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Toward Real-Time Detection of Object Lifting Using Wearable Inertial Measurement Units*

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***Abstract*— Back injuries and other occupational injuries are common in workers who engage in long, arduous physical labor. The risk of these injuries could be reduced using assistive devices that automatically detect an object lifting motion and support the user while they perform the lift; however, such devices must be able to detect the lifting motion as it occurs. We thus developed a system to detect the start and end of a lift (performed as a stoop or squat) in real time based on pelvic angle and the distance between the user's hands and the user's center of mass. The measurements were input to an algorithm that first searches for hand-center distance peaks in a sliding window, then checks the pelvic displacement angle to verify lift occurrence. The approach was tested with 5 participants, who performed a total of 100 lifts of four different types. The times of actual lifts were determined by manual video annotation. The median time error (absolute difference between detected and actual occurrence time) for lifts that were not false negatives was 0.11 s; a lift was considered a false negative if it was not detected within two seconds of it actually occurring. Furthermore, 95% of lifts that were detected occurred within 0.28 s of actual occurrence. This shows that it is possible to reliably detect lifts in real time based on the pelvic displacement angle and the distance between the user's hands and their center of mass.**

***Clinical Relevance*— Real-time detection of the beginning and end of a lift using wearable sensors could be used to trigger assistance from devices such as back-assist exoskeletons, which may reduce the incidence of occupational injuries in diverse professions.**

I. Introduction

Workers in occupations involving extensive lifting are at an increased risk of back injury, low back pain, musculoskeletal disorders, and disability; this represents a major health issue worldwide [1]–[3]. To help alleviate these risks, back-assist exoskeletons have been introduced to support human workers during lifting by physically supporting the trunk and reducing biomechanical loads [4]. Most such exoskeletons are passive devices: they have no motors, and instead support workers simply using mechanical structures that reduce the load on the lower back and potentially store energy using elements such as springs [4]–[8]. However, while passive devices have been shown to reduce low back muscle activity, they are not capable of generating high forces and torques that can help with lifting.

As an alternative to passive devices, active exoskeletons have motors to augment the movements of the wearer [4]. While more expensive than passive devices, active back-assist exoskeletons have demonstrated positive effects on muscle loading and spinal moments in several studies [4], [9]–[11]. A recent review found that, while both passive and active exoskeletons can reduce the activity of the back muscles, active exoskeletons reduce L5/S1 moments more effectively than passive exoskeletons and increase the number of lifting cycles the lifter can perform [4].

Ideally, the motors of an active exoskeleton should operate only when the user is lifting an object; assistance at other times would waste power and potentially perturb the user. However, the wearer is not always performing lifting motions, and most back-assist exoskeletons do not currently have the ability to detect a lift; thus, they do not know when to deliver assistance [12]. These exoskeletons generally rely on the user to activate the aid using joysticks or control buttons. While this is a reasonable approach, a better option would be to have the exoskeleton automatically know when to engage instead of relying on the user. This, however, necessitates the need for sensors and algorithms that can determine when a lift is being performed.

Kawai et al. [13] created a system capable of detecting lifts using an artificial neural network with the user's electromyographic (EMG) signals as inputs. While the system was successful, the EMG sensors required gelled electrodes that may not be appropriate for occupational environments. Even if the sensors could be used in occupational environments, surface EMG signals exhibit high intersubject variability due to different activity levels and activation patterns in muscles; furthermore, they exhibit intrasubject variability due to factors such as sweat [14], [15]. As a result, an EMG-based recognition system would need to be extensively calibrated and trained for each user [14], [15], which is impractical if the system should be used by different people on different days. Thus, it would be preferable to perform lift detection based only on mechanical sensors.

A practical approach to real-time lift detection in a back-assist exoskeleton was presented by Chen et al. [12]. Hip joint encoder sensors embedded in the exoskeleton as well as an inertial measurement unit (IMU) were used to record the hip joint angle and the Euler angles of the trunk. While the study showed that real-time detection was possible, it used sensors integrated in the exoskeleton, which may not be available in all exoskeletons. Furthermore, without monitoring the arm measurements, it would be difficult for the system to distinguish between sitting down and a lift. Thus, the aim of our own work was to develop other real-time lift detection methods based on other signals as possible alternatives.

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A previous study by our group introduced an offline (non-real-time) system that detected lifts based on the distance of the hands to the user's center of mass (CoM) using the Xsens inertial measurement system (IMU) [16]. Since this distance was greatest when an object was picked up and when it was put down, peaks in the signal were used to identify the start and end of a lift. This approach worked well for offline data and was able to detect multiple different types of lifts but was not suitable for real-time lift detection since it relied on manual presegmentation of data as well as access to future values. This study thus aims to improve our group's previous work in two ways. First, the algorithm is modified to work in real time. Second, the algorithm is expanded to use pelvic angle in addition to the distance of the hands to the CoM.

II. Materials and Methods

A. Sensors

The Xsens Link (Xsens Technologies BV, Enschede, Netherlands) is a set of 17 IMUs all connected to a common transmitter that are attached to a specially designed suit using straps placed onto the feet, lower legs, upper legs, pelvis, shoulders, sternum, head, upper arms, forearms, and hands. The sensors consist of 3D gyroscopes, accelerometers, and magnetometers [17], which allow body segment positions and orientations to be calculated using a biomechanical model created from the wearer's body measurements (joint angles, segment orientation, segment acceleration, etc.). The basic sensor performance is characterized as follows: static accuracies for roll/pitch and heading are 0.2 and 0.5 degrees, respectively; dynamic accuracy is 1 degree root-mean-square; accelerometer range is ±16 g; and gyroscope range is ±2000 degrees/s. The sampling frequency in this study was 120 Hz.

B. Study Protocol

The study protocol was approved by the University of Wyoming Institutional Review board. Four lift types were performed: straight squats, straight stoops, twisted squats, and twisted stoops. Squatting and stooping are common techniques used to pick up objects. A squat is defined as starting from a standing position with a straight back, bending the knees to get closer to the ground, and then lifting using the legs**.** A stoop is defined as starting from a standing position, bending at the waist, and then lifting with the back**.** For purposes of this study, a twisted lift is defined as one where the lifter's pelvic rotation angle changes by more than 30 degrees during a lift, while a straight lift is defined as one where the pelvic rotation angle changes by less than 30 degrees (though participants were asked to not twist at all during straight lifts). Both straight and twisted lifts were included to test whether the algorithm could detect lifts regardless of the lifter's initial orientation (since the lifter is not always initially lined up with an object).

In the study, five participants with no motor or cognitive issues that would affect lifting (one woman and four men, mean height 178.8 ± 8.9 cm, mean weight 80.3 ± 13.0 kg) performed a series of twisted and straight stoops/squats while picking up, carrying, or putting down a small approximately 30x30x30 cm box that weighed approximately 2.3 kg (5 lb). When participants picked up or let go of the box, they had to rise back to a standing position before being able to let go or pick up the box again (i.e., they could not drop the box and immediately pick it up again without straightening). Each participant performed 25 straight squats, 25 straight stoops, 25 twisted squats, and 25 twisted stoops in random order, interspersed with approximately 120 seconds total of walking around the laboratory that served as control intervals with no lifting.

A lift was defined as either a pickup or drop-off of the object since the data measured when the user performed a pickup or drop-off were identical. This can be seen in Figures 1 and 2, where the first and third peaks correspond to pickups and the second and fourth correspond to drop-offs. The order of lifts was constant between participants, and the different lift types were not performed in blocks (e.g., the 25 straight squats were not all done together).

C. Lift Detection Algorithm

While all data were collected prior to algorithm development, they were used to develop and test the real-time lift detection algorithm by feeding the data to the algorithm sequentially (one sample at a time).

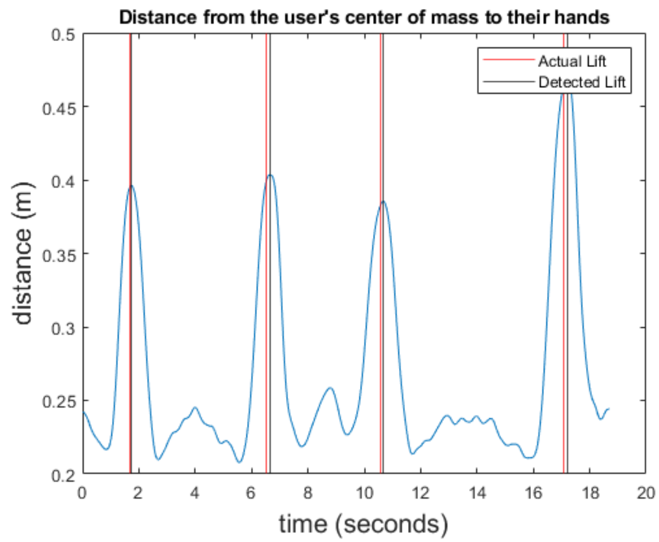

Figure 1. The distance between the hands and the center of mass as a function of time, with detected lifts and actual lifts marked.

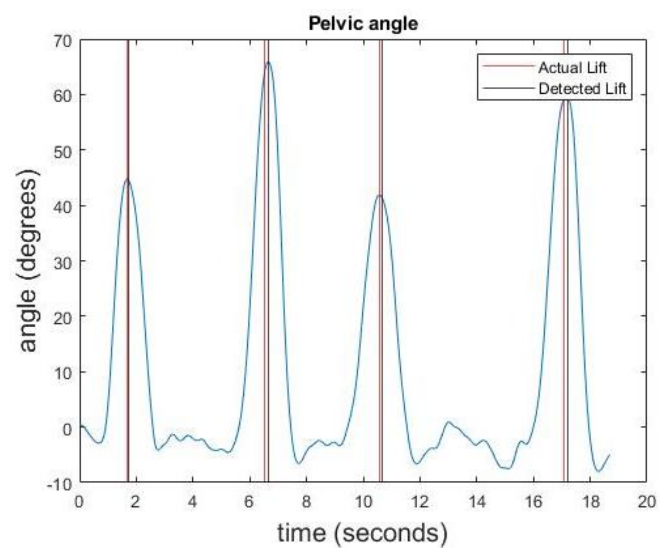

Figure 2. The pelvic angle as a function of time, with detected and actual lifts marked.

Our previous study [10] found the distance between the user's hands and the user's CoM to be indicative of a lift. Based on a visual inspection of the data, the pelvic flexion angle (henceforth referred to simply as 'pelvic angle') was also found to be a promising indicator of a lift. Other studies corroborate this finding, as it was shown that performing a squat requires the lifter to flex their pelvis [18]. Figure 2 shows a pelvic angle measurement during a series of consecutive lifts. The pelvic angle also serves to filter out any peaks that form in the distance from the user's hands to the user's CoM arising from motions such as jittering or raising hands while walking. In such cases, the pelvic angle change would not be great enough to elicit a lift detection.

Since peaks in the Euclidean distance between the hands and the CoM were indicative of a lift, a buffer was used to store the last five measurements of the distance between the hands and the CoM. The algorithm then checked if the third value in the buffer was the highest value in the buffer (indicating a peak). The algorithm then checked this value to see if it was above a predefined threshold of 0.25 meters. This was done to help prevent small peaks caused by other events (e.g., jitters) from being misdetected as a lift. This buffer introduced a two-sample (~16 ms) delay in the lift detection, but this was considered acceptable.

If the distance value was above the predefined threshold, then the pelvic angle was checked. The value of the pelvic angle must also cross a minimum angle threshold of 20 degrees, with the threshold being the same regardless of whether the lift was a squat or a stoop. If this requirement was met, a lift was detected at that time. After detection of a lift, another lift could not occur until the lifter's pelvic angle became at least 10 degrees lower than the pelvic angle at the time the lift had been detected (i.e., until the lifter had straightened by at least 10 degrees). This reduced false detections since another lift should not occur before the lifter completes the current lift.

To calibrate the system for individual users, the initial pelvic angle value at the beginning of the 100-lift study protocol was recorded and subtracted from all subsequent pelvic angle measurements. This made the threshold a universal value for all users.

D. Accuracy Metrics

The goal of this system was to detect in real time when a lifter either picked up or set down an object, with the aim of later using this to trigger lift assistance from a device such as an exoskeleton. Thus, the main performance metric was the time error: the absolute time difference between the actual and detected pickup/drop-off time, which would affect how quickly an assistive device can respond to a lift. The actual pickup and drop-off times for a lift were determined by watching the recorded video of the lifts and manually labeling when the participant picked up or dropped off the box.

A lift was classified as a false positive if a lift was detected when one had not occurred within two seconds while a false negative was defined as the system failing to detect a lift within two seconds of it occurring.

III. Results

The median value of the time error (i.e., 50th percentile of time error distribution) was 0.11 seconds. Table I shows the median time error for each participant as well as the 25th, 75th, and 95th percentiles of the time error distribution. Furthermore, it shows the percentage of actual lifts that were false negatives and the percentage of detected lifts that were false positives.

IV. Discussion

The results show that it is possible to detect a lift in real time using the pelvic displacement angle and the distance from the hands to the lifter's CoM. There were only 1.13% false positives and 0.49% false negatives, and the remaining lifts were detected with a median error of 0.11 seconds. The algorithm also worked well with different users even though only one calibration step (subtracting initial pelvic angle) was performed and there was thus practically no subject-specific training. While we initially expected baseline pelvic angle to have little variation between participants, subtracting this initial angle did significantly improve results and was thus included in the system.

As a next step, the system's accuracy could potentially be improved further by performing user-specific calibration of the other thresholds or by incorporating additional measurements. At the same time, the relative simplicity of the system may be beneficial if we expect it to be used with a large number of users. Thus, alternatively, we could recruit a large sample of participants (both male and female) to determine 'optimal' user-independent thresholds and measurements.

A. Use with Assistive Devices

The system's main application would be to trigger assistance from an active exoskeleton or other assistive device during lifting. As exoskeleton wearers may engage in other activities (e.g., walking around a warehouse) in addition to lifting, the proposed system could help ensure that assistance is only provided when needed. For example, in warehouse settings, the exoskeleton could provide intelligent support whenever the user needs to lift or set down an object, decreasing the strain on the wearer's back and consequently the risk of injury. By incorporating the distance between the user's hands and CoM, the system would also avoid false positives due to, e.g., sitting down, which were shown to be problematic for simpler lift detection in previous work [12].

TABLE I. PERCENTILES OF TIME ERROR OF DETECTION IN SECONDS AS WELL AS THE PERCENTAGE OF FALSE POSITIVES (FP) AND FALSE NEGATIVES (FN). "TOTAL" INDICATES THE RESULT WHEN THE LIFTS OF ALL 5 PARTICIPANTS ARE POOLED TOGETHER.

Participant	Time error percentiles & false positives/negatives					
	25th	***50th***	***75th***	***95th***	***FP***	***FN***
1	0.08	0.13	0.18	0.28	1.38	1.38
2	0.08	0.12	0.19	0.61	1.87	0.00
3	0.08	0.12	0.14	0.22	0.00	0.00
4	0.05	0.08	0.11	0.16	0.00	0.00
5	0.06	0.09	0.15	0.28	2.50	0.00
Total	0.07	0.11	0.15	0.28	1.13	0.49

The real-time lift detection could also be combined with automated real-time identification of the type of lift (e.g., stoop vs. squat) similarly to the offline algorithms used in our previous work [16]. This would allow the exoskeleton not only to engage/disengage assistance, but also to choose among different assistive strategies to provide the most appropriate assistance for the type of lift. For example, some active exoskeletons are already able to make use of multiple control strategies, and could switch between them based on real-time lift detection and recognition [11].

The lift detection system is independent of the specific assistive device and could thus be used to trigger assistance in a variety of devices. For example, many active back exoskeletons already have both motors and joint angle sensors [4], and could provide assistance using their motors based on a combination of pelvic angle obtained through built-in sensors as well as the distance between the hands and CoM obtained through a separate IMUs. Alternatively, some authors have proposed the use of semi-active exoskeletons that would not apply strong torques through limb-mounted motors, but would instead use micromotors to adapt the exoskeleton's mechanical structure (e.g., increase its stiffness) based on the currently performed activity [6], [7]. Such semi-active devices could make use of the same lift detection system; while they would provide less assistance, they would also have lower weight and power consumption due to the lack of large motors.

B. System Limitations

Two limitations of the hardware and software used in the study should be mentioned. First, the algorithm was used with the Xsens commercial IMUs system, which is efficient and accurate, but both expensive and suboptimal for real-time use. Thus, future versions of the system may investigate the use of cheaper IMU systems; while these would likely suffer from somewhat lower accuracies, the tradeoff between decreased cost and decreased accuracy would likely be worthwhile. Second, the system is currently unable to differentiate between the user picking up and dropping off an object, which may be suboptimal if the goal is, e.g., only to provide assistance when the user is actually holding the object. Similar limitations are seen in, e.g., passive exoskeletons that provide assistance whenever the user bends regardless of the specific activity [7]. If it is critical to differentiate between a pickup and drop-off, the system could be expanded with, e.g., EMG sensors on the forearm similarly to the work of Toxiri et al. [11].

V. Conclusion

This paper demonstrated the ability to detect the beginning and ending of a lift in real time using only wearable inertial sensors. The detection algorithm eliminated the need to pre-segment data while also avoiding sensors that rely on biologically created signals. Based only on the pelvic angle and the distance between the hands and the user's CoM were used, 95% of the lifts were detected within 0.28 s of the lift occurring while failing to detect a lift only 0.49% of the time. In the future, the lift detection system could be used with active exoskeletons, detecting the pickup or drop-off of an object and alerting the exoskeleton to provide support.

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