Measuring Fatigue through Heart Rate Variability and Activity Recognition: A Scoping Literature Review of Machine Learning Techniques

Karla Gonzalez[1], Farzan Sasangohar[1], Ranjana K. Mehta[2], Mark Lawley[1], Madhav Erraguntla[1]
[1]Industrial and Systems Engineering, Texas A&M University
[2]Environmental and Occupational Health, Texas A&M University

A scoping literature review was conducted to summarize the current research trends in fatigue identification with applications to human activity recognition through the use of diverse commercially available accelerometers. This paper also provides a brief overview of heart rate variability and its effect on fatigue. The linkage between recognizing an individual's unique physical activities, and its possible feedback to manage fatigue levels were explored. Overall, triangulation of heart rate variability and accelerometer data show promise in identify chronic cognitive and physical fatigue levels.

INTRODUCTION

Millions of American workers suffer from fatigue each year. Fatigue has been linked to more than 328,000 traffic accidents each year, resulting in more than 109,000 injuries and 6,400 deaths (AAA Foundation, 2014). Insomnia, which is one of the contributors of fatigue has been shown to cost the U.S. economy about $63 billion annually in lost productivity, and sleep-deprived workers face lower earnings, loss of cognitive ability, and lower job performance (Kessler et. al, 2011). While job demands cannot always be controlled, an effective approach to managing and preventing fatigue can be created to reduce fatigue's negative impact on safety.

Desmond & Hancock (2001) define fatigue as "a transition state between alertness and somnolence." Soames-Job & Dalziel (2001) define fatigue as "a state of muscles and the central nervous system in which prolonged physical activity or mental processing, in the absence of sufficient rest, leads to insufficient capacity or energy to maintain the original level of activity and/or processing." Three different types of fatigue are discussed in the literature: physical/peripheral, emotional, and cognitive/mental. Physical fatigue can be a consequence of prolonged activation of muscles. Emotional fatigue is also known as chronic fatigue. Moreover, cognitive/mental fatigue relates to the inability to keep mental focus (Tanaka et al., 2009).

Chronic Fatigue Syndrome (CFS) can be either clinically evaluated or unexplained. Other symptoms of CFS are the following: feeling sick after doing physical work, feeling as he/she is never fully-rested even after sleeping a long time, major memory and concentration problems, headaches, muscle, joint, and/or lymph node pain, as well as sore throat (Fakuda et al., 1994). There is currently a discrepancy between patients reporting symptoms of CFS and what physician understand as chronic fatigue because this phenomenon is not explained by medical conditions. Symptoms include suffering of continuous fatigue for at least 6 months, despite efforts to sleep well and to reduce physical activity (Boneva et al., 2007).

While fatigue can disappear after a period of rest, long-term or chronic fatigue cannot be easily fixed. A common way to measure fatigue is by recording an individual's heart activity through an electrocardiogram (ECG) analysis over the length of a day. Computer analysis outlines the person's heartbeats (often described as QRS complex) and derive time domain features that can give an overall sense of the heart's behavior (Task Force of the European Society of Cardiology, 1996).

Non-chronic fatigue is measured explicitly through subjective measurements and implicitly through (psycho)physiological and behavioral tests like electroencephalography (EEG) and Multiple Sleep Latency Test (MLST), respectively (Handbook of Operator Fatigue, 2012). It is important to measure fatigue immediately or in real-time because people may not effectively recognize their level of fatigue as evident by fatigue-related driving incidents. There is a need to obtain this information non-invasively and without work obstruction in order to monitor fatigue causes properly.

In addition to ECG, more recently a combination of heart rate variability (HRV) and accelerometer data for activity classification have been used as proxy measures for fatigue. The goal of this paper is to present a scoping literature review of current research trends in fatigue identification with applications to human activity recognition and heart rate variability. This paper will also explore the link between machine learning's capability of recognizing an individual's unique work activities, and possible feedback to manage a person's fatigue level.

METHODS

A scoping literature review was conducted on articles published from 1985-2016 documenting human activity recognition in relation to fatigue. Focus of this scoping review was on HRV and accelerometer sensors used in human activity recognition studies, the type of data collected, as well as the machine learning methodologies applied to human activity recognition.

Several databases including Google Scholar and Web of Science were searched using a combination of keywords such as *human activity recognition*, *heart rate variability*, *fatigue*, and *accelerometer data,* and *commercially available accelerometers*.

Inclusion criteria used were: a) studies related to accelerometer data analysis, HRV, and fatigue, b) published as a full-text article in a peer-reviewed journal or conference proceedings, c) articles written or translated into English, and d) articles published after January 1985. There were 39 reviewed papers that were not included in the study because despite containing some of the keywords, they had a different focus. Four papers were used strictly for background information on HRV.

RESULTS & DISCUSSION

Heart Rate Variability (HRV)

HRV reflects the buildup of self-regulatory strength in the body when an individual is performing a stressful task that involves high levels of mental load such as planning how to escape an emergency situation. Segerstrom & Nes (2007) suggest that people can overcome self-regulatory fatigue and thus high motivation depending on time factors could prevent self-regulatory failure. Parasympathetically mediated inhibitory system has shown to be associated with self-regulation (Segerstrom & Nes, 2007). Unlike surviving dangerous and physically demanding situations that involve fight or flight reactions, self-regulation is cognitively demanding. This mechanism halts future negative actions which results in usage of the vagal nerve's decision to cut physical energy depletion to focus body energy for the brain's use so it can perform mental tasks better (Fairclough & Houston, 2004; Porges, 2001). In addition, Fairclough & Houston (2004) showed that a prolonged Stroop task, which is a cognitively challenging task, increased HRV over the length of the experiment.

The following time domain HRV parameters are often used when analyzing central nervous system behavior using ECG heart rate activity data:

SDNN. the standard deviation of the normal to normal R-R interval which is the cycle length of heart beats monitored for 24 hours.

SDANN. the standard deviation of the average normal to normal R-R intervals of 5 minute chunks of ECG data.

SDN index. the average of the 5 minute standard deviations of the normal to normal R-R intervals. This allows to measure the inconsistency due to heartbeat cycles that last less than 5 minutes.

RMSSD. the square root of the mean squared differences of consecutive normal to normal R-R intervals.

NN50. the number of consecutive normal to normal R-R intervals that are more than 50 milliseconds (ms) apart from each other.

pNN50. the ratio derived by dividing NN50 by the total number of all normal to normal R-R intervals.

In addition, according to Boneva et al. (2007), the following frequency domain HRV parameters are often used when analyzing central nervous system data:

Low frequency power ($LF[ms^2]$). Usually ranging from .04-.15 Hertz (Hz).

Very low frequency power ($VLF[ms^2]$). lower than or equal to .004 Hz.

Total power ($TP[ms^2]$). the variance of the normal to normal interval over the analysis time.

High frequency power ($HF[ms^2]$). Ranging from .15 Hz-.4 Hz.

LF/HF Ratio. HRV has been accepted widely as a consistent and reliable measure of mental workload. Mean heart rate has proven to be a decent measure of physical workload and stress (Wickens, Gordon, & Liu, 2004). Segerstrom & Nes (2007) shows that HF level (vagal nerve activity) decreases during mental tasks that make people tired which amounts to an increase in LF/HF ratio.

Boneva et al. (2007) showed that when a person with CFS is sleeping, heart rate (HR) increases, but HRV's LF, VLF, and TP values actually decrease. While it is known that medications such as antidepressants, among others, can alter HRV, there has been no correlation found between medication intake and having a higher HR or lower HRV. Furthermore, these characteristics do not completely explain why sufferers of CFS are forced to reduce activity levels. In addition, increased HR in CFS subjects was shown to be correlated with standardized and validated measures for fatigue as an impairment (Boneva et al., 2007).

HRV is affected by the type of activity. Next, we provide a review of accelerometer sensors and activity classification methods enabled by accelerometer data.

Accelerometer Sensors

Through the review, 43 commercial accelerometers, 8 lab-made accelerometers, and 4 mobile phone accelerometer applications were studied. It is important to note that some studies used or reviewed more than one accelerometer. For example, Plasqui & Westerterp (2007) compared eight unique accelerometers and a pedometer. From the reviewed sensors, 5 were uniaxial, 7 biaxial, 20 triaxial, and 1 quadriaxial accelerometers. All the mobile phone applications had an M7 motion coprocessor. All the lab-made accelerometers were triaxial. There was no particular trend on where to place the sensors to identify walking intensity and 1-4 axis were used successfully for this classification. The information collected included: accelerometer name, axis complexity, body placement, types of activities used to interpret, accelerometer range, sampling frequency (in Hertz), weight (grams), and data presentation (real time or retrospective). The literature review intended to identify how currently commercially available accelerometers have been used to identify different types of activities. It was found that some of the publications often combine parts of different sensors to fit their customized design (e.g., in Prasad and Sarma (2007), a GPS named "T2" and a triaxial accelerometer from Athletic Data Innovations). Other times, such as in Karantonis et al. (2006), biaxial accelerometers were mounted orthogonally to each other to provide a triaxial perspective.

The most common activity studied (37 sensors) using accelerometers was the intensity of walking and step counting. Studies used a combination of uniaxial, biaxial, and triaxial accelerometers placed on the hip, waist, lower back, chest, wrist, pant pockets, and arm. Intrusiveness, wearability, and comfort were discussed as the main variables used in the selection and adoption of different accelerometers in various studies. Only Akintola et al. (2016) had the integration of HRV and accelerometer data comparison but it was to compare the performance of Equivital EQ02 Lifemonitor with Holter.

Activity Classification

The review focused on different physical activities studied and classified by the researchers, as well as methodologies used for activity classification.

Physical activity classifications. Figure 1 illustrates the Human Activity Groups identified in this review. Studies included Khan et al. (2010) and Dernbach et al. (2012). The most popular category was "walking." It included *regular walking, slow walking, fast walking, jogging, running, standing still, climbing upstairs,* and *going downstairs*. The "falling" category group included *active fall* (a person that was running trips and falls), *inactive fall* (*standing still* and *falling down*), *falling from chair*, and *unspecified falling* (1 article). The "exercise" category included *sit-ups, jumping, biking/cycling,* and *dancing.* The "resting" category included *sitting down*, *lying down* (as in a supine position), and *resting* (unspecified manner). "House chores" included *vacuuming, cleaning, cooking, sweeping, watering plants,* and *scrubbing.* "Personal care" category included brushing *teeth, taking medication,* and *washing hands.*

Transition categories include going from *lying/standing*, *standing/lying down*, *lying down/sitting*, *sitting down/lying down*, *sitting down/standing up*, *standing up/sitting down*, *walking/standing*, *standing/walking*, and *circuit* (*sitting/walking/lying down/standing/walking/sitting*). Other activities included *driving, working on a computer/typing, riding an elevator up/down, gesticulating,* and *talking with a person.*

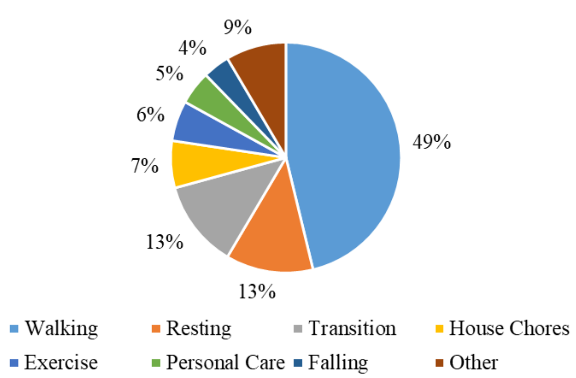

Figure 1. Frequency of human activity groups studied

Accelerometer features/statistics used. While sensors were used on different parts of the body in various studies such as wrist, waist, chest, or ankle, common features were usually used. The most popular features were mean, standard deviation, and correlation of each of the 3-axis which were used in 7 studies each. Broadly stated, descriptive statistics through time domain features are popular and show promise to predict human activities through accelerometer readings.

Table 1 lists the frequency of the data features used by the reviewed articles. Simple features, such as average and standard deviation of axis data, were heavily used. Angle features that calculated the difference in angle movements between the X, Y, and Z axes were also common. Energy features calculate the amount of energy consumed in each axis. Thresholds features included use of specific acceleration cut-offs for each intensity category that helped distinguish between low, medium, and high intensity activities.

Table 1. Accelerometer features/statistics used in the literature

Data Features	Frequency
Simple	35
Angle	12
Energy	7
Fast Fourier Transform (FFT)	3
Thresholds	3
Root Mean Square (RMS)	2
Average Peak of Frequency (APF)	2
Other	13

Methods used to analyze accelerometer data. The study with the most varied techniques was Ravi et al. (2005) with 5 methods using the Weka Toolkit (Decision Tables, Decision Trees [C4.5], K-Nearest Neighbor [KNN], Support Vector Machine [SVM], and Naïve Bayes) as well as Boosting, Plurality Voting, Bagging, Stacking with Ordinary Decision Trees (ODTs), and Stacking with Meta Decision Trees (MDTs). In their study, Ravi et al. (2005) collected data from a triaxial accelerometer around participant's waist with ± 4 g and at 50 Hz sampling frequency. Moreover, the study used all of these human activity recognition methods by only calculating mean and standard deviation of X, Y, and Z axis values, energy expenditure in each axis, as well as the correlation between the 3 axes. This is important because it reiterates the strength of descriptive statistics and the body's energy expenditure link to human activity intensity since they allowed to distinguish between low intensity activities (*walking*, *standing still* and *brushing teeth*), medium intensity (*vacuuming* and *walking*), and high intensity (*running*, *sit-ups*, and *going up/down stairs*).

Mannini & Sabatini (2010) also used 10 techniques through three main approaches: probabilistic approach (Naïve Bayes, Gaussian Mixture Model [GMM], Logistic Regression, and Parzen Classifier), geometric approach (SVM, Nearest Mean, KNN, and Artificial-Neural Networks [ANN]), and C4.5. The most frequently used methodologies were Multilayer Perceptron/Artificial-Neural Networks (same as ANN) and Weka Toolkit adopted in five studies. The data collection using Weka Toolkit was done through five biaxial sensors placed in the ankle, leg, wrist, waist, and upper arm.

He & Jin (2008) used a triaxial accelerometer placed inside pant pocket with 100 Hz frequency and range of ± 3 g. The study proposed an autogressive (AR) model that identified four activities in three different levels of intensity: low-intensity (*standing still*), medium-intensity (*walking*) and high-intensity (*jumping* and *running*) through SVM with over 92% accuracy.

These results are more accurate than simply using FFT features and descriptive statistics through time domain features.

Multilayer Perceptron yielded over 93% accuracy for simple activity classifications and 50% accuracy for complex activities. In particular, simple activities retained their high classification accuracy even when paired with complex activities (Dernbach et al., 2012).

Yang, Wang, & Chen (2008) used a triaxial wrist accelerometer to classify the following activities: *standing still*, *walking*, *running*, *vacuuming*, *brushing teeth*, *sitting down*, *scrubbing*, and *working on computer*. It had the best average accuracy (95%) when using three hidden layers in the pre-classifier, five in the static classifier, and seven in the dynamic classifier. In this study, higher recognition rate was observed for Multilayer Perceptron than KNN.

Lester, Choudhury, & Borriello (2006) applied lab-made sensors into a variation of sensor locations (shoulder, waist, dominant wrist). For all three sensors combined (all sensors, shoulder, waist, and wrist combinations), Hidden Markov Model lassifier was observed to have higher accuracy than static classifier.

Bayat, Pomplun, & Tran (2014) used two locations (in-hand and in-pocket) for the 100 Hz android triaxial accelerometer. This study showed that in-hand sensor location is better suited than in-pocket when using Multilayer Perceptron, SVM, Random Forest, Logistic Model Tree (LMT), Simple Logistic Regression, and Logit Boost.

Khan et al. (2010) were able to classify several activities using with ANN, AR, Linear Discriminant Analysis (LDA), Single-Level Human Activity Recognition Algorithm (SLHARA), and a Hierarchical Human Activity Recognition Algorithm (HHARA). It was found that the best strategy to transition movements was HHARA with around 98% accuracy. It was also very good at differentiating between low-intensity activities like *lying down*, *sitting down*, and *standing still*. This is important because it has been shown that even though it is difficult to perform, HHARA can be a great way to distinguish between all types of activities without using any other machine learning techniques. Khan et al. (2010) had an inadequate amount of training data, yet it reported around 98% correct activity classification through its hierarchical recognition scheme. This suggests that their newly proposed model can obtain high activity recognition accuracy without a large amount of training data.

Győrbíró, Fábián, & Hományi (2008) placed the triaxial accelerometer with 50 Hz frequency in the dominant wrist, ankles, and hip. Using ANN and C4.5, the team accomplished around 80% correct activity recognition for three different intensity levels: low-intensity (slow cycling), medium-intensity (*walking* and *slow-fast-slow cycling intervals*) and high-intensity (*running* and *fast cycling*). This is significant because it shows that the use of multiple sensors can compensate for the inherent error collected in the accelerometer data for doing an activity in different intensities. So, multiple sensors can be used to more accurately distinguish between walking fast or slow, where distinguishing between these two walking intensities may be difficult when using only one accelerometer (usually around the chest or around the pelvic area).

Casale, Pujol, & Radeva (2011) used Decision Trees, Bagging, Boosting, and Random Forest to distinguish between *walking*, *standing still*, *climbing stairs*, *working on a computer*, and *talking*. Despite using a lab-made triaxial accelerometer placed on the chest area, the most useful strategy to discriminate between these different activities was Random Forest resulting in 94% overall classification accuracy.

Karantonis et al. (2006) placed two 100 Hz biaxial sensors orthogonally to create a triaxial spectrum sensor around the waist and achieved 83% accuracy for walking and 96% for falling detection through the use of normal signal magnitude area threshold classification.

CONCLUSION

While methods such as HRV analysis show promise in detecting both cognitive and physical fatigue, identifying different physical activities seem necessary to improve the accuracy and robustness of this detection. Such robustness is necessary particularly in diagnosing chronic fatigue since current methods do not use pathophysiology of central nervous system and no definitive treatment has been offered for chronic fatigue (Tanaka et al., 2009).

The review of wide range of accelerometer sensor positioning, activities identified using accelerators and methods used show promise in the efficacy of these methods for fatigue detection and prevention. However, it is important to note that while good activity recognition from waist, hip, or foot location can be achieved, the best placement to check HR data is either the wrist or the chest area due to the close proximity to key blood vessels to check the pulse.

The review had several limitations. Due to the proprietary nature of the commercially available activity algorithms, one cannot readily compare them side by side to see which one is superior. In addition, an exhaustive review of available activity tracking tools is beyond the scope of this review.

Future efforts may benefit from focusing on the development of quantifiable fatigue risk assessment models based on ECG and accelerometer data collected in real-time using wearable non-invasive sensors such as smartwatches. These data features will be analyzed using C4.5, Multilayer Perceptron, and HHARA schemes given their accuracy levels for studies with large number of activity classifications. The final outcome could be a smartwatch application that can advise individuals to take job breaks or go to sleep before the person gets too fatigued. This will allow the comparison of HRV and accelerometer data to understand how different activities affect fatigue. Eventually, this could lead to quantifiable breaks for mental work just like there are for physical work in the manufacturing setting. Developing a quantifiable fatigue risk assessment model can also help individuals with resistance against poor behaviors (e.g., alcohol or tobacco consumption). As mentioned before, this is due to the link between fatigue people having less motivation to maintain their goals. In addition, an understanding of common human activity recognition models can aid in the understanding of machine learning and data analysis techniques for stress management.

REFERENCES

2014 Traffic Safety Culture Index - AAA Foundation. (2014). Retrieved November 15, 2016, from https://www.aaafoundation.org/sites/default/files/2014TSCIreport.pdf Retrieved October 15, 2016, from https://www.ncbi.nlm.nih.gov/pubmed/21886353

Akintola, A. A., Pol, V. V., Bimmel, D., Maan, A. C., & Heemst, D. V. (2016). Comparative Analysis of the Equivital EQ02 Lifemonitor with Holter Ambulatory ECG Device for Continuous Measurement of ECG, Heart Rate, and Heart Rate Variability: A Validation Study for Precision and Accuracy. *Frontiers in Physiology, 7*. doi:10.3389/fphys.2016.00391

Balto, J. M., Kinnett-Hopkins, D. L., & Motl, R. W. (2016). Accuracy and precision of smartphone applications and commercially available motion sensors in multiple sclerosis. *Multiple Sclerosis Journal – Experimental, Translational and Clinical, 2*, 205521731663475. doi:10.1177/2055217316634754

Bayat, A., Pomplun, M., & Tran, D. A. (2014). A study on human activity recognition using accelerometer data from Smartphones. *Procedia Computer Science*, *34*, 450–457. doi:10.1016/j.procs.2014.07.009

Boneva, R. S., Decker, M. J., Maloney, E. M., Lin, J.M., Jones, J. F., Helgason, H. G., Reeves, W. C. (2007). Higher heart rate and reduced heart rate variability persist during sleep in chronic fatigue syndrome: A population-based study. *Autonomic Neuroscience*, *137*(1-2), 94–101. doi:10.1016/j.autneu.2007.08.002

Casale, P., Pujol, O., & Radeva, P. (2011). Human Activity Recognition from Accelerometer Data Using a Wearable Device. *Pattern Recognition and Image Analysis Lecture Notes in Computer Science,* 289-296. doi:10.1007/978-3-642-21257-4_36

Choi, S., & Yi, G. (2016). Energy Consumption and Efficiency Issues in Human Activity Monitoring System. *Wireless Personal Communications, 91*(4), 1799-1815. doi:10.1007/s11277-016-3321-x

Dernbach, S., Das, B., Krishnan, N. C., Thomas, B. L., & Cook, D. J. (2012). Simple and complex activity recognition through smart phones. *2012 Eighth International Conference on Intelligent Environments*. doi:10.1109/ie.2012.39

Düking, P., Hotho, A., Holmberg, H.-C., Fuss, F. K., & Sperlich, B. (2016). Comparison of Non-Invasive Individual Monitoring of the Training and Health of Athletes with Commercially Available Wearable Technologies. *Frontiers in Physiology, 7*. doi:10.3389/fphys.2016.00071

Fairclough, S. H., & Houston, K. (2004). A metabolic measure of mental effort. *Biological Psychology, 66*(2), 177-190. doi:10.1016/j.biopsycho.2003.10.001

Fukuda, K., Straus, S. E., Hickie, I., Sharpe, M. C., Dobbins, J. G., &Komaroff, A. (1994). The Chronic Fatigue Syndrome: A Comprehensive Approach to Its Definition and Study. *Annals of Internal Medicine, 121*(12), 953-959. doi:10.7326/0003-4819-121-12-199412150-00009

Győrbíró, N., Fábián, Á., & Hományi, G. (2008). An activity recognition system for mobile phones. *Mobile Networks and Applications*, *14*(1), 82–91. doi:10.1007/s11036-008-0112-y

Handbook of Operator Fatigue. (2012). Farnham, GB: Ashgate. Retrieved from http://www.ebrary.com

He, Z.-Y., & Jin, L.-W. (2008). Activity Recognition from acceleration data using AR model representation and SVM. *Proceedings of the Seventh International Conference on Machine Learning and Cybernetics.*

Hollewand, A. M., Spijkerman, A. G., Bilo, H. J., Kleefstra, N., Kamsma, Y., & Hateren, K. J. (2016). Validity of an Accelerometer-Based Activity Monitor System for Measuring Physical Activity in Frail Older Adults. *Journal of Aging and Physical Activity, 24*(4), 555-558. doi:10.1123/japa.2014-0290

Karantonis, D. M., Narayanan, M. R., Mathie, M., Lovell, N. H., & Celler, B. G. (2006). Implementation of a real-time human movement Classifier using a Triaxial accelerometer for ambulatory monitoring. *IEEE Transactions on Information Technology in Biomedicine*, *10*(1), 156–167. doi:10.1109/titb.2005.856864

Khan, A. M., Lee, Y.-K., Lee, S. Y., & Kim, T.-S. (2010). A Triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical Recognizer. *IEEE Transactions on Information Technology in Biomedicine*, *14*(5), 1166–1172. doi:10.1109/titb.2010.2051955

Kwapisz, J. R., Weiss, G. M., & Moore, S. A. (2011). Activity recognition using cell phone accelerometers. *ACM SIGKDD Explorations Newsletter*, *12*(2), 74. doi:10.1145/1964897.1964918

Lester, J., Choudhury, T., & Borriello, G. (2006). A Practical Approach to Recognizing Physical Activities. *Lecture Notes in Computer Science Pervasive Computing,* 1-16. doi:10.1007/11748625_1

Liu, Y., Zhu, S. H., Wang, G. H., Ye, F., & Li, P. Z. (2013). Validity and Reliability of Multiparameter Physiological Measurements Recorded by the Equivital Lifemonitor During Activities of Various Intensities. *Journal of Occupational and Environmental Hygiene, 10*(2), 78-85. doi:10.1080/15459624.2012.747404

Mannini, A., & Sabatini, A. M. (2010). Machine learning methods for classifying human physical activity from on-body accelerometers. *Sensors*, *10*(2), 1154–1175. doi:10.3390/s100201154

Paul, S. S., Tiedemann, A., Hassett, L. M., Ramsay, E., Kirkham, C., Chagpar, S., & Sherrington, C. (2015). Validity of the Fitbit activity tracker for measuring steps in community-dwelling older adults. *BMJ Open Sport & Exercise Medicine, 1*(1). doi:10.1136/bmjsem-2015-000013

Plasqui, G., & Westerterp, K. R. (2007). Physical Activity Assessment with Accelerometers: An Evaluation Against Doubly Labeled Water**. Obesity, *15*(10), 2371-2379. doi:10.1038/oby.2007.281

Porges, S. W. (2001). The polyvagal theory: Phylogenetic substrates of a social nervous system. *International Journal of Psychophysiology, 42*(2), 123-146. doi:10.1016/s0167-8760(01)00162-3

Prasad, N., & Sarma, A. D. (2007). Preliminary analysis of grid ionospheric vertical error for GAGAN. *GPS Solutions, 11*(4), 281-288. doi:10.1007/s10291-007-0068-6

Ravi, N., Dandekar, N., Mysore, P., & Littman, M. L. (2005). Activity Recognition from Accelerometer Data. *American Association for Artificial Intelligence.* 1541-1546.

Kessler, R.C., Berglund, P.A., Coulouvrat, C., Hajak, G., Roth, T., Shahly, V., Shillington A.C., Stephenson. J.J. & Walsh, J. K. (2011). Insomnia and the Performance of US Workers: Results from the America Insomnia Survey. *Sleep, 34*(9), 1161-1171. doi:10.5665/sleep.1230

Sandroff, B. M., Motl, R. W., Pilutti, L. A., Learmonth, Y. C., Ensari, I., Dlugonski, D., Klaren, R.E., Balantrapu, S., & Riskin, B. J. (2014). Accuracy of StepWatch™ and ActiGraph Accelerometers for Measuring Steps Taken among Persons with Multiple Sclerosis. *PLoS ONE, 9*(4). doi:10.1371/journal.pone.0093511

Segerstrom, S. C., & Nes, L. S. (2007). Heart rate variability reflects self-regulatory strength, effort, and fatigue. *Psychological Science*, *18*(3), 275–281. doi:10.1111/j.1467-9280.2007.01888.x

Tanaka, M., Mizuno, K., Tajima, S., Sasabe, T., & Watanabe, Y. (2009). Central nervous system fatigue alters autonomic nerve activity. *Life Sciences*, *84*(7-8), 235–239. doi:10.1016/j.lfs.2008.12.004

Task Force of the European Society of Cardiology (1996). Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. Circulation, 93(5), 1043–1065. doi:10.1161/01.cir.93.5.1043

Trost, S. G., Mciver, K. L., & Pate, R. R. (2005). Conducting Accelerometer-Based Activity Assessments in Field-Based Research. *Medicine & Science in Sports & Exercise, 37*(Supplement). doi:10.1249/01.mss.0000185657.86065.98

Vanroy, C., Vissers, D., Cras, P., Beyne, S., Feys, H., Vanlandewijck, Y., & Truijen, S. (2013). Physical activity monitoring in stroke: SenseWear Pro2 Activity accelerometer versus Yamax Digi-Walker SW-200 Pedometer. *Disability and Rehabilitation, 36*(20), 1695-1703. doi:10.3109/09638288.2013.859307

Wetten, A. A., Batterham, M., Tan, S. Y., & Tapsell, L. (2014). Relative Validity of 3 Accelerometer Models for Estimating Energy Expenditure during Light Activity. *Journal of Physical Activity and Health, 11*(3), 638-647. doi:10.1123/jpah.2011-0167

Wickens, C. D., Gordon, S. E., & Liu, Y. (2004). *An Introduction to Human Factors Engineering*. Upper Saddle River, NJ: Pearson Prentice Hall.

Yang, J.-Y., Wang, J.-S., & Chen, Y.-P. (2008). Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers. *Pattern Recognition Letters*, *29*(16), 2213–2220. doi:10.1016/j.patrec.2008.08.002