## **Introduction**

Workplace fatigue is a multidimensional phenomenon having a causality relation with the risk of traumatic injuries and decrements in the work performance [1-3]. About 57% of the U.S. workforces have experienced fatigue at least once in a week and worker fatigue have imposed an economic burden for an amount of $101 billion [4, 5]. This degradation in physical capacity is the result of exorbitant manual exertions or repetitious activities associated with the prolonged occupational tasks [6]. Proper monitoring and detection of physical fatigue is necessary to avoid the short-term discomfort and motor control problems as well as the long-term health issues, e.g., *chronic fatigue syndrome*,causing a raise in the rate of absenteeism, presentism, and unemployment [7-9].

Fatigue monitoring and exposure assessment methods was traditionally limited to subjective visual inspection. These methods fail to comprise the generalizability in various fatiguing activities and do not consider the combinative aspect of fatigue indicators in terms of both physical characteristics and external risk factors [10-13]. The existing real-time fatigue monitoring and prediction studies are limited to driver fatigue mainly due to sleep deprivation by means of facial expression and eyelid movement analysis [14-16]. However, for physical fatigue assessment, the current methods are confined to a change detections *pre-* and *post-fatigue* imposed by the in-lab designed exhaustive activities rather than a continuous monitoring and prediction while performing realistic occupational tasks. The current techniques for physical fatigue detection include fitness-for-duty tests for ability evaluations of the workers prior to start their jobs, recording of the sleep patterns, brain activity monitoring by electroencephalography (EEG), or muscle local activity monitoring using electromyography (EMG) [17, 18]. Meanwhile, human fatigue condition can be reflected by the physiological variables from the wearable sensors, e.g. heart rate (HR) or kinematics, subject information of individual characteristics, e.g. gender or body fat percentage, and in different task conditions, e.g. gait or rowing [2, 3, 19-21]. Recently, an increasing number of studies have been devoted to the prediction and classification of human fatigue using statistical and data mining techniques based on the informative kinematics of different body locations from wearable sensors and/or subject information [2, 3, 22-26]. In one study, Zhang et al. [24] applied different support vector machine (SVM) classifiers on different kinematic features from an inertial measurement unit (IMU) on trunk during squatting exercises until exhaustion. In another study by Karg et al. [21], the changes in gait kinematics *pre-* and *post-exhaustion* were analyzed from the structural and dynamical cues by principal component analysis (PCA) and Fourier transform on the data from motion capture system using rowing ergometer. However, in these studies, the realistic occupational tasks for fatigue inducement as well as fatigue prediction were not taken into account. In a recent study by Baghdadi et al. [3], a template matching pattern recognition technique along with SVM were utilized to classify between *fatigued* and *non-fatigued* states in gait from the kinematic data of a single IMU on the ankle during a simulated manufacturing task of manual material handling. Maman et al. [2] used wearable sensors data on different body locations to detect physical fatigue while performing occupational tasks. However, the intention of their fatigue prediction models excluded a comprehensive data fusion approach for combining multisource information and analyzing the subsequent metrics. Therefore, there is a lack of consensus on how to perform effective data fusion of wearable sensors and subject information for individualized risk evaluation and continuous fatigue monitoring [27]. The effectiveness of monitoring system in exposure measurement and the detection of a fatigue occurrence point depends on the capability of the system in fatigue prediction to avoid any potential health and safety incident. This requires an accurate and continuous monitoring of a quantified level of physical and physiological exposure in the workers.

This paragraph introduces “accurate and continuous monitoring of a quantified level of physical and physiological exposure”. Such information provide a relatively sufficient pool of features for fatigue assessment. But in practice, instrumenting a large of number of sensors on human as well as collecting subject information from them are burdensome, if possible, to achieve. It is therefore important to identify a subset of sensors and subject information from multisource data fusion techniques and propose a combined metric for the fatigue assessment.

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