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Automated ergonomic risk monitoring using body-mounted sensors and machine learning

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ABSTRACT

Workers in various industries are often subject to challenging physical motions that may lead to work-related musculoskeletal disorders (WMSDs). To prevent WMSDs, health and safety organizations have established rules and guidelines that regulate duration and frequency of labor-intensive activities. In this paper, a methodology is introduced to unobtrusively evaluate the ergonomic risk levels caused by overexertion. This is achieved by collecting time-stamped motion data from body-mounted smartphones (i.e., accelerometer, linear accelerometer, and gyroscope signals), automatically detecting workers' activities through a classification framework, and estimating activity duration and frequency information. This study also investigates various data acquisition and processing settings (e.g., smartphone's position, calibration, window size, and feature types) through a leave-one-subject-out cross-validation framework. Results indicate that signals collected from arm-mounted smartphone device, when calibrated, can yield accuracy up to 90.2% in the considered 3-class classification task. Further post-processing the output of activity classification yields very accurate estimation of the corresponding ergonomic risk levels. This work contributes to the body of knowledge by expanding the current state in workplace health assessment by designing and testing ubiquitous wearable technology to improve the timeliness and quality of ergonomic-related data collection and analysis.

1. Introduction

With advancements in mobile technology, modern smartphones are now equipped with a host of sensors which can capture location and motion-related data of a person within the environment. These devices have the potential to facilitate everyday life in various ways by giving users contextual information about their activities, interests, and surroundings without being obtrusive and interruptive. In addition, compared to other classes of data-capturing devices, smartphones are more ubiquitous (thus more affordable) and intuitive to use, can be controlled and operated remotely (using the cloud technology), and require a relatively lower maintenance and operating costs. The value of using smartphones in domains such as healthcare, wellbeing, and behavioral analysis has been investigated over the past few years. For example, smartphones are being used for monitoring patients and elderly people [1–3]. In addition to health monitoring, smartphones can also be used in managing and promoting human well-being [4,5]. Also, smartphone technology can be integrated with behavioral health care [6]. For instance, Timmons et al. [7] used audio and global positioning system (GPS) data from smartphones to unobtrusively and remotely monitor the behavior of young couples. Furthermore, smartphone's built-in inertial measurement unit (IMU) can be utilized to prevent work-related injuries, for example, fall from a height [8], shoulder injury [9], and upper-limb injury [10]. Particularly, recent studies have explored the potentiality of smartphone sensor in preventing musculoskeletal disorders (MSDs) associated with awkward posture [11,12].

MSDs are major health issues that affect a large number of individuals across many occupations and industries (e.g., from office space work to manufacture and construction), leading to long-term disability and economic loss [13]. MSDs refer to a group of disorders or injuries resulting from the stress in a person's inner body parts (e.g., muscles, nerves, tendons, joints, cartilages, and spinal discs) while the person moves [14,15]. Examples of MSDs include Carpal Tunnel Syndrome (CTS), Tendonitis, and Bursitis [16,17]. MSDs caused particularly due to the activities in a workplace are referred to as work-related musculoskeletal disorders (WMSDs). In 2009 alone, direct workers' compensation costs due to WMSDs were amounted to be more than $50 billion in the U.S. [18]. Moreover, workers exposed to major WMSDs may face permanent disability that can prevent them from carrying out their professional tasks and, in severe cases, regular everyday tasks

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[15]. In 2015, workers employed by the private sector in the U.S. required a median of 12 days to recover from WMSDs before they could return to work [19].

The construction industry is considered as one of the most ergonomically hazardous occupations [20]. Compared to other industries, construction activities are more physical and labor-intensive. Moreover, with increasing complexity and scope of construction projects, workers (especially those with limited skills and training) often find themselves performing tasks that are beyond their natural physical limits [21]. This sustained physical labor over a long period of time can trigger WMSDs which in turn adversely affect the project budget, schedule, and productivity. In 2015, the WMSD-related incident rate (number of illnesses and injuries per 10,000 equivalent full-time workers) was 34.6 [19]. WMSDs are the major source of concern in other industries as well. Among all goods-producing sectors, workers in the manufacturing, agriculture, forestry, fishing, and hunting sectors, and among all the service-providing sectors, workers in the transportation, warehousing, healthcare and social assistance sectors are reported to be more exposed to WMSDs [20]. Nursing assistants, laborers, and freight, stock and material movers experienced the highest number of WMSD cases in 2013 [20].

To prevent WMSDs, various health and safety organizations have established rules and guidelines to identify the risks associated with performing certain tasks. Such efforts aim at the ergonomic design of project tasks, tools, and workplace to match physical jobs with workers' natural body capacities. As an example, the prevention through design (PtD) initiative, introduced by the National Institute for Occupational Safety and Health (NIOSH), aims at limiting and ultimately preventing occupational injuries, illnesses, and fatalities that can be achieved by eliminating the potential risks to workers at the source as early as possible in a project life cycle [22]. Since a proper PtD practice requires prior identification of the risk factors, it is necessary to collect adequate spatiotemporal work-related data. The collected data, if properly analyzed and interpreted, can be used to promote workers' safety and health by improving the quality of job training and eliminating potential ergonomic risks in the workplace.

Field practices of data collection are traditionally based on self-reporting, manual observation, or the use of sophisticated sensor networks. Such practices, however, are time-consuming, naturally obtrusive, and require technical knowledge that may not be available among construction practitioners. Therefore, the objective of this research is to design and test a methodology where an unobtrusive and automated data processing framework is used to calculate ergonomic risks associated with occupational tasks, in particular, those comprising the use of excessive force (overexertion). In the designed methodology, mobile technology (smartphones) is used to collect multi-modal time-motion data from the workers while they perform different activities. Next, machine learning will be used to recognize workers' activities, and then, activity duration and frequency information will be extracted. The output of this step will be subsequently used to identify the ergonomic risk levels for each worker. Calculated risk levels can be used to identify major sources of ergonomic risks which can help workers and decision-makers (e.g., project managers, safety officers, superintendents) to take proper actions to preemptively limit and ultimately eliminate such risks by redesigning high-risk activities and/or workspaces.

2. Literature review

With 33% of all cases, the U.S. Bureau of Labor Statistics [19] ranks overexertion first in the leading events or exposures that cause WMSDs. By definition, overexertion is the event category that includes injuries related to exerting an excessive force beyond the body's capacity. Activities that require force can be categorized into two groups: lifting/lowering/carrying (category-1), and pushing/pulling (category-2) [23]. A risk factor is defined as a condition present in the workplace that is directly responsible for health hazards [17]. For example, applying excessive force to lift a heavy object can be considered as a risk factor for overexertion. However, the mere presence of a risk factor is not sufficient to evaluate the risk associated with a task, rather the risk also depends on the extent of the risk factor [17]. Determining if an exposure or a risk factor will result in WMSDs depends on intensity, duration, and frequency, or a combination of these factors [24]. Intensity, duration, and frequency refer to how much, how long, and how often, respectively, one is exposed to a risk factor. Generally, risk level rises with the increase of these factors. For instance, if a worker forcefully (i.e., intensity factor) and repetitively (i.e., frequency factor) pushes a heavy object for a long period of time (i.e., duration factor), the worker is exposed to WMSDs (e.g., back pain). These are regulated by the Occupational Safety and Health Administration (OSHA), which has provided a set of empirical rules assessing the risk of activities according to their type, duration, and frequency.

Towards this goal, three different approaches have been practiced in general: (1) self-assessment, (2) observational, and (3) direct measurement [25]. In self-assessment, workers are asked to provide risk-related data. Though this approach has low initial cost and is straightforward, researchers have stated that workers' self-assessments on exposure levels are often imprecise, unreliable, and biased [26]. The observation-based approach involves real-time assessment or analysis of the recorded video. But it is mostly impractical in nature due to the substantial cost, time, and technical knowledge required for post-analysis of large amounts of non-heterogeneous data [24].

Unlike the previous two approaches, direct measurement uses tools to collect workers' posture- and motion-related data. Examples of this approach include but are not limited to using off-the-shelf micro-electro-mechanical sensors (MEMS), e.g., IMUs, and vision-based sensors. Vision-based sensors such as Red-Green-Blue (RGB) camera and Kinect suffer in extreme lighting conditions and optical occlusions [27]. For this reason, wearable sensors such as IMUs have gained more popularity for being inexpensive, easy to install and maintain, and requiring minimum training for data collection and human activity recognition (HAR) [28]. Moreover, previous studies have shown that when compared to the depth-based sensors (e.g., Kinect), IMUs are superior for detecting movements of body parts because they are more sensitive than Kinect (i.e., capable of capturing subtle movements), more robust (i.e., capable of providing stable data), and have higher sampling rate (e.g., > 50 Hz, while the maximum frequency for Kinect is 30 Hz) [27]. While previous studies in this area have revealed some of the shortcomings of the direct measurement approach including high initial investment cost, maintenance cost, and technical knowledge to interpret data, compared to other approaches, this method by far yields the most valid assessment of risk factors [24,29].

In order to overcome the implementation challenges of direct-measurement approach, the authors used smartphones as a data collection device. Recent work has explored the merit of built-in smartphone IMU sensors to collect input data for machine learning algorithms to identify field activities and to estimate activity durations [30–33]. We have to note that compared to traditional physical activity recognition (e.g., walking, running, and sitting) [34–38], the activities performed in construction sites are much more complex in nature (e.g., loading, unloading, lifting, lowering, carrying, pushing, and pulling). Previous efforts in identifying construction activities include the use of single-sensor (i.e., accelerometer) data to identify masonry work [39,40]. Particularly, Ryu et al. [40] have used data from wrist-worn accelerometer sensors to classify more subtle mason's actions (e.g., spreading mortar, laying bricks, adjusting bricks, and removing excess mortar). While past work has mainly focused on activity recognition, the literature is rather limited and fragmented about the prospect of identifying ergonomic risks, particularly those associated with overexertion, from the outcome of multi-sensor HAR. Therefore, the applicability and robustness of existing methods are to a large extent unexplored in overexertion-related ergonomic risk assessment. Given