DEVELOPMENT OF AN ALGORITHM FOR AUTOMATICALLY ASSESSING LIFTING RISK FACTORS USING INERTIAL MEASUREMENT UNITS

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The objective of this study was to develop an algorithm for automatically processing data collected with inertial measurement unit (IMU) wearable devices to measure lifting risk factors for low back disorders. Five IMU sensors attached to five body segments were used for developing the algorithm. The algorithm consists of two modules running in parallel for detecting the beginning and ending of a lifting event as well as the vertical height (V) of the object lifted by two hands and the horizontal (H) distance between the object and the body during the lift. The motion synchronization feature of wrists' motion data were used to train the lifting detection module using a machine learning approach. This module achieved a training accuracy of 85%. In the second module, the forearm length and gyroscope data of four sensors are proposed for calculating trunk flexion angle, V and H during a lift.

INTRODUCTION

Musculoskeletal disorders (MSDs) are a major workplace health problem and economic burden. Recent data showed that workplace overexertion injuries were estimated to cost $15.1 billion a year, accounting for about 25% of the total workers' compensation cost (Liberty Mutual Research Institute for Safety, 2014). Low back disorders (LBDs) are the largest contributor to the total workers' compensation cost. The total health care expenditures incurred by individuals with low back pain alone in the United States reached $90.7 billion a year (Luo et al., 2003).

To control and prevent MSDs in the workplace, accurate quantifications of risk factors are imperative. Substantial evidence has shown that work-related physical risk factors are the main source of LBDs (Bernard et al; NRC 2001; da Costa and Vieira E., 2009). These physical risk factors include heavy/repetitive manual lifting, awkward posture, and long work hours. Combinations of these physical risk factors may lead to an increasing risk of developing LBDs (Lu et al., 2014). Reductions of work-related physical risk factors have been the main goal of ergonomic interventions. To assess the effectiveness of ergonomic interventions in reducing risks for MSDs, ergonomic checklists or video task analyses are commonly used by practitioners. However, these observational risk assessment methods with the primary goal of quantifying postural risks are subjective, resource intensive; and cannot effectively quantify a variety of postures used by the worker during an 8-hour workday (Callaghan at al., 2001; Lu et al., 2015).

Direct reading measurements of postural risk exposures were developed by several researchers in the 90's (Radwin and Lin 1993; Bhattacharya et al., 1999; Marras et. al., 1995; Freivalds et al., 2000), but the complex and bulky set ups did not seem to be an attractive option for field applications. Because of their small and light weight features, inertial measurement unit (IMU) devices are becoming popular as a new tool to track whole body postures for ergonomic risk assessments (Battini et al, 2014). Many recent studies utilizing IMU devices for ergonomic research have developed useful algorithms for measuring body postural angles, primarily the trunk flexion angle (He and Jin, 2009; Battini et al, 2014; Dahlqvist, et al., 2016). Manual repetitive lifting has been identified by many studies as one of the main risk factors for MSDs (Bernard et al., 1997; NRC, 2001). However, algorithms for processing data from IMU sensors have not been developed for identifying the duration of a lifting task as well as other lifting risk factors, such as the vertical distance between the load and the floor (V) and the horizontal distance (H) between the load and the center of the two ankles. These two variables are identical to the V and H used in the revised National Institute for Occupational Safety and Health lifting equation (RNLE) and considered important risk factors associated with LBDs (Waters et al., 1994). The identification of lifting tasks and their associated risk factors using IMU sensors, therefore, provides valuable risk information for interventions.

The purpose of the study was to develop an algorithm for processing IMU sensor data in real-time to measure physical risks associated with two-handed manual lifting.

METHODS

Overview of Algorithm

Figure 1 shows the workflow of the developing algorithm for processing data from IMU sensors (Kinetic Inc.) to measure lifting risk factors. The input is the 6-axial IMU data (accelerometer and gyroscope in 3 axes respectively) at 25 Hz from each of the 5 sensors attached to the subject's specific body landmarks (Figure 2). Sensor data are fed into two major modules including the lifting detection module and the sensor fusion module that runs in parallel. The lifting detection module detects the occurrence of a lifting event with the timestamps of the beginning (BOL) and the ending (EOL) of the event. The sensor fusion module keeps track of the device

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orientations in real-time at 25 Hz and provides the angle of the sensor in three dimensions relative to the ground. The sensor fusion model is primarily used for correcting the gyroscope data for estimating the orientations of the body segments during a dynamic workplace environment.

Lifting Risk Variables

To determine physical risk factors associated with two-handed manual lifting, the BOL and EOL are required to be identified first. Once the two time instants are determined, lifting risk factors during the lifting duration can be estimated with IMU sensors. Three main lifting task variables used in this study are trunk flexion angle, V and H. The V and H variables are identical to those used for the revised NIOSH lifting equation (Waters et al., 1994) and the American Conference of Governmental Industrial Hygienists Threshold Limit Values (TLVs) for lifting.

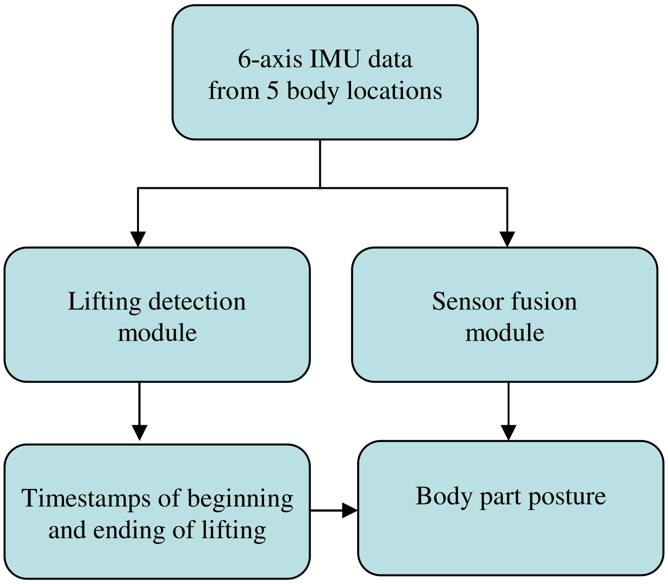

Figure 1. Workflow of the developing algorithm

Lifting Detection

The detection of the exact timestamps of the BOL and EOL is executed by a two layer algorithm. The lower layer uses data from two wrist sensors as input to check the motion synchronization feature of the two wrists during lifting; and output a binary result of the onset of synchronization and no synchronization. The higher layer or representative motion detection is a digital signal processing (DSP) layer that monitors certain events that have high correlations with the features of lifting, such as bending over and reaching out with arms. This layer is run only when the lower layer detects synchronization.

Synchronization of Wrist Sensor Data

The lifting detection module constantly monitors motions (i.e., acceleration and rotation) of the two wrist sensors and makes a decision on the level of synchronization of their motions. We assume that the two wrist sensors have high levels of synchronized motion when an object is held and moved by both hands. This assumption is based on the property of a non-elastic lifting objective that couples the accelerations and rotations of the wrist sensors. Figure 3 demonstrates the motion feature of two wrist sensors in synchronization.

Machine Learning Algorithm

Consumer grade IMU sensors (Kinetic Inc.) were used for collecting a training dataset. Data were collected on 6 subjects performing two categories of activity: 1) performing common activities while holding a rigid box for and 2) performing common activities without holding the rigid box. More specifically, for the holding-box activities, subjects performed activities of walking, turning around, raising and lowering arms while holding a rigid box for 30 seconds each. For the arm free activities, subjects repeated the above activities without holding the rigid box. The total data collection times for activities (1) and (2) were about 5 and 15 minutes, respectively.

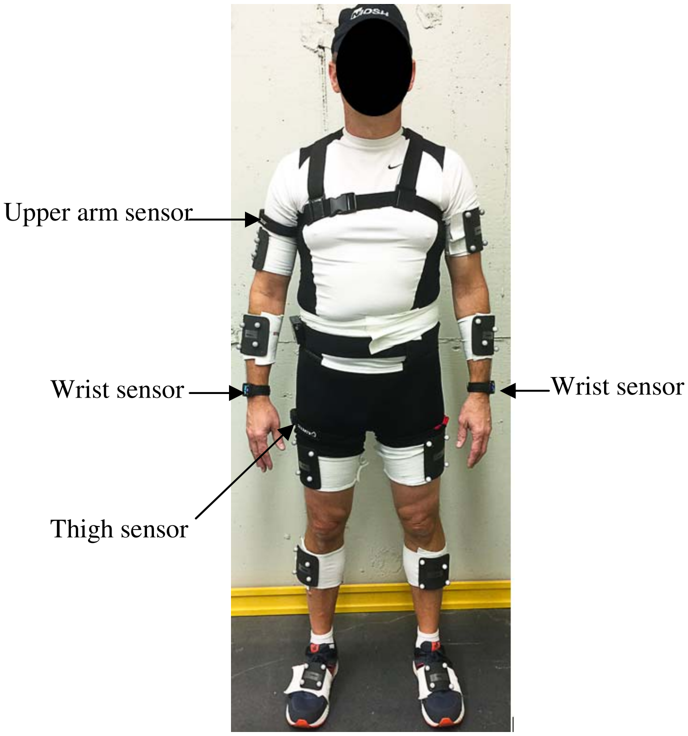

Figure 2. Locations for five IMU sensors (one sensor located on the T12 region on the upper back is invisible).

The lift detection module is data driven and built using a machine learning approach. A typical sliding window approach (Spriggs et al., 2009; Bulling et al., 2014; Moncada-Torres a t al., 2014; Attal at al., 2015) with a window of 2.5 seconds and a 0.5 second overlap was employed. For each window, IMU data from both wrist sensors were used to extract features which best represented synchronization of the wrist motions. A binary classification model was trained using a random forest classification algorithm (Liaw et al., 2002). Open source languages R and Python/C++ random forest tools were used for programming the algorithm. The binary training labels were prior-known from one of the two categories of activity. This approach was used to detect whether the two wrists were in synchronization at a 0.5 second step size over a 2.5 second long window. Namely, a decision was made based on previous 2.5 second data and updated every 0.5 second. The ratio of training and validation datasets is 5:1, resulting in a use of 25 minutes of hands synchronized data for training and 5 minutes of data for validation. This module achieved a training accuracy of 83%~85% detection rate, and about 32% in false alarm rate (Powers, 2011).

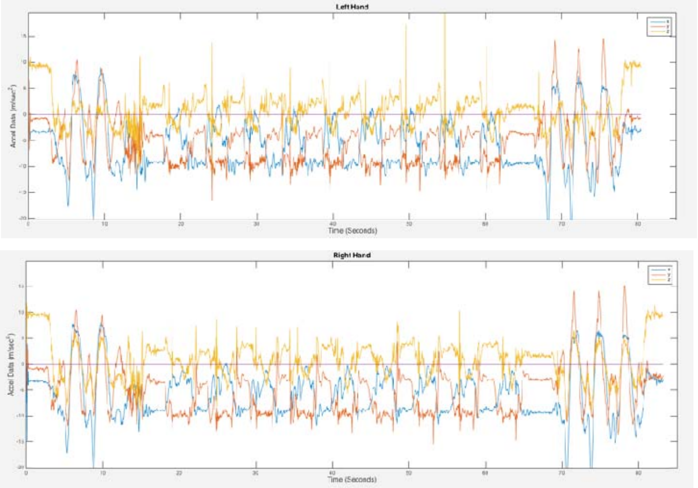

Figure 3. Demonstration of the motion feature of two wrist sensors in synchronization. Three axial accelerator data are presented from one lifting trial. The motion synchronization features of two lifting events at the beginning and three lifting events at the ending of each were extracted for training the module using a machine learning approach.

Representative Motion Detection

The motion detection layer or the higher layer is necessary in that the lower layer only provides a binary decision over a 2.5 sec window without providing the exact starting and ending moment of a lifting event. This module is aimed to detect certain events that are highly likely to happen during lifting events by tracking the motion data of certain body parts. Sample motions include: extending arms out together, bending over and turning around in whole body motion. Each of these motions are extracted from sensor data of corresponding body parts as a one dimensional signal. The signal has peaks at the moment of these events. These signals are combined together to amplify the signature event. The exact moment of BOL and EOL will then be available using the peaks of the combined signal. This higher layer only runs when the lower layer detects the motion synchronization feature of the two wrists. The lower layer remain idle when both wrists are not in synchronization, such as walking.

Sensor Fusion

IMU sensors typically contains three dimensional data from accelerometer and gyroscope sensors, respectively. The accelerometer sensor, measuring three dimensional linear acceleration, produces a vector sum of the acceleration caused by gravity and the acceleration caused by motion. The gravity acceleration provides the device orientation information if it can be isolated from the sum. The gyroscope measures the three dimensional angular velocity (i.e., rotation rate) (Fixlin, E., 1996; You et al., 2001), and the track of history indicates the changes of device orientation. However, the track has to be done by an integral from angular rate to angles, which generates a large accumulative drift (Lee and Jung, 2009). An extended Kalman filter algorithm, similar to that used by Rigatos and Tzafestas (2007), was designed to fuse the accelerometer and gyroscope data of a single device and then output gravity vector information (from accelerometer data) with motion induced acceleration and bias of gyroscope data attenuated. This gravity vector gives information of device orientation in real time.

Calculations of Trunk Flexion Angle, V and H

This sensor fusion is applied to all the individual sensors prior to calculations of the lifting risk variables. The trunk flexion angle is directly available from gyroscope data in the upper back sensor placed on the T12 region of the spine. A calibration for the trunk flexion angle should be performed to account for the natural lordosis of the spine while standing upright. This means that the trunk flexion angle should be calibrated by subtracting the slight angle from the earth vertical line using the data collected during quiet upright standing.

Body segment lengths and the angular data of four sensors (Figures 4 and 5) are input to the equations below for calculating V and H. As demonstrated in Figure 3, the redundant information of the left wrist sensor was ignored in calculating the two variables.

$$V = L_{back} \times \cos(\theta_{Back}) + L_{Thigh} \times \cos(\theta_{Thigh}) + L_{calf} - L_{UA} \times \cos(\theta_{UA}) - L_{FA} \times \cos(\theta_{FA})$$

$$H = L_{UA} \times \sin(\theta_{UA}) + L_{FA} \times \sin(\theta_{FA}) + L_{Back} \times \sin(\theta_{Back}) - L_{Thigh} \times \sin(\theta_{Thigh})$$

The slight Q_{calf} angle during lifts is assumed to have little effect on the calculations of the lifting risk variables. Therefore, this angle is ignored in the above equations. In these equations, the lengths of the body segments of a subject may be measured to improve the accuracy of the calculations. However, to simplify the calculation process, we propose using the means of the population anthropometric data (Chaffin et al., 1999). Based on the population average data, we used the forearm length as the basic unit to estimate the lengths of other body segments. The resulting estimation is that the length of the upper arm (L_{UA}) is equal to the forearm (L_{FA}), whereas the length of the upper leg (L_{Thigh}) or the lower leg (L_{Calf}) is 1.2 times L_{FA}. The length of the spine (L_{back}) is estimated to be 1.4 times L_{FA}. The body length ratio model is depicted in Figure 4.

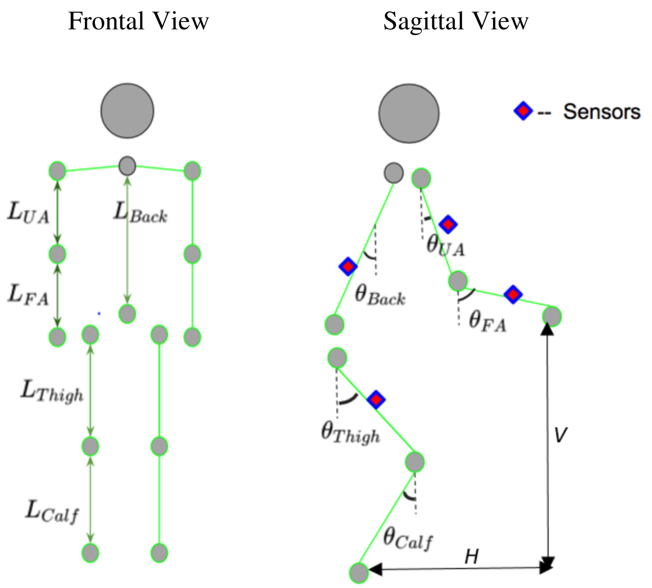

Figure 4. Body length ratio model and angular data of four sensors used for estimating V and H.

This body length ratio model simplifies the preparation process of using the IMU based wearable sensor system for calculating V and H. The user needs just the measurement of the subject's forearm length for using the algorithm. Because the calculations of V and H are based on the actual measurement of the forearm length, V and H are calculated as actual distances.

RESULTS AND DISCUSSION

This paper describes the development of an algorithm for processing IMU data with an aim of automating measurements of several lifting risk factors including the time instants of the onset of a lifting event, the lifting duration, trunk flexion angle, V and H of the lift. Once the onsets of lifting tasks are determined, the frequency of the lifting tasks can be estimated using the time period of interest.

We used a hybrid approach to identifying a lifting event first using a machine learning algorithm, followed by sensor fusion and mathematical equation based calculations of the lifting variables. Because the modules can run in parallel, the workflow of the algorithm is suitable for developing direct-reading wearable systems. The algorithm can also be deployed on a computer or a mobile device to process wirelessly transmitted IMU data in near real time.

Using a training dataset, the lifting module achieved an accuracy of 83%~85% detection rate, and about 32% in false alarm rate. The accuracy of the synchronization detection layer may be further improved with a larger amount of training data.

The forearm length and gyroscope data of four sensors relative to the gravity are proposed for calculating trunk flexion angle, V and H during lift. The accuracy of the mathematical equations for calculating the lifting risk variables, however, is yet to be evaluated.

Several limitations of the algorithm are worth mentioning. First, the body length ratio model used in this study simplifies the data collection process at a cost of reduced accuracy. Second, the algorithm cannot be applied to one handed or two handed lifting with uneven lifting movements of the two wrists. Third, the algorithm is not designed for lifting tasks involving trunk rotation or lateral movements.

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