviation Manufacturing Workers

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Abstract— **Work-Related Musculoskeletal Disorders (WMSDs) transpire when injuries to the musculoskeletal system (e.g. muscles, ligaments, tendons, and nerves) occur due to high fatigue inducing work-related activities, where repetitive movements and muscle strain are prevalent. However, it is challenging to quantify the risk of injury due to the assortment of tasks that factory workers may perform. Nevertheless, wearable sensors are a viable outlet that can unobtrusively capture biometric data in order to calculate objective measures, such as fatigue, which increases the risk of developing WMSDs. This paper presents a novel wearable sensor-based ergonomic monitoring system (ErgoRelief), which has been designed to predict fatigue within the context of aviation factory work. An experiment has been undertaken whereby thirty participants completed a series of repetitive tasks whilst wearing our sensor system. Results of multiple linear regression models demonstrate a maximum Adjusted R^2 Score of 0.9259.**

I. Introduction

Work-Related Musculoskeletal Disorders (WMSDs) arise due to multiple factors, such as repetitive motion, excessive force, and awkward and/or sustained postures, which cause injuries or disfunctions affecting muscles, bones, and joints [1]. Aviation manufacturing workers are more susceptible to suffering WMSDs, compared to other industries, as the nature of the majority of tasks requires components to be handmade [2]. The occurrence of WMSDs cause great discomfort to individuals and are a significant economic burden, which cost the US approximately $215 billion dollars annually [1].

As WMSDs can be caused by an array of risk factors, these factors need to be accurately monitored for effective risk reduction and prevention. However, due to the diversity of activities and tasks that workers encounter, it is challenging to monitor all factors in parallel. Nevertheless, fatigue has been proven to be strongly related to the severity of symptoms, such as pain and depression, which contribute to WMSDs [3]. Currently, there is not a gold standard to quantify fatigue [4, 5]. Existing fatigue measurement methods can be classified as subjective or objective [4]. Many self-report questionnaires for assessing fatigue have been developed, which rate both physical and mental fatigue [4]. However, a significant challenge is that there are considerable inconsistencies between how people feel and their understanding of their feelings. Additionally, collecting questionnaires can be cumbersome and time-consuming. However, the revolution of the Internet of Things enables devices to continually monitor human activity, utilizing non-invasive wearable sensors, whilst sensors deployed in the working environment can collect contextual information, such as external force and noise. Such data can be amalgamated to monitor fatigue objectively by measuring biometric information, such as body postures, heart rate, and external force, and reported to employees to prevent WMSDs [5-7].

The current state-of-the-art undertakes research to monitor ergonomic risks using either wearable or non-wearable sensors and provides workers with simple and straightforward feedback, such as joint angles and ergonomic scores only [7, 8]. However, work is limited that utilizes data from both wearable and non-wearable sensors to perform ergonomic analysis, whilst also providing workers with constructive advice about their current body conditions, in order to improve their situational awareness. To address these issues, this paper presents the framework of a novel wearable sensor-based ergonomic monitoring system (ErgoRelief), which has been designed to measure body fatigue levels utilizing a number of wearable and non-wearable sensors to record body part motion, external force, and heart rate data. The framework posited supports workers in monitoring their body condition by providing adequate time-of-need instruction or advice.

The paper is organized as follows. Section II illustrates the details of the proposed framework. Section III and IV discusses the methodology, results, and discussion. Finally, the conclusions and future work are depicted in Section V.

II. The ErgoRelief Framework

The ErgoRelief framework has been designed to perform ergonomic monitoring utilizing a number of wearable and non-wearable sensors. This system is set within the context of aviation manufacturing and aims to measure fatigue levels during repetitive tasks, whilst providing feedback and data analytics. Fig. 1 illustrates a high-level overview of the system. Three components, including data collection, analysis, and visualization, two stakeholders (aviation manufacturing workers and factory operations) form the feedback loop.

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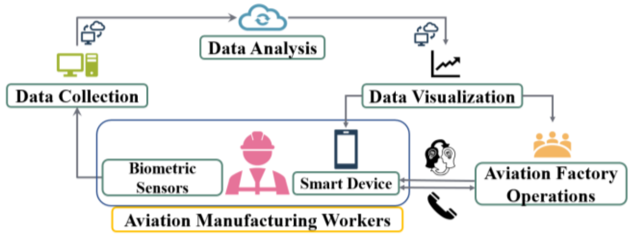

Figure 1. ErgoRelief System Framework

The first aspect of the framework is raw data collection. Sensors in ErgoRelief included wearable, which are attached to the worker's body, and non-wearable, which are deployed in the workplace. The sensors act as the data source to collect biometric data, including motion, external force exerted on the human body, and physiological data, including heart rate. The data is then subjected to data analysis, where it will be pre-processed (e.g. data cleaning and filtering) and the worker's current body fatigue level can be deduced using machine learning techniques.

The data visualization aspect targets at providing interactive feedback to workers to support their activities, as well as insight to factory operations on workplace health and safety. Additionally, the utilization of smartphones allows bi-directional communication to be enabled between workers, their teams, and factory operations. For instance, workers can be alerted through an alarm beep and vibration signal when they have maintained a high fatigue level for an extended period of time, whilst factory operations are able to provide professional and on-time safety advice to workers. Workers are also able to report any unexpected conditions to their lead, and/or operations and/or management.

In summary, we propose a framework for ergonomic monitoring that engages a variety of stakeholders and is aimed at improving factory-wide situational awareness. In the framework, biometric data is collected, analyzed, and visualized to aviation manufacturing workers and operations utilizing a number of sensors that form a network focused around the worker. This framework postulates that by detecting and decreasing fatigue, workers' safety and productivity can significantly improve. To demonstrate the feasibility of this framework, an initial experiment has been conducted to quantify the relationship between biometric data and fatigue levels.

III. MATERIALS AND METHODS

In order to demonstrate aspects of this framework, an experiment has been conducted that consists of four repetitive tasks that have been designed to simulate common tasks that aviation manufacturing workers may encounter. The platform consists of several wearable and external sensors that have been employed to measure biometric data, motion, and force. It should be noted that the visualization and feedback aspects of the framework are outside the scope of this paper.

A. Participants

Thirty participants (13 males, 17 females) have been included in the experiment, with an age range from 20 to 54 (mean = 25.67, standard deviation = 6.66). Participants did not have a history of cardiovascular illness or any physical injuries prior to the experiment. This experiment has been approved by the University of Queensland Ethics Sub-Committee.

B. Experiment Design

According to [9], the most common physical tasks that factory workers encounter are lifting, lowering, pushing, pulling, carrying or moving of a load. Additionally, complex aviation manufacturing and assembly tasks are designed based on these fundamental tasks, including assembling primary parts using hand tools and joining different structures [2]. Taking this into account, four repetitive tasks have been designed to simulate daily aviation factory work, including:

1. **Two-handed Trolley Pushing/Pulling:** A trolley is positioned in front of the participant with the handle height at 80cm. Participants are required to push the trolley away at a distance of 5m and pull it back.
2. **Two-handed Box Carrying:** Two chairs are positioned on each side of the participant, with the horizontal distance at approximately 60cm from the body center. A box is placed on the chair at the right-hand side of the participant. Participants are required to pick up the box and move it from one chair to another.
3. **Two-handed Box Pushing/Pulling:** A table is positioned in front of the participant that is 90cm high with a box on top of it. Participants are required to push the box away to a distance of approximately 60cm and pull it back.
4. **Two-handed Box Lifting:** Participants are required to lift up a box with two hands from the floor to hip height, hold for 3 seconds, and lower it down to the floor.

Each task has been performed using a variety of weights that ranged from light to heavy, including:

1. Two-handed Trolley Pushing/Pulling: 3kg, 40kg, 80kg.
2. Two-handed Box Carrying: 3kg and 5kg.
3. Two-handed Box Pushing/Pulling: 3kg, 10kg, 20kg.
4. Two-handed Box Lifting: 3kg and 5kg.

For each task and weight, participants were required to perform two 10-minute repetitions of the task. There was a 5-minute resting period after each repetition. After each task, participants were also asked to completely rest and recover before commencing the next task. During each repetition, participants were allowed to control their posture and the speed while completing the task.

The Two-handed Box Lifting and Two-handed Box Carrying tasks took approximately 1 hour each to complete, whilst the Pushing/Pulling tasks took approximately 1.5 hours each to complete. As an incentive, after completing the experiment, participants were each paid using a $50 gift card.

C. Data Collection

The wearable aspect of the system utilizes six Shimmer3™[1] Inertial Measurement Unit (IMU) sensors (see Fig. 2a) and a Shimmer3™ photoplethysmogram (PPG) optical pulse ear clip (see Fig. 2b). The IMU sensors were utilised to capture raw 3-axis acceleration and 3-axis angular

[1] https://www.shimmersensing.com

velocity, whilst the PPG sensor captured Blood Volume Pulse, which was used to derive heart rate. The Shimmer3™ sensors were configured at a sample rate of 100.21Hz and data was stored on the internal microSD card inside each sensor. Each IMU was fastened to six different body parts, including the hip, upper spine, left arm, right arm, right forearm, and right shank, whilst the PPG ear clip has been clipped to the left ear lobe and was connected to the Shimmer3™ sensor on the left arm (see Fig. 3).

The non-wearable sensor aspect of the system contained a Sparkfun™[2] Load Cell (see Fig. 4a) and a Bertec™[3] Force Plate (see Fig. 4b). The Force Plate has been utilised to capture raw 3-axis Ground Reaction Force, 3-axis Torso Moment, 2-axis Center of Pressure, and 2-axis Centre of Gravity. The Load Cell's handle has been attached to the box during each task to measure the hand's exertion force against the box. The load cell and force plate were configured at a sample rate of 10Hz and 100Hz respectively, and data was logged directly to a PC through a wired connection. Both the Shimmer3™ sensors and Load Cell have been used throughout the entire experiment. The Force Plate has not been included in the Two-handed Trolley Pushing/Pulling task, as this task requires participants to walk and move off the force plate.

Additionally, at the beginning and end of each repetition and task, subjective ratings of fatigue have been captured via the Borg Scale Questionnaire [10]. This questionnaire required participants to rate their level of exertion on a scale from 6 to 20, whereby 6 related to no exertion, whilst 20 represented very hard exertion. Participants were also required to be relaxed before starting each task.

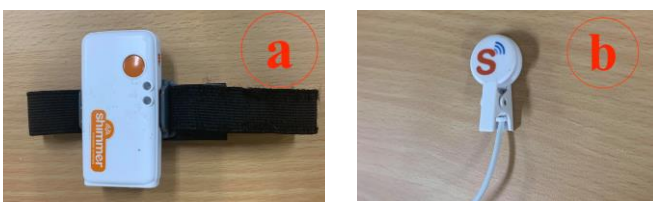

Figure 2. a) Shimmer3™ GSR+ Unit and b) Shimmer3™ PPG-to-HR ear clip

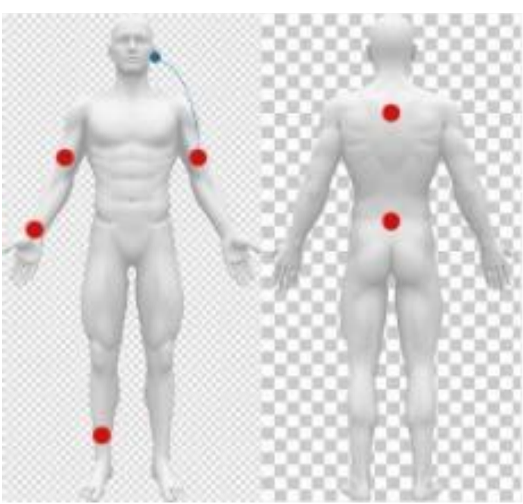

Figure 3. Shimmer3™ Wearable Sensor Placement

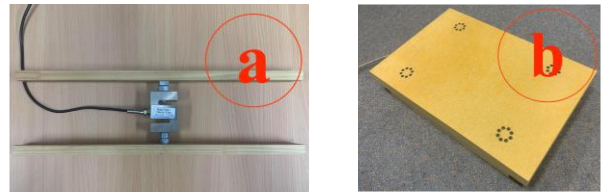

Figure 4. a) Load Cell – 200kg, S-Type (TAS501) b) Force Plate FP4060-NC

D. *Experimental Measures*

The data processing procedure that has been followed is depicted in Fig. 5. The collected data has been synchronized to a consistent timestamp, resampled to 100Hz to avoid inconsistent sampling rates between sensors, and filtered before analysis [11-13]. Acceleration, Force Plate, and Load Cell data have been filtered using a 2^{nd} order zero-phase Butterworth low-pass filter, with a cutoff frequency of 3Hz [14, 15]. Angular Velocity data has been filtered using a 2^{nd} order zero-phase Butterworth high-pass filter, with a cutoff frequency of 0.1Hz [16]. Furthermore, the PPG signal has been filtered using a 2^{nd} order zero-phase Butterworth band-pass filter, with a cutoff frequency from 0.5Hz to 3.5Hz [17].

Both time and frequency domain features have then been extracted using a 30-second sliding window, with 50% overlapping area [18]. Time domain features included 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles, mean, standard deviation, inter-quartile range, kurtosis, mean absolute deviation, and autocorrelation. Frequency domain features included DC component, spectral energy, spectral entropy, peak frequency, and peak power. Features from all participants per task were combined into one datasheet.

IV. Results and Discussion

The aim of the analysis is to demonstrate the relationship between fatigue and various types of predictors to determine the best predictor of fatigue using multiple linear regression (MLR) models. The MLR approach has been chosen as a method to determine the strength of the relationship between independent and dependent variables before further analysis.

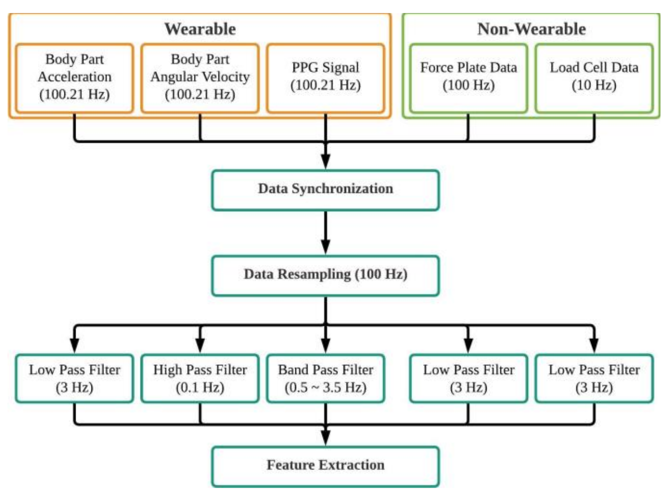

Figure 5. Data Processing Procedure

[2] https://www.sparkfun.com/products/14282

[3] https://www.bertec.com/products/force-plates

This was undertaken on a per task basis and includes using three different data sets, which each act as the independent variables. This includes 1) biometric predictors only (extracted from the wearable sensors), 2) external predictors only (extracted from the force plate and load cell), and 3) a combination of both biometric and external predictors. Table I displays the number of predictors in each data set. It should be noted that the Force Plate was not utilized in the Two-handed Trolley Pushing/Pulling task, as participants were required to move off the plate.

Subjective ratings of fatigue, which have been extracted from the Borg Scale Questionnaire, have been utilized as the dependent variable. As participants completed the questionnaire before and after each repetition, a change score has been calculated that represents their overall feeling of fatigue. This has been calculated by subtracting their initial self-reported level of fatigue away from their post rating (i.e. post-rating – pre-rating). As such, each repetition has a corresponding fatigue level. This is advantageous as it provides a variable rating between repetitions that occur within the same task.

In MLR analysis, a small p-value indicates that there is a strong relationship between the dependent and independent variables. Therefore, backward elimination has been implemented to trim the independent variables with high p-values in order to simplify the MLR model. This process iteratively removes the independent variable with the highest p-value, until the p-values for all independent variables are below a threshold, which is typically 0.05 [19]. Measurements of model performance have been evaluated using Adjusted R^2 Score and Root-Mean-Square Error (RMSE). The Adjusted R^2 Score is a relative measure that indicates the percentage of the variation of the dependent variable that can be explained by the independent variables and is adjusted depending on the number of predictors in the model. RMSE is an absolute measure that calculates the square root of the variance of the residuals to evaluate the models fit to the data.

Fig. 6a and Fig. 6b illustrate the task specific MLR model performances based on the Adjusted R^2 Scores and RMSE, respectively. The results demonstrate that the Adjusted R^2Scores using only the external predictors performs relatively poorly in comparison to the other datasets for the task of predicating fatigue. The highest Adjusted R^2 Score of 0.5853 and lowest RMSE of 1.1861 were achieved during the Two-Handed Box Pushing/Pulling task. As the Adjusted R^2 Score results are lower than 0.6, this illustrates that the external sensors alone are not suitable for predicting fatigue. However, the addition of the biometric predictors significantly improves the results.

TABLE I. NUMBER OF PREDICTORS FOR EACH DATA SET

Data Set	Number of Predictors
Biometric Data Set	1187
External Data Set	11 (Two-handed Trolley Pushing/Pulling) 121 (Other 3 tasks)
Biometric + External (Full) Data Set	1198 (Two-handed Trolley Pushing/Pulling) 1308 (Other 3 tasks)

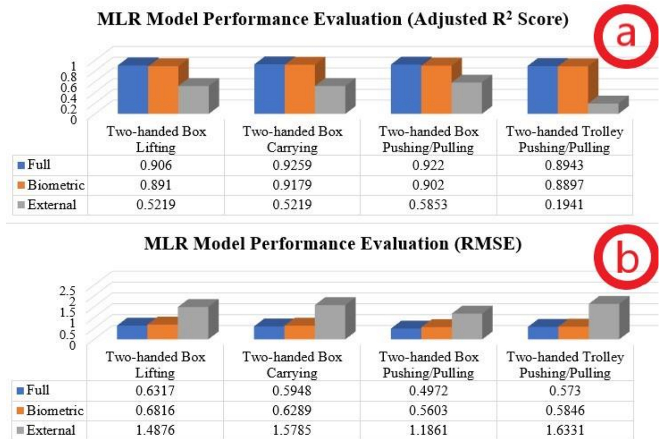

Figure 6. MLR Model Performance Evaluation

The highest Adjusted R^2 score of 0.9179 was achieved from the Two-handed Box Carrying task, whilst the Two-handed Box Pushing/Pulling task produced the lowest RMSE of 0.5603. This illustrates that biometric predictors are capable of suitably predicting fatigue.

The combination of both biometric and external predictors marginally improves the results, with the full system achieving a maximum Adjusted R^2 Score of 0.9259 from the Two-handed Box Carrying task and lowest RMSE of 0.4972 from the Two-handed Box Pushing/Pulling task. The results illustrate that the addition of the biometric predictors to the external predictors (i.e. the full system) improves and does not hinder the model's performance.

In comparison to other systems, our setup has utilized both biometric and external predictors, which demonstrates an improved model for predicting fatigue. Although non-wearable sensors have been included in other works, they are mostly used in conjunction with cameras in a laboratory environment [7]. A benefit of our study is that non-wearable (external) sensors have been used in conjunction with wearable biometric sensors to undertake a more comprehensive analysis, which has demonstrated improved results over using these sensors in isolation. We have also evaluated the performance between biometric and external sensors and have statistically demonstrated that the wearable biometric sensor system outperforms the non-wearable external sensors. This indicates that the wearable biometric sensors are greater predictors of fatigue.

Moving forward, although the framework has been tested with a number of basic repetitive physical tasks, the workflow can be expanded to include more complex aviation-related tasks in the future, including fabrication, assembly and maintenance. This drives the future directions of the research in relation to reducing WMSDs, as by predicting the onset of fatigue enables systems to be developed that can alert stakeholders to this state so that they can take proactive steps to reducing and recovering from this state. Over time, safer work habits can be developed to reduce the onset of developing WMSDs.

V. CONCLUSIONS AND FUTURE WORK

This paper posits a framework for a novel wearable sensor-based ergonomic monitoring system (ErgoRelief). An experiment has been conducted to simulate basic repetitive aviation factory work and demonstrate the relationship between three different types of data, including biometric, external and a combination of both to predict fatigue. Results of the analysis illustrate that utilizing both types of data (i.e. biometric and external data) produces the optimum results. Future work aims to build on these results by constructing a machine learning model with a front-end user interface, which will be utilized to detect body fatigue levels and provide real-time feedback to workers and any supporting operation group.

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