Holistic Fatigue Estimation For Various Manual Handling Tasks

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Summary

A system was developed to estimate holistic fatigue during manual handling work. Participants performed a manual handling protocol until exhaustion, while fatigue was quantified using a fatigue composite index (FCI). Neural networks were trained to classify tasks using kinematics, then estimate the FCI. Using an inertial measurement unit (IMU) on the T8 vertebrae, task was classified with 93.17% accuracy and the addition of heart rate (HR) data allowed the FCI to be estimated with an average Pearson's correlation of $r = 0.59$. These components comprise a system capable of estimating fatigue during manual handling using unobtrusive devices.

Introduction

Estimating workplace fatigue can inform the provision of breaks, technique reminders, or job rotations to mitigate injury and accident risk [1]. Using kinematics from IMUs is a practical, unobtrusive approach to estimate fatigue. However, the system must be capable of adapting to various tasks, and it is desirable to estimate holistic fatigue as continuous value to improve the preventative capabilities beyond classifying fatigue states [2]. Thus, the objectives of this work were to:

- Develop models to classify six manual handling tasks.
  - Compare classification performance between raw versus fused IMU data.
  - Conduct a sensitivity analysis on IMU combinations.
- Quantify fatigue using a novel composite index (FCI).
- Develop task-specific models to estimate the FCI.

Methods

Participants ($N = 24$) performed a simulated manual handling protocol involving six tasks with a crate: walk, stand, pull, lift, carry, and push until exhaustion. Kinematics were measured using an Xsens MVN Link system (Movella, USA) comprised of 17 IMUs. Data were processed with two methods: raw (RAW) or sensor fusion to obtain orientation and position (FUSION). Tasks were manually labelled, then used to train fully connected neural networks (ANNs). Classification performances between RAW and FUSION were compared, then the better method was employed for a sensitivity analysis of eighteen combinations, each comprised of one to six IMUs.

To quantify fatigue, self-reported fatigue level, maximal lift strength, electromyography median frequency of seven muscles, HR, HR variability (low to high frequency ratio), and pelvic jerk magnitude were measured throughout the protocol and combined into the FCI. The FCI ranged from 0 – 1, where larger values indicated greater fatigue. Task-specific ANNs were trained to estimate the FCI using T8 IMU and HR data. All models were trained using k-fold cross-validation in TensorFlow 2.12, where $k = 8$ (three participants per fold).

Results and Discussion

52,920 tasks were performed by all participants over 36.7 hours ($\mu = 92$ min, $\sigma = 50$ min). RAW led to marginally lower loss ($\mu_{RAW} = 0.17$, $\mu_{FUSION} = 0.19$) and greater accuracy ($\mu_{RAW} = 94.93\%$, $\mu_{FUSION} = 94.39\%$) and weighted average F1-score ($\mu_{RAW} = 94.96\%$, $\mu_{FUSION} = 94.41\%$) compared to FUSION ($p < 0.01$). The sensitivity analysis showed that as more IMUs were used, performance generally improved, with accuracies ranging from 90.25 – 94.26%. The strongest performance with one IMU was on the T8 vertebrae (accuracy = 93.17%).

The FCI captured an increase in fatigue throughout the protocol, shown in Figure 1. Using task-specific models, the FCI was estimated using the T8 IMU and HR with an average Pearson's correlation of $r = 0.59$ and mean absolute error = 0.05. The performance on each task is presented in Table 1.

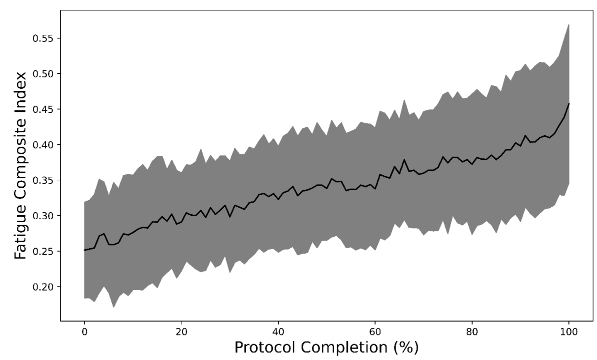

Figure 1: The mean (black line) and standard deviation (grey shading) of the fatigue composite index across protocol completion.

Table 1: The Pearson's correlation coefficient (r) and mean absolute error (MAE) on the task-specific estimations of the FCI.

	Walk	Stand	Pull	Lift	Carry	Push
r	0.626	0.504	0.647	0.622	0.614	0.527
MAE	0.056	0.053	0.049	0.047	0.050	0.048

Conclusions

Holistic fatigue was estimated with small errors and moderate correlations, which may be further improved with additional modelling. Combined in cascading ensembles, these models can perform task recognition and fatigue estimation in near-real time using minimal instrumentation, capable of mitigating the risk for fatigue-related injuries and accidents.

Acknowledgments

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References

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