Advancing Safety Surveillance Using Individualized Sensor Technology

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Abstract

This research aims to presents a data fusion approach for the assessment of physical workload that can improve fatigue detection using physical and physiological metrics. The sensor system gathers data from a heart rate monitor and accelerometers placed at different locations on the body including chest, wrist, hip and ankle. Three common manufacturing tasks of manual material handling, prolonged walking and bending, and small parts assembly were tested. At this point, two body kinematics metrics of jerk and posture were extracted and analyzed across the three participants and tasks for fatigued and non-fatigued states. A significant variation between the data from different tasks and sensor locations was observed, which can improve the ability of task classification and detection of different states (i.e., fatigue vs. non-fatigued) in the human body.

Background

Timely and accurate fatigue detection using advance sensory system during the work can significantly reduce the workplace accidents and injuries. Studies have been conducted for fatigue and workload classifications using elaborate systems consisted of multiple sensors. This research aims to develop a simple sensor-based exposure assessment system for the fatigue state classification, through real-time data collection and analysis of physical and physiological risk factors using a minimum number of sensors attached to the body, for the prescription of appropriate in situ intervention.

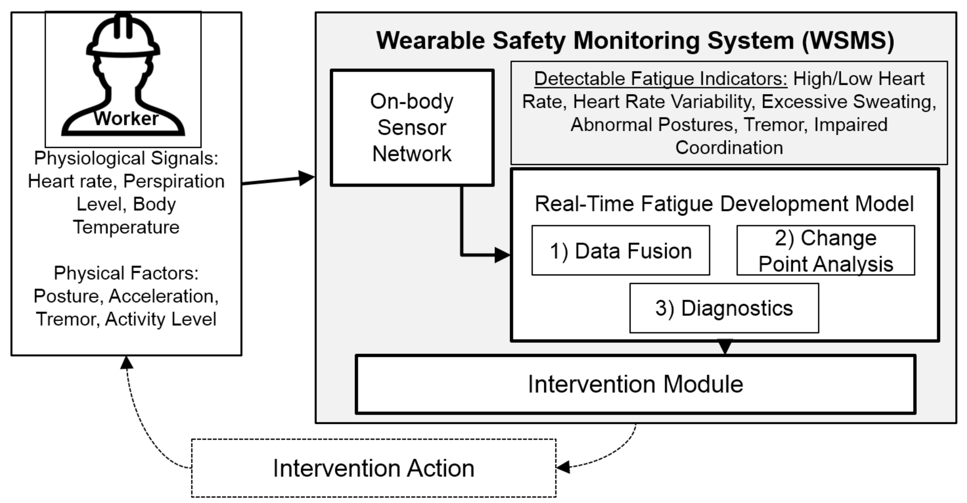

Figure 1. Proposed system architecture and relationship of biosensor technologies to detectable conditions

Hypothesis: a real-time exposure assessment system will allow for detection of at-risk individuals based on identification of fatigue and behavior deviations to enable intervention prior to injury.

Project Goals

- Specific Aim 1. Identify the appropriate combination of sensors and on-body locations for optimal, real-time fatigue monitoring.
  - What are appropriate metrics for quantifying worker fatigue?
  - Which combination of biosensors and data fusion techniques will be most sensitive and effective for monitoring fatigue and safety for individuals at work?
  - What is the optimal number of sensors for minimal intrusion while maintaining accurate assessment?
  - Where should the sensors be placed on the body for accurate exposure assessment?

Table 1. Fatigue indicators and their corresponding sensors for measurement

Fatigue Indicator	Measure	Sensor
Excessive sweat level	Electrodermal response	Skin electrodes - conductance
Physiological stress	Heart rate variability	Skin electrodes - electrocardiogram
Change in posture/motion	Accelerations and inclination angles	Inertial measurement unit (IMU)
Decrements in motor control and coordination	Movement variability	IMU
Physiological tremor	Movement variability	IMU
Changes in work output and task completion time	Movement durations and repetitions	IMU

- Specific Aim 2. Model fatigue development to distinguish between a worker's normal state and fatigued (statistically "out-of-control") state.
  - What info needs to be extracted from the WSMS sensors to maximize the differences between the "in-control" (non-fatigued) and "out-of-control" (fatigued) states?
  - How can one understand the variability in the non-fatigued states to minimize the possibility for false positives, and use this understanding in real-time monitoring?
  - What are the impacts of worker characteristics and job demands/instructions on fatigue development?

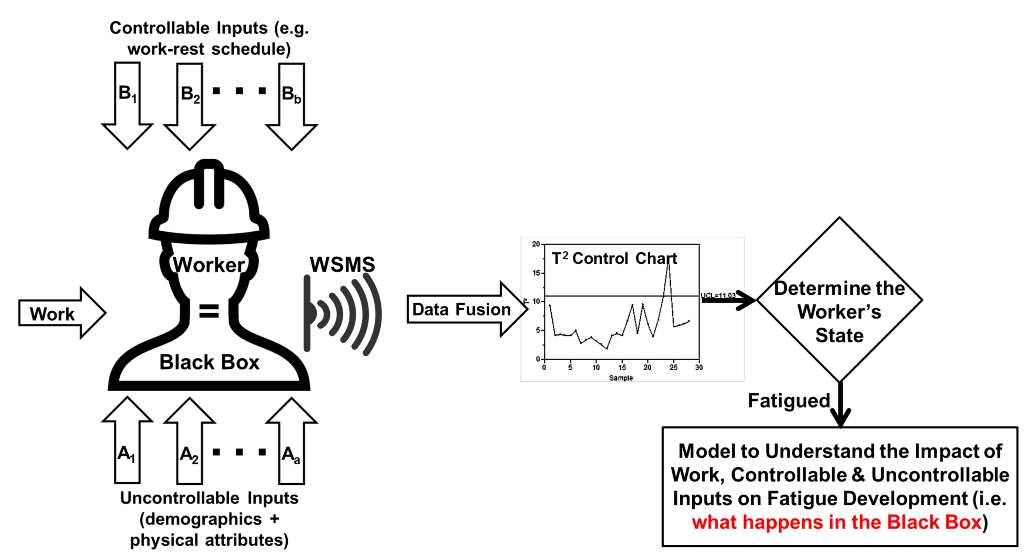

Figure 2. Processes followed for converting sensor signals into meaningful representations of worker fatigue state.

- Specific Aim 3. Determine the effect of individual worker interventions by measuring work exposures and recovery time to return to in-control state.
  - How can we create a taxonomy of safety interventions (relevant to fatigue) based on their contribution to the important fatigue indicators/attributes?
  - How can we model the expected impact of each of these interventions on an individual's fatigue score using the diagnostic model of fatigue development?
  - Is the developed model valid based on experimental results?

Experimental Procedures

The sensor system used in this study was Shimmer3 which is a wearable wireless sensor unit containing an accelerometer, a gyroscope and a magnetometer with selectable ranges and integrated 10 degrees of freedom (DoF). Low noise filtered acceleration data was acquired using this inertial measurement unit (IMU) attached to different landmarks (i.e., ankle, hip, chest and wrist) at the rate of 51.2 Hz. A Polar heart rate (HR) sensor was also used to detect the HR of subject during the whole experimental session. Three physical tasks was performed by each subjects; **Material handling, Assembling and Walking** with each tasks being three hours long.

In addition to physical tasks, two mental tests (i.e., Balloon Analogue Risk Task (BART) to consider the risk-taking behavior and a Psychomotor Vigilance Task using a software for personal computer (PC-PVT)) were designed for the participant to take before the main task as a baseline and after that to compare the variations. Furthermore, ratings of subjective exertion and discomfort using Borg's scale 6-20 every 10 minutes, subjective fatigue level (scale 1-10) every 30 minutes, and NASA Task Load Index (TLX) on five 7-point scales every 60 minutes were asked for getting the perceived rate of fatigue and discomfort as a measure for the validation of fatigue development analysis.

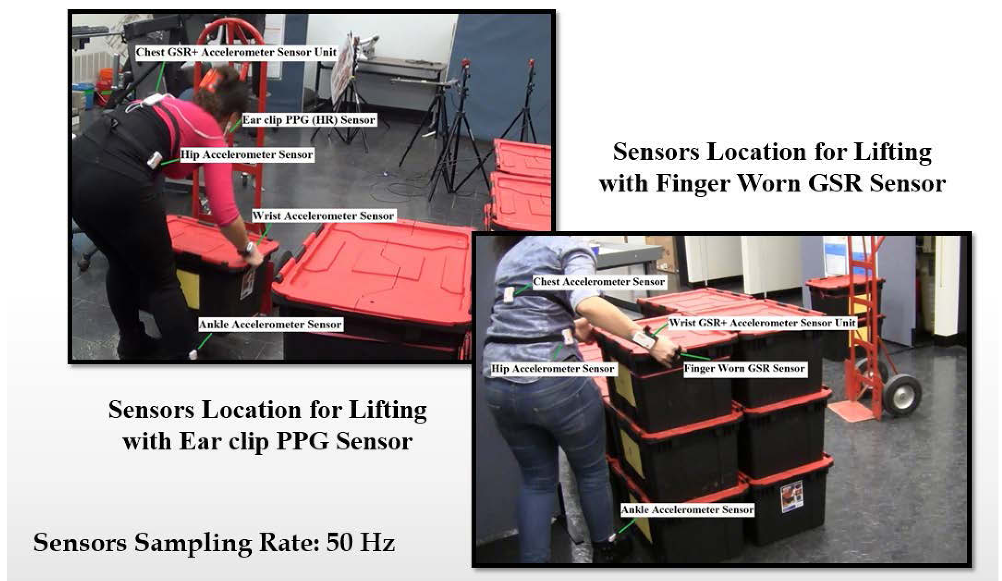

Figure 3. Shimmer IMU sensors setup

Figure 4. Polar heart rate sensor setup

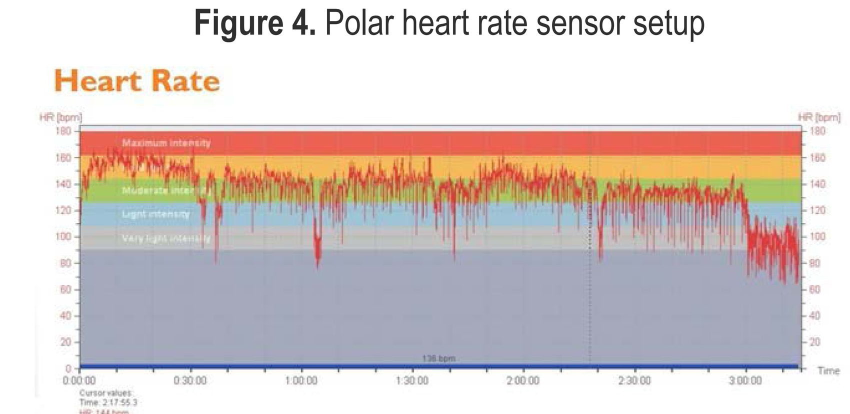

Figure 5. Heart rate sample from Polar sensor

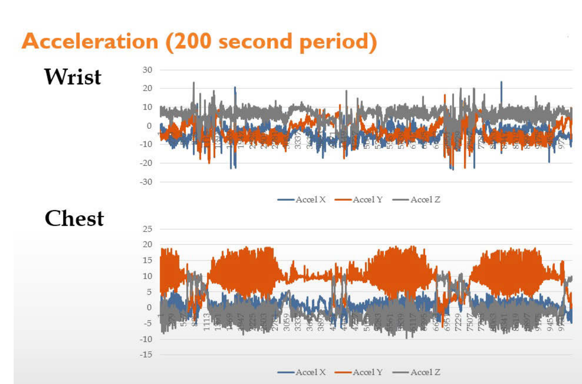

Figure 6. Acceleration sample from Shimmer IMU

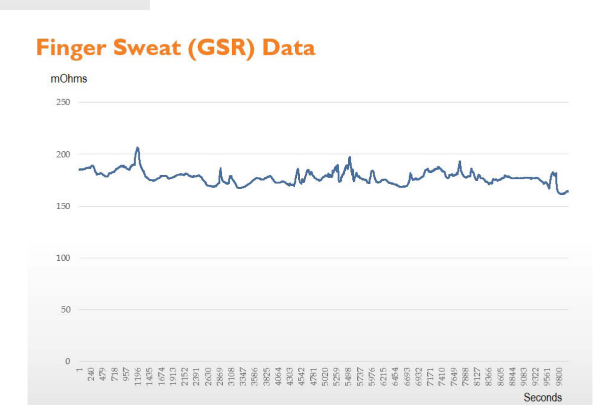

Figure 7. GSR sample from Shimmer sensor

LabVIEW Program

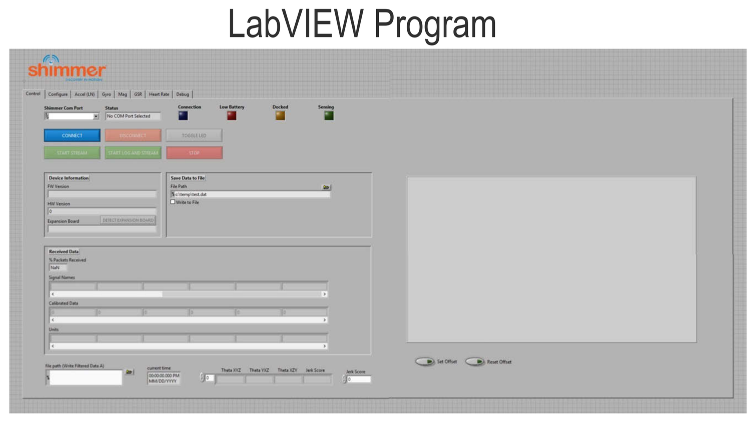

Figure 8. Front Panel of the LabVIEW program

Program:

- Gathers the data from accelerometers in real time and filters them using Kalman filter to get the orientation and jerk
- Shows and plots the real time data for acceleration, GSR, and sensor orientation and saved the data in a file.

Results

- Changing in the value of metrics after getting fatigued
- Location dependency of the sensors to capture more accurate and sensitive metrics
- Distinguishing between the tasks using the data from different sensors

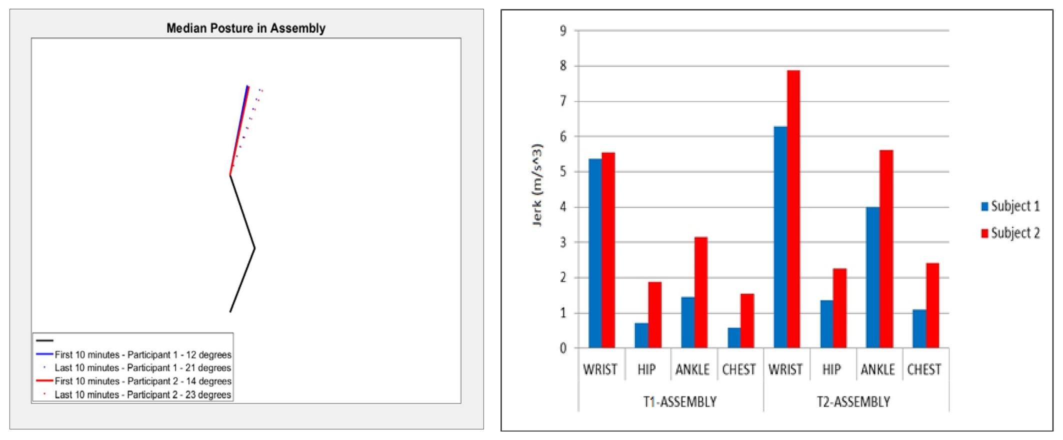

Figure 9. Median Posture and RMS of Jerk in fatigued and non-fatigued states in assembly task

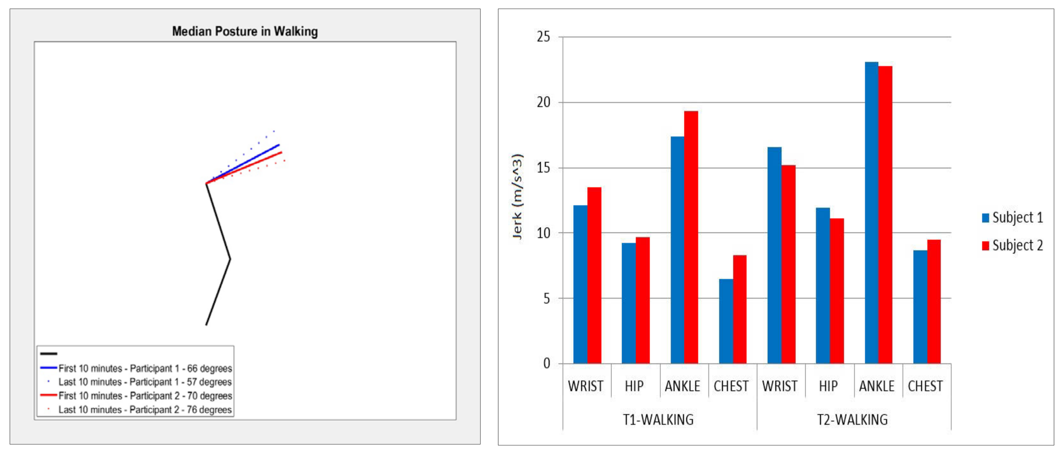

Figure 10. Median Posture and RMS of Jerk in fatigued and non-fatigued states in walking task

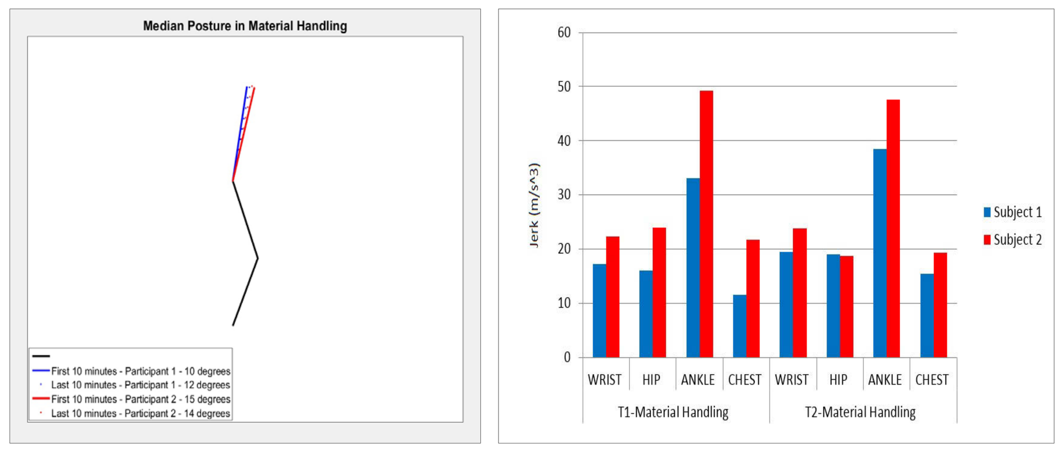

Figure 11. Median Posture and RMS of Jerk in fatigued and non-fatigued states in material handling task

Conclusion and Future Work

- Applying the classification techniques on the time series data to classify the fatigue vs. non- fatigued states
- Collecting more data of the rest of subjects and applying statistical analysis to validate the results
- Including all the collected data (e.g., HR, GSR, PVT, BART) and applying data fusion techniques to come up with a simplified metric

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Acknowledgements

- American Society of Safety Engineers (ASSE) Foundation.