

A short review on physiological monitoring during working activities

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Abstract

Introduction: Temperature extremes, load carriage, inadequate sleep, information overload, dehydration, and impaired nutrition, are common risks associated with many occupational activities, including those for whom optimal functioning is critical at all times. These safety-sensitive occupations include firefighters, first responders, police officers, physicians, airline pilots, soldiers, and those operating heavy machinery. In any of these cases, the resulting interaction between occupational stress and individual susceptibility to illness demands careful management. This represents a dual challenge to organizations responsible for the well-being of personnel who engage in strenuous tasks, imposing requirements to be vigilant for or, even, curtail situations that result in high physiological strain. The emergence of wearable physiological monitoring technologies could prove advantageous in this regard. Purpose: To our knowledge, no review gathering the applicability of these systems within occupational groups has been conducted. Therefore, this review aims to summarize current progress in the development of wearable physiological monitoring systems for occupational applications. Methodology: Five databases were accessed (SCOPUS, PubMed, Science Direct, Academic Search Complete and Web of Science) and a total of 12 keywords were combined to develop a search on journal articles from January 2014 to January 2019. Study eligibility based on active workers participants and assessment methods not interfering with normal tasks development and involving harmless procedures. Furthermore, investigations conducted with prognostic health-related goals were filtered. Results and Discussion: Nineteen studies were analyzed in this review. In general, their goals were directed to quantifying the impact of specific physically demanding tasks or validating newly proposed methods for classifying the effects of different levels and workloads of occupational tasks based on workers' physiology. Identified occupational groups mostly included construction workers, drivers, and firefighters. Retrieved papers highlighted the importance of field monitoring to provide a chance to timely detect any abnormal condition in the worker's physiology that might be affected by working conditions or environmental stresses. Conclusions: Wearable sensors proved to be a valid tool for assessing physiological status in simulated and real working environments. Future research perspectives should be focused on validation of standardized procedures within bigger samples and involving a variety of safety-sensitive professions. Finally, based on physiology and novel computational techniques, it was observed that further developments should be concentrated in the algorithms that allow low-cost sensors to be used in operational settings to provide the continuous subjects' status promoting to sustain their given tasks in a safer and healthier way.

Keywords: Physiological monitoring, Occupational health, Review.

INTRODUCTION

Athletes must compete with very high metabolic demands in outdoor temperature extremes. Miners and steelworkers are exposed to high heat conditions (Butlewski, Dahlke, Drzewiecka, & Pacholski, 2015; Chen, Chen, Yeh, Huang, & Mao, 2003). Firefighters, first responders, and soldiers often wear personal protective equipment that imposes additional thermal burdens from insulation and extra carried weight (Buller, Welles, & Friedl, 2018) while exposed to extreme environments, inadequate sleep, information overload, dehydration and even impaired nutritional status (Lieberman et al., 2005). As a result, decrements in workplace performance, health, and safety are typically encountered. This represents a dual challenge to organizations responsible for the well-being of personnel who engage in strenuous tasks, imposing requirements to be vigilant for, or even curtail, situations that may result in high physiological strain in healthy personnel and also to identify and protect vulnerable individuals. The emergence and increasing interest in wearable physiological monitoring devices can help to address this challenge but requires that the right questions are asked in sourcing, developing, validating and applying such technologies (Stacey, Hill, & Woods, 2018). Wearable physiological monitoring can provide predictions about an individual's health and performance from their real-time physiological state (Raskovic, Martin, & Jovanov, 2004). However, available systems



27 - 28 JUNE 2019 FEUP PORTO - PORTUGAL

mostly do not satisfy the requirements for occupational use. Even when they offer more than raw physiological data, computed information is usually based on proprietary algorithms that cannot be properly reviewed and validated. The critical component of a real-time physiological monitoring system is the algorithm that turns data into useful and actionable knowledge for a worker or a small unit leader. Useful information from these systems is defined as vitally important alerts that can be acted on to affect the outcome of operations and improve safety and effectiveness (Friedl, 2018). To our knowledge, no comprehensive search of the literature has been developed in this regard. Thus, a review is proposed to find relevant information about the current progress of these physiological monitoring systems and their potential applications for occupational settings.

METHODOLOGY

This review was limited to research articles and articles in press published in peer-reviewed journals in the English language. It was conducted in Scopus, PubMed, Science Direct, Academic Search Complete and Web of Science databases and narrowed to articles published between January 2014 and January 2019. The 12 identified keywords were combined as follows:

((("physiolog*monitor*") OR ("noninvasive monitor*") OR ("medical monitor*") OR ("wearable sens*")) AND ((assessment) OR (occupational) OR (model) OR (fatigue) OR (algorithm) OR (worker) OR (training) OR ("physical exertion")))

The search focused on investigations developed within working-age active participants and incorporated both females and males with no additional restrictions. Study selection was based on three phases of exclusion: applying filters from databases, eliminating repeated records and analyzing each article individually to remove studies in which no prognostic health objectives were pursued, procedures were not developed within active working-age subjects, or no noninvasive methods were used. Finally, inclusion criteria were those investigations in which noninvasive objective physiological assessment methods were applied, and measurements were developed during real or simulated working activities.

RESULTS

Nineteen studies were selected for this review. Their primary characteristics are summarized in Table 1. In total, they included 406 participants. From them, 17 out of the 19 (two using the same sample (Pancardo, Acosta, Hernandez-Nolasco, Wister, & Lopez-de-Ipina, 2015; Pancardo, Hernández-Nolasco, & Acosta-Escalante, 2018)) indicated gender distributions, denoting 12.86% of women and 87.14% of men participants. All subjects were part of the healthy active working population. Mean age values ranged from 22.7 to 43.8 years old. All used comparisons with previous or basal levels of the same subjects. No control group was observed. Occupational groups were diverse: four studies were developed within construction workers (Antwi-Afari, Li, Seo, & Wong, 2018; Aryal, Ghahramani, & Becerik-Gerber, 2017; Hwang, Seo, Jebelli, & Lee, 2016; Lee, Lin, Seto, & Migliaccio, 2017), three involved drivers (Boon-Giin, Boon-Leng, & Wan-Young, 2014; Choi, Koo, Seo, & Kim, 2018; Fu, Wang, & Zhao, 2016), two included firefighting personnel (Davis & Gallagher, 2014; Sol, Ruby, Gaskill, Dumke, & Domitrovich, 2018) and, office workers (Boerema, Essink, Toenis, van Velsen, & Hermens, 2016), pilots (Hidalgo-Munoz et al., 2018), custodial staff (Pancardo et al., 2015; Pancardo et al., 2018), operators from drillship (Mehta et al., 2017), ironworkers (K. Yang, Ahn, Vuran, & Aria, 2016), manufacturing workers (Baghdadi, Megahed, Esfahani, & Cavuoto, 2018) and law enforcement personnel (Yokota, Karis, & Tharion, 2014) were observed in one paper each. Two investigations, in which a specific



profession was not defined were also evidenced: one reported a sample of cold-exposed workers (Austad, Wiggen, Færevik, & Seeberg, 2018) and the other examined a multidisciplinary group of postal, construction and office workers and drivers (L. Yang et al., 2018). Lastly, observing the context in which assessments were carried out, most of them (10 studies) considered real working scenarios (Davis & Gallagher, 2014; Fu et al., 2016; Hwang et al., 2016; Lee et al., 2017; Mehta et al., 2017; Pancardo et al., 2015; Pancardo et al., 2018; Sol et al., 2018; L. Yang et al., 2018; Yokota et al., 2014) while 7 were developed through laboratory trials (Antwi-Afari et al., 2018; Aryal et al., 2017; Austad et al., 2018; Baghdadi et al., 2018; Boon-Giin et al., 2014; Choi et al., 2018; Hidalgo-Munoz et al., 2018). Only two performed measurements contrasting real and experimental contexts (Boerema et al., 2016; L. Yang et al., 2018).

Author (year)	Approach	Sample	Assessed parameters	Wearable sensors	Data processing and analysis
(Antwi-Afari et al., 2018)	A novel methodology to classify loss-of- balance events.	10 construction workers	Foot plantar pressure distribution.	Moticon SCIENCE (Moticon GmbH, Munich, Germany)	Supervised machine learning algorithms to learn the unique foot plantar pressure patterns.
(Aryal et al., 2017)	A novel approach for real-time monitoring.	12 construction workers	HR, Tsk, RPE.	Heart rate monitor, EEG sensor and a construction safety helmet fitted with 4 infrared temperature sensors.	Several supervised machine learning algorithms tested to explore the applicability of the monitored variables for fatigue predictions.
(Austad et al., 2018)	Cold stress assessment.	11 cold exposed workers	HR, T, Tsk, VO ₂ , T, RH, activity.	Smart jacket with integrated sensors (Tsk, movement, temperature, humidity), custom- made sensor belt (HR, Tsk, air humidity and temperature on the chest/back). Indirect calorimetry (Oxycon Pro, Jaeger, Hoechberg, Germany)	Descriptive statistics at group and individual levels.
(Baghdadi et al., 2018)	Method to classify non-fatigued vs. fatigued states	20 manufacture workers	ACC.	IMU Shimmer3 (Shimmer, Dublin, Ireland)	Matlab R2015b. Simple machine learning algorithm.
(Boerema et al., 2016)	Sedentary behavior profile.	27 office workers	Activity.	Promove 3D activity sensor	Statistical analysis of variances (ANOVA)
(Boon-Giin et al., 2014)	Method to classify driving mental fatigue.	20 drivers	EEG, respiration signals.	EEG sensor, respiration sensor, microprocessor, Bluetooth module, Google Nexus 5	Support vector machine classifier
(Choi et al., 2018)	Proposal of wearable device-based system.	28 drivers	Photoplethysmogram, galvanic skin response, rate of rotation, T, ACC.	New device parts: for PPG (SFH7050 OSRAM, AFE4404 Texas Instruments) accel and gyro (MPU-6050 InvenSense), temperature (HDC1008 Texas Instruments), MCU (MSP430G2553 Texas Instruments).	A support vector machine-based classification method.
(Davis & Gallagher, 2014)	Quantify physiological demands.	25 firefighter trainees	HR, air consumption, body part discomfort.	Garmin Forerunner 110 monitors (Garmin International, Olathe, KS)	Descriptive statistics.
(Fu et al., 2016)	Dynamic fatigue detection model.	12 professional long-distance bus drivers	EEG, electromyogram and respiration signals.	Biofeedback 2000 x- pert system	A dynamic fatigue detection model based

Table 1. Studies characteristics



27 - 28 JUNE 2019	
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Author (year)	Approach	Sample	Assessed parameters	Wearable sensors	Data processing and analysis
					on Hidden Markov Model (HMM).
(Hidalgo-Munoz et al., 2018)	Determine cardiovascular, emotional and cognitive correlations.	20 private pilots	HR, HRV.	BrainVision Recorder 1,21 (Brain Products GmbH, Gilching, Germany)	Matlab 2016a, statistical analysis on STATISTICA version 12.
(Hwang et al., 2016)	Accuracy of photoplethysmogram sensor.	11 construction workers (drywall, masonry, electrical operations).	HR	photoplethysmography (PPG) sensor embedded in a wristband-type activity tracker	Two methods for data synchronization: manual comparison with two smartphone applications (i.e., Polar Beat and Wahoo Fitness) and phase- shifting algorithms (Hampel filter)
(Lee et al., 2017)	Reliability of wearable sensors.	6 roofers.	HR, HRV, ACC, EE, metabolic equivalents, sleep quality.	Zephyr BioharnessTM 3 sensors (Medtrionic, Dublin, Ireland). ActiGraph GT9X unit (ActiGraph, LLC, Pensacola, Florida)	Algorithms from ActiLife (version 6.13.1). Analysis of variance ANOVA.
(Mehta et al., 2017)	Comparison of objective and subjective fatigue assessment methods.	10 operators from drillship.	HR, ACC.	EQ02 LifeMonitor, Equivital™, Cambridge, UK.	Separate mixed effects analyses of variance (ANOVA), Pearson's correlations.
(Pancardo et al., 2015)	Design and development of real- time personalized monitoring for objective estimation of Occupational Heat Stress	20 cleaning staff	Movements, HR, T, humidity.	Samsung Galaxy S4 (Android 4.2.2 Jelly Bean Operation System, octa-core chipset, 1.6-GHz Quad + 1.2 GHz Quad CPU) Smartphones containing an accelerometer, STMicroelectronics LSM 330, and a Sensirion SHTC1 humidity and temperature sensor. Gene Activ accelerometer wristband: ZephyrWireless Bluetooth Heart Rate Monitor for Android and Windows Phone 8, an Omron Sphygmomanometer Model HEM-742INT, a Basis B1 Fitness Wristband and a Multifunction Digital Thermometer OBI 292312.	An application to estimate VAM, physical effort, and the workload was developed with the Java 6.0 language using the ADT tool v22.3.0- 887826. To analyze the values obtained from the accelerometer MATLAB Version R2014a was used.
(Pancardo et al., 2018)	HR-based personalized method to assess perceived exertion.	20 cleaning staff	HR	Basis B1 Fitness Wristband, Omron Sphygmomanometer Model HEM742INT.	Prototype developed with the Java 6.0 language using the ADT tool v22.3.0-887826; implemented over a Samsung Galaxy S4, an Android 4.2.2(JellyBean) Operation System, an octa-core chipset, and a 1.6GHz Quad+1.2GHz Quad CPU.



Author (year)	Approach	Sample	Assessed parameters	Wearable sensors	Data processing and analysis
(Sol et al., 2018)	Physical demands of hiking in wildland firefighting.	131 wildland firefighters	HR, Tco, speed and elevation gain.	Wireless thermometer capsule (Jonah ingestible sensor, Mini Mitter, Bend, OR), Hidalgo Equivital Physiological Monitor (Equivital, UK).	Independent t tests, two-way analysis of variance (IHC vs Type II and hike types) tests. Data analysis using SPSS (SPSS Inc, Chicago, IL)
(K. Yang et al., 2016)	Method to automatically detect near-miss falls based upon kinematic data	5 ironworkers	kinematic data (acceleration, angular velocity)	wearable inertial measurement units (WIMUs)	Semi-supervised learning algorithm (i.e., one-class support vector machine).
(L. Yang et al., 2018)	Wearable system through a mobile application for assessment of different types and levels of workloads.	8 workers (2 postal workers, 2 construction workers, 2 office workers, 2 drivers)	HR	vest with four texdrodes made with conductive Shieldex Fabric P130+B manufactured by STATEX GmbH (Bremen, Germany)	Android-compatible application. Algorithm by Skotte et al. was applied.
(Yokota et al., 2014)	Examine thermal strain levels.	30 law enforcement personnel	HR, Tco.	Chest strap sensor (EquivitalTM EQ-01; Hidalgo Ltd., Cambridge, UK).	Statistical analysis.

DISCUSSION

This review focused on the assessment of continuous physiological responses of occupational tasks. Mostly, studies' goals were directed to quantifying the impact of physically demanding activities or validating newly proposed methods for classifying the effects of different levels and workloads of occupational tasks based on workers' physiology. In general, they highlighted the importance of field monitoring to timely detect any abnormal condition of the worker that might be affected by working or environmental stresses (Hwang et al., 2016). Since most of the investigations were developed within real working environments, the feasibility of performing continuous assessments during regular occupational situations was indeed demonstrated. Among retrieved articles, a variety of occupational groups were assessed. Studied professions included construction workers, drivers, firefighters, pilots, ironworkers, cleaning staff and law enforcement personnel of military sites. The encountered interest on some of these occupations was justified as they correspond to safety-sensitive professions, in which effective human performance is crucial to a successful outcome (Barger, Lockley, Rajaratnam, & Landrigan, 2009). Furthermore, a notable focus was evidenced on construction workers (included in five out of the 19 articles). Construction work typically involves physically demanding tasks performed in harsh environmental conditions, which can cause fatigue and lead to poor judgment, poor quality of work, increased risk of accidents and reduction in productivity (Aryal et al., 2017). Consistently, among retrieved papers, the clear interest was on assessing fatigue (Aryal et al., 2017; Hwang et al., 2016; Lee et al., 2017; L. Yang et al., 2018) and developing methods for preventing risks of accidents (Antwi-Afari et al., 2018). On the other hand, observing monitoring methods (Table 1), several wearable sensors were identified, and their simultaneous use for multivariable measurement was a clear tendency. Noteworthy is the fact that the only wearable system used in more than one selected study was the Equivital LifeMonitor (Hidalgo Ltd., Cambridge, UK). As Mehta et al. (2017) indicated, the validity, reliability, and applicability of this system for sleep and ambulatory monitoring of multiple physiological parameters during construction and firefighting work have been previously demonstrated (Gatti, Schneider, & Migliaccio, 2014; Liu, Zhu, Wang, Ye, & Li, 2013; Savage et al., 2014). Among selected studies, three included this system to obtain physiological data from operators in drillship (Mehta et al., 2017), wildland firefighters (Sol et al., 2018) and law enforcement personnel (Yokota et al., 2014). In all cases it



proved advantageous for obtaining measurements in field conditions and, HR assessment was observed as the focus assessed variable. Thus, it can be inferred that the tendency on the usage of validated procedures is maintained and future perspectives could be oriented to test the other referred methods within bigger samples and during real-life operations. Finally, observing physiological variables, cardiac responses to specific occupational activities were the most considered assessment goal among retrieved papers. HR was included in 11 out of the 19 final articles. Based on current work physiology literature, this can be explained as this variable has shown to be sensitive to changes in physical and mental fatigue (Borg, Hassmén, & Lagerström, 1987; Hankins & Wilson, 1998), as well as sleep and circadian issues (Carney et al., 2014; Kang et al., 2015). Collectively, findings not only suggest the relevance of multivariable approaches that include monitoring of cardiac responses along with validated fatigue indicators (thermal responses and scales of perceived exertion) but also confirm the need of inclusion of other variables such as metabolic equivalents (Lee et al., 2017) and respiratory signals (Boon-Giin et al., 2014; Fu et al., 2016). Finally, despite being assessed in few of the selected articles, approaches such as foot plantar distribution (Antwi-Afari et al., 2018) also proved to be beneficial for prognostic goals in occupational settings and could be included in future research works. Lastly, observing data processing methods, support vector machine classifiers and algorithm-based applications for smartphones suggest the evolution of data management with the tendency of assessing traditional fatigue physiological indicators (HR, acceleration, respiration signals) but through newly available computational techniques.

CONCLUSIONS

In this review, the evidence of current progress in the development of physiological monitoring systems and their applications for occupational settings is compiled. Selected studies indicate the feasibility of devices using physiological signals to examine the impact of occupational tasks and improve the management of health-related negative consequences in the near future. With a basis in physiology and application of principled computational techniques, it was demonstrated that future perspectives should be focused in the algorithms that allow simple low-cost sensors to be used in operational settings and provide the continuous subjects' status promoting to sustain their given tasks in a safer and healthier way.

Funding

This work was accomplished during the period of a research scholarship granted by the Doctoral Program of Occupational Safety and Health of the University of Porto.

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