Proceedings of the IISE Annual Conference & Expo 2022
K. Ellis, W. Ferrell, J. Knapp, eds.

Wearable Motion and Force Sensing to Determine Force Exertion and Task Recognition for Ergonomic Analysis

Matthew Krugh, Flanagan Waldherr, Suruchi Gujarathi, Scott Kerner, and Laine Mears
Automotive Engineering, Clemson University, Greenville, SC, USA

Abstract

Work-related musculoskeletal disorders contribute to significant loss in productivity and higher costs for employers. This research utilizes body-worn motion and hand-worn force sensors to provide non-intrusive and continuous recognition of tasks, estimate force exertion, and evaluate if operators are working in safe ergonomic ranges. Work-related motions such as lifting, carrying, pulling, and pushing are measured with varied loads up to 10 kg, and then recognized performed using the IBM Watson cloud service platform. The experiments use sequential and quasi-static postures and mimic those commonly found in an automotive assembly environment. Classification performance included generating 70 input features based on 6 motion and 4 force inputs and three of the resulting classifier had a greater than 90% accuracy in simultaneously classifying both the weight being carried and the task being completed. Future work includes measuring non-quasi-static motions and integrating additional sensors, such as those from smart tooling, which tracks tool position and orientation, to provide a continuous and unobtrusive evaluation of worker exertion and risk of musculoskeletal disorder.

Keywords
Musculoskeletal disorder, wearable sensor, Industry 4.0, task recognition.

1. Introduction

Work related injuries constitute a significant cost in manufacturing: a field whose nature tends to contribute to their development due to the prevalence of strenuous, repetitive tasks. As a result, manufacturers are motivated to conduct ergonomic evaluations and engage in live monitoring to ensure employees' movements do not cause undue physical strain. Ongoing advances in both sensing and machine learning capabilities permit the application of new techniques to such efforts. This paper builds upon prior literature by varying the task type and amount of weight grasped by participants and data were collected by both motion and normal force sensor integrated into a work glove.

2. Related Research

Musculoskeletal disorders (MSDs) are injuries caused by the use of muscles, tendons, and ligaments, and frequently result from motions which involve a high degree of repetition or awkward positioning: both common in manufacturing environments. The United States Bureau of Labor Statistics' Survey of Occupational Injuries and Illnesses reports that in 2018, 30 percent of occupational injuries involving days away from work involved MSDs [1]. Furthermore, it lists manufacturing among the industries most affected by this lost productivity, while laborers and maintenance personnel are listed in the ten most impacted occupations. Consequently, manufacturers have a considerable incentive to ensure that tasks reside within ergonomically safe ranges.

The proliferation of wearable devices within the Industry 4.0 paradigm [2] has allowed efforts to characterize and monitor ergonomic information beyond simulation and observation, including continuous, live monitoring: both in research and industrial applications [3]. Efforts in this area have expanded considerably in recent years, resulting in many proposed systems of sensors with varying types, quantities, and locations on the body [4]. Examples include sensors measuring the forces exerted by wearers [5, 6] and various types of body-worn motion sensors [7].

Analysis of the large quantities of data generated through the use of such sensors has benefited from recent and rapid advances in the capability and accessibility of machine learning technologies [3]. This application helps expedite the processing of collected data in controlled experiments [8] and enables analysis supporting the real-time monitoring of workers' ergonomics [7, 9].

3. Methodology

A series of tests was conducted to determine if operators wearing the sensor glove system performed in a safe ergonomic range. Force signals were captured through Tacterion sensors placed on the right hand. Acceleration and gyroscopic information were also collected through an accelerometer within the circuit. The circuit utilized a breadboard and was placed in a forearm sleeve of each participant. A simple plastic container was used for each test with weights placed inside ranging from 0-10 kg. Each participant completed seven actions with 0, 1.0, 2.0, 5.0, and 10.0 kg in the container. A light cloth material was placed in the container to mitigate the shifting of weights during tests. The actions are detailed in the Task Descriptions subsection below. Tests were repeated 3 times each for a total of 105 tests per person and 420 tests across all four participants. Participant grip pressure was not controlled to include greater variability in the collected data.

The sensors were incorporated into a wearable glove as seen in **Figure 1** left. The sensors included four normal force sensors (Tacterion GmbH plyon) and a six-axis accelerometer and gryoscope (MPU-6500). The wearable unit was controlled with a Teensy 3.2 microcontroller and data was sent over wired USB to an experimenter's PC for storage.

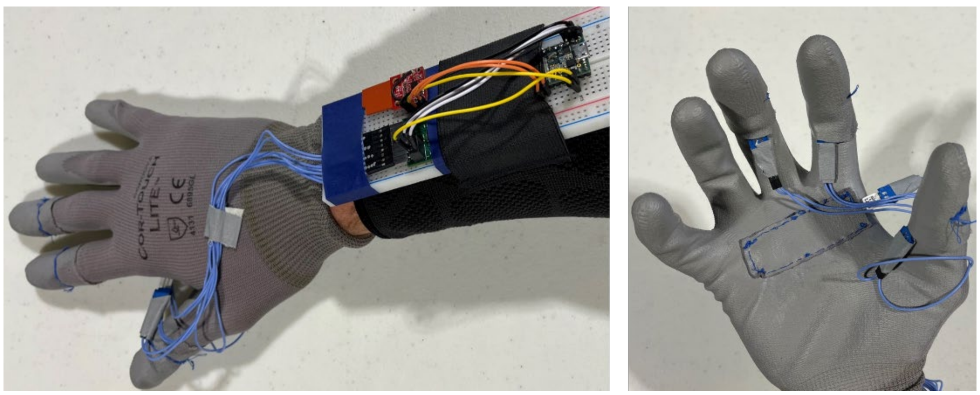

Figure 1: Wearable sensor glove **(left)** circuit affixed to a forearm sleeve; **(right)** sensors

The force sensors constituted three 16x16mm square sensors on the thumb, index, and middle fingertips and a 50x10mm rectangular sensor placed on the palm near the base of the fingers. The sensors were manually sewn into a standard nitrile dipped work glove. The sensors are shown attached to the glove in **Figure 1** right. For the exploratory study of this work, the sensor placement was chosen based on observations of production associates on an automotive assembly line and student participants in a production simulation laboratory, as well as past literature that examined associate finger engagement during manual assembly processes [10].

3.1 Test Setup

All experiments were performed after Institutional Review Board approval. Participants donned the glove with force and motion sensors attached on their right hand, they were asked to ensure that the sensors aligned with their fingertips and that the wrist module remained in the same place throughout testing. To complete the required movements, participants were provided a plastic box with handles containing the requisite weight for each case. In completing these tasks, they utilize a 6 m long walkway for the carry task and a table with a standing position marked alongside it for the remaining tasks. The ergonomic range limit from the marked position on the floor was 30 cm from the table edge. This marking was the target for the short push and pull tasks.

3.2 Task Descriptions

Seven tasks were completed by each participant and replicated three times using the weighted box. Participants were instructed to complete these tasks as they naturally would. This effort focused on keeping the participants in a comfortable posture, and aimed to measure natural movements. After each action, the participants were asked to return to a neutral standing position.

- Lift from Floor: Participants lift the box from the marked point on the floor using both hands and holds the box in a comfortable position for 7 seconds while in a standing posture. When prompted, the participant places the box onto the table. A visual representation of the steps for this task are shown in **Figure 2**.
- Lift from Table: Participants lift the box from the table using both hands and holds the box in a comfortable position for 7 seconds while in a standing posture. When prompted, the participant places the box onto the table.
- Short (Ergonomic) Push: While standing at the end of the table, participants push the box using their right hand to the marked ergonomic limit (30 cm).
- Short (Ergonomic) Pull: While standing at the end of the table, participants pull the box with their right hand from the ergonomic limit (30 cm) to the table's edge.
- Long (Less-ergonomic) Push: While standing at the end of the table, participants push the box using their right hand as far as they can without lifting their feet or leaning on the table.
- Long (Less-ergonomic) Pull: While standing at the end of the table, participants pull the box using their right hand to the table's edge without lifting their feet or leaning on the table.
- Carry: Participants stand at the assigned starting mark with the box in their hands. When prompted, the participant walks a distance of 6 meters to the finish mark.

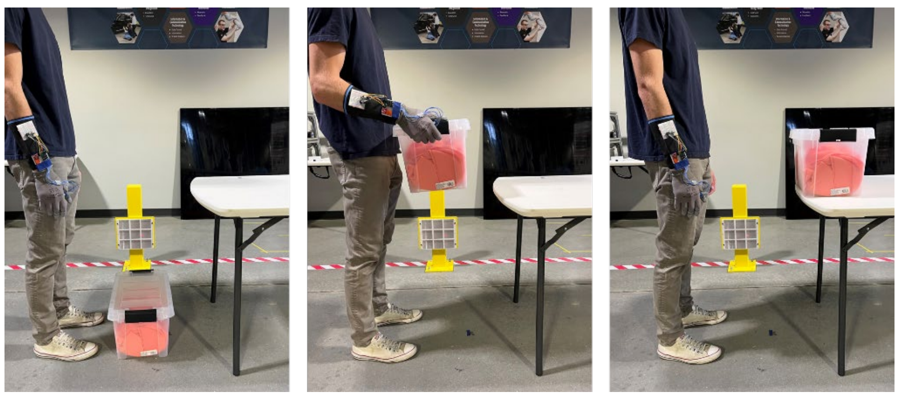

Figure 2: Participant completing the Lift from Floor action

4. Results

The data classification was completed on the IBM Watson Cloud service using a Jupyterlab notebook running Python 3.8.12 and Scikit Learn 1.0.2. The data were collected offline and uploaded to cloud storage for processing. The primary goal of this classification was to evaluate performance in predicting both the task being completed and the weight of the object being grasped by the user during the task. Data from all participants were included in the analysis to build a generalized classifier independent of the participant data included.

The data were scaled to a 0-1 range based on the known sensor output limits and any outliers were removed. Scaling the input data better accounts for the varied ranges of input feature scale from the sensors, this is used to match the relative feature magnitudes. The motion and force data were separated due to being collected at 500 Hz and 30 Hz respectively and synchronized by using a sliding window to step through the data. The sliding window used a one second width and 0.5 second step over. The resulting windows were labeled by both the task and weight. A breakdown can be found in **Table 1**. Variations in the number of windows were expected due to the natural variations in the time it takes for individuals to complete tasks.

Feature extraction provided additional derived data to better inform the learning and generalization of the classifier. The features used were selected based on past literature in characterizing body worn sensors and included the signal mean, variance, minimum value, maximum value, and area under the curve which resulted in 70 total features. Area under the curve was calculated using the composite trapezoidal rule to integrate the signal. It was noted that co-linearity and correlations were observed between resultant features. Future work is included to examine the feature selection in depth and reduce the total number of input features computed.

Table 1. Breakdown of dataset window counts by task and weight

Label	Sum	0 kg	1 kg	5 kg	10 kg
Carry	524	141	134	119	130
Lift Floor	1228	309	302	296	321
Lift Table	1132	282	287	286	277
Pull Long	318	74	74	86	84
Pull Short	234	61	50	57	66
Push Long	302	72	63	79	88
Push Short	274	74	60	61	79

Multiple model types were trained on the dataset and were selected based on prior literature and past experiences with modeling body worn sensor data. The top seven performing models will be presented classifying both task and weight; Support Vector Machine (SVM) with Linear kernel, SVM using a Radial Basis Function Kernel (RBF), k=3 Nearest Neighbors, Random Forest, Naïve Bayes, Decision Tree, and Adaboost Ensemble Classifier. The data were evaluated using three measures, Accuracy (ACC), Balanced Accuracy (Bal ACC), and the Matthew's Correlation Coefficient (MCC). ACC provides overall classification performance, but in cases of imbalanced data where one class is larger than the others, accuracy is not as reliable as it tends to overestimate the ability to predict the majority class [11]. From **Table 1**, a class imbalance is present in the data. The second metric, Bal ACC is commonly used on datasets with unequal distributions as it considers class-balanced sample weights. Finally, the MCC was used, which measures the classification quality and includes both true and false positives and negatives. MCC is generally regarded as providing a more balanced measure of classification model performance even when the classes are very different sizes [12, 13]

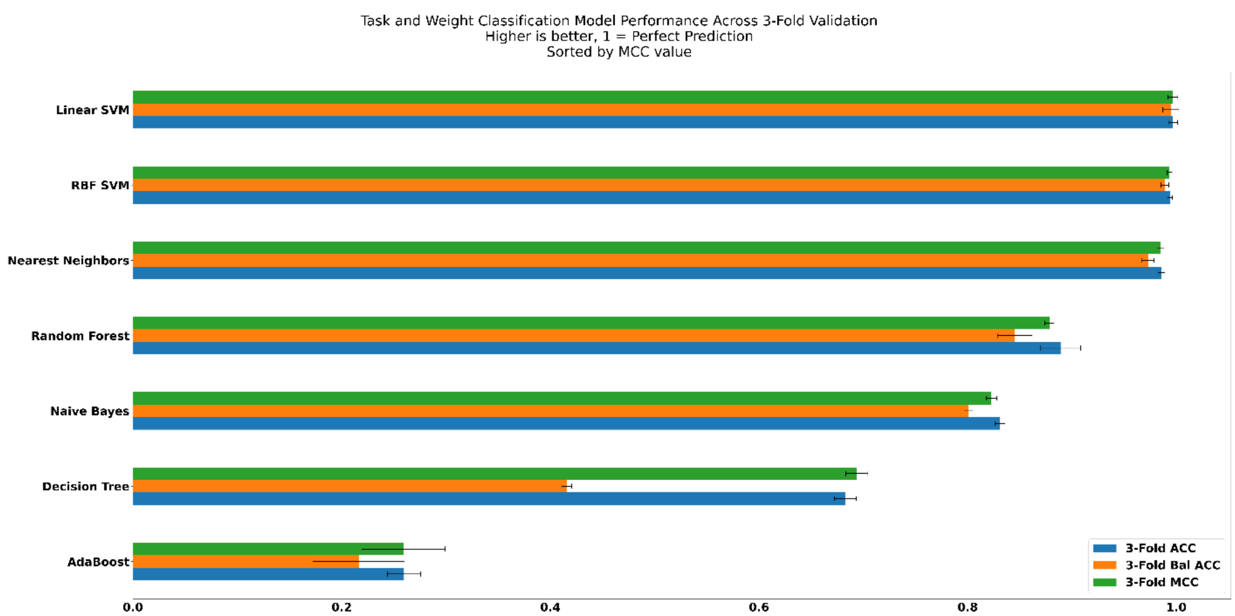

Figure 3: Classifier performance considering both task type and grasped weigh

To further validate the performance of the top models, k-fold cross-validation was completed for each model using 3 folds and shuffled data. K-fold cross-validation holds out a portion of the dataset during training of the classifier. The partitioning used is propagated through the dataset by splitting the dataset into k smaller sets or folds and training the model using k–1 folds. The model is then iteratively trained on each split of folds until all folds have been used for both training and testing. The resulting performance metrics for each iteration or split are used to compute the average value. The k-fold method provides an increased percentage of training data allowed the resulting classifier to learn from more data points, potentially encompasses more data variability when compared to the more common fixed 60% training/40% testing dataset split. The data collected was time series data that changes over time and different areas of the dataset contain differing distributions of information. By iterating over the full dataset, the resulting classifier is validated against all variability in the collected dataset.

From the model classification performance in **Figure 3**, the two SVM and Nearest Neighbor classifiers achieved over 0.9 out of a possible 1.0 indication perfect classification performance in predicting both task type completed and the weight being grasped. The high classification performance of the models indicates the use of the integrated force and motion sensors are sufficient on quasi-static variable weight tasks. Further work is needed to expand the types of tasks, weight levels, and non-quasi-static movement.

5. Conclusion

This work detailed collecting worker data across 7 tasks and 5 weights using an instrumented glove with integrated force and motion. The classification accuracy achieved greater than 90% in describing both the weight borne and the task type. The high performance of the classifier underscores the potential for a multi-sensor approach using low-cost body-worn sensors for continuous evaluation of real-time ergonomics. Future extensions of this work include evaluation of additional task types, non-quasi-static movements, and further integration with smart tooling.

Acknowledgments

This material is based upon work supported by Clemson University SUCCEEDS Grant No. 1402649. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of Clemson University.

References

[1] Occupational injuries and illnesses resulting in musculoskeletal disorders (MSDs). Available from: https://www.bls.gov/iif/oshwc/case/msds.htm.

[2] Kong XTR, Luo H, Huang GQ, Yang X. Industrial wearable system: the human-centric empowering technology in Industry 4.0. Journal of Intelligent Manufacturing. 2019 12;30:2853-69.

[3] Lee S, Liu L, Radwin R, Li J. Machine Learning in Manufacturing Ergonomics: Recent Advances, Challenges, and Opportunities. IEEE Robotics and Automation Letters. 2021 7;6:5745-52.

[4] Stefana E, Marciano F, Rossi D, Cocca P, Tomasoni G, Lopomo F, et al. Wearable Devices for Ergonomics: A Systematic Literature Review. Sensors 2021, Vol 21, Page 777. 2021 1;21:777.

[5] Kerner S, Gunasekar S, Vedant RM, Krugh M, Mears L. Parametrization of manual work in automotive assembly for wearable force sensing. Journal of Manufacturing Systems. 2021 4;59:686-700.

[6] Chihara T, Sakamoto J. Exerted force estimation using a wearable sensor during manual material handling. Human Factors and Ergonomics in Manufacturing Service Industries. 2021 5;31:239-48.

[7] Nath ND, Chaspari T, Behzadan AH. Automated ergonomic risk monitoring using body-mounted sensors and machine learning. Advanced Engineering Informatics. 2018 10;38:514-26.

[8] Tognetti A, Carbonaro N, Zupone G, De Rossi D. Characterization of a Novel Data Glove Based on Textile Integrated Sensors. In: 2006 International Conference of the IEEE Engineering in Medicine and Biology Society; 2006. p. 2510-3.

[9] Oyekan J, Chen Y, Turner C, Tiwari A. Applying a fusion of wearable sensors and a cognitive inspired architecture to real-time ergonomics analysis of manual assembly tasks. Journal of Manufacturing Systems. 2021 10;61:391-405.

[10] Krugh M, Vedant RM, Garimella RS, Baburaj A, Wescoat E, Mears L. Associate Finger Engagement During Manual Assembly in Automotive Production for Smart Wearable Systems. Procedia Manuf 2019;39:251–9. doi:10.1016/j.promfg.2020.01.332.

[11] Akosa J. Predictive accuracy: A misleading performance measure for highly imbalanced data. In: Proceedings of the SAS Global Forum. vol. 12; 2017.

[12] Boughorbel S, Jarray F, El-Anbari M. Optimal classifier for imbalanced data using Matthews Correlation Coefficient metric. PLOS ONE. 2017 6;12:e0177678.

[13] Chicco D, Jurman G. The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. BMC Genomics. 2020 12;21:6.