Estimation of Lifting and Carrying Load During Manual Material Handling

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Abstract. Low back injuries and low back pain are often caused by improper task execution, overuse or lack of guidance and training. Our current understanding of dose-response relationships between risk factors that contribute to these injuries remains unclear. Enhanced monitoring of risk factors contributing to injuries could provide more complete exposure-response information. It is difficult to continuously monitor workers and their exposures to ergonomic risk factors using existing technologies. This paper presents a practical approach to advance continuous measurements of common risk factors by quantifying the weight of an object during lifting and carrying, lift frequency and lift duration during manual material handling (MMH). We estimate these parameters based on the ground reaction forces (GRF) and considering trunk dynamics. The results show that by considering trunk dynamics and applying simple signal processing techniques, we can precisely estimate these risk parameters. These parameters can then be used to estimate injury risk of workers. The developed methodology is designed for real-time continuous monitoring applications and sets the foundation for future development of in-field monitoring of workers with wearable sensors.

Keywords: Manual material handling · Injury risk estimation
Ground reaction force · Low back pain · Wearable sensors

1 Introduction

Low back injuries (LBI) and especially low back pain (LBP) rank among the most prevalent sources of occupational musculoskeletal disorders. Low back injuries (LBI) and especially low back pain (LBP) are often caused by improper task execution, overuse and lack of guidance and training [1, 2]. Our current understanding of the dose-response relationships between risk factors that contribute to these injuries remains unclear. Part of the reason for our incomplete understanding of how risk factors contribute to injuries is due to difficulties obtaining comprehensive exposure information for individuals working complex tasks. Often, exposures are estimated from snap-shots of work tasks, interviews with workers, periodic observations or "representative" video measurements.

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The goal of this study was to develop a practical approach to advance continuous measurements of the risk factors of LBP as defined in the revised NIOSH lifting equation (RNLE) [3, 4]. A recent study monitored hand forces during MMH using an instrumented force shoes and an inertial motion capture suit [5]. However, full-body motion capture system is inconvenient for in-field measurements. In this paper, we focus on quantifying the weight of an object, lifting frequency and lift duration during manual material handling (MMH) using limited number of body segment acceleration measurements. The proposed methodology is designed to enable continuous real-time monitoring and data collection, with the intent to establish robust methods for using wearable sensor technologies for collecting ergonomic risk factor measurements in the workplace.

2 Methods

2.1 Testing Protocol

We recruited a young healthy male participant with no previous musculoskeletal disorders or back pain history to perform the MMH tasks, see Fig. 1. These tasks included lifting, lowering and side-to-side positioning/transferring of the 5.25 kg (11.6 lbs) box with proper handles. The subject lifted the box from the ground on one side of the platform and put it on the table in the center and lifted it again and lowered it to the other side, see Fig. 1. The process was then repeated in the reverse direction. The total vertical lifting distance was 60 cm (23.5 in.) and the horizontal distance between the lifts was 1 m (39 in.). The box handles were positioned 25 cm (10 in.) from its bottom. To add larger variability in task executions, the subject was asked to perform lifts at a slow and fast self-selected speeds for controlled and quick, jerky movements performed in squatting and stooping postures. While performing lifting tasks, the subject was constantly standing over two force plates to continuously collect the complete ground reaction force (GRF) data.

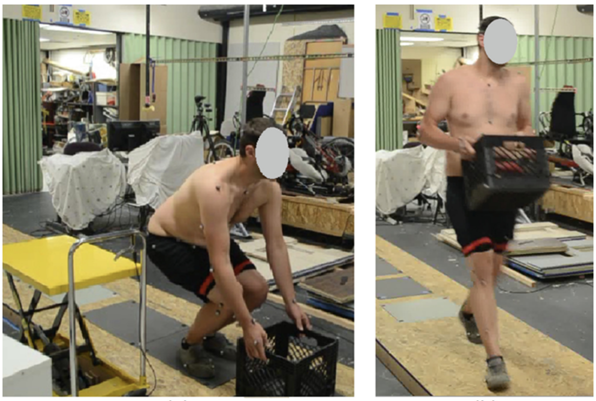

(a) (b)

Fig. 1. Subject performing (a) lifting and (b) carrying task during the experiments.

In addition, the subject was asked to walk on a custom walkway (0.9 m × 9.6 m) with and without carrying a box with a mass of 18.25 kg (40.2 lbs). The walkway contained a total of six force plates (three Bertec, Columbus, OH, USA and three AMTI, Watertown, MA, USA) measuring GRF data.

Forty-seven reflective markers were placed on a subject to capture whole body kinematics. Three additional markers were placed on the box to capture the kinematics of the handling object. Kinematic data were collected using an optical motion capture system (OptiTrak, NaturalPoint Inc, Corvalis, OR, USA) with a 120 Hz sampling frequency. The force plate data and motion capture data were synchronized using an external analog trigger signal. The subject was informed about the testing protocol and signed the informed consent form approved by the Institutional Review Board at the University of Utah.

2.2 Data Processing

All six force plate data were recorded at 1200 Hz, filtered using a fourth-order Butterworth filter with a cut-off frequency of 10 Hz and down sampled to 120 Hz to match the kinematic data. Kinematic data were filtered using a fourth-order Butterworth filter with a 5 Hz cut-off frequency [6].

2.3 Load Estimation Algorithm

Load mass was estimated by subtracting the subject's body mass and limb dynamics from the GRF for the lifting and carrying trials. We estimate load mass as:

$$m_{\mathrm{Load}} = \left(F_{zGRF} - m_{\mathrm{Subject}} * g - \sum\nolimits_{i=1}^{n} m_i * a_i\right)/g \tag{1}$$

where F_{zGRF} is the z-axis component of GRF (normal force), $m_{Subject}$ is the body mass of the subject, g is the gravitational constant, and m_i and a_i are the mass and acceleration of the individual body parts, respectively. We separately subtracted dynamics of either the whole body (n = 9) or trunk only dynamics (n = 1) for comparison purposes. In the whole body dynamics, we included the dynamics of nine body parts; left and right thighs, shanks with feet, upper arms, forearms with hands and trunk-neck-head part. The segment masses and center of mass locations were determined as in [6]. All calculated load estimations were averaged over the duration of the lifting event and compared to the known weight of the load/box.

Lifting Events. The lifting events were detected based on the estimated lifting object mass signal (m_{Object}) that was filtered using a second-order Butterworth filter with a 1 Hz cut-off frequency and averaged with a moving time window interval. The time window was 1.5 s for the data considering trunk only dynamics and 0.75 s for data considering whole body dynamics. Fixed thresholds of 3 kg and 1.5 kg, were set to detect the start and end of the lifting events, respectively. Kinematics of the box (i.e. the absolute velocity of a single marker attached to the box) were used as a reference to determine the actual start and end of the lifting events. Automatic detection of the start and end of the event was determined when the object's velocity exceeded and dropped below the threshold velocity value of 0.03 m/s, respectively.

The time duration of the lifting events was computed as the difference between the start and end of the lifting event. We computed this separately for the events determined using box marker data and from the lifting load estimation data considering whole body dynamics and trunk dynamics only.

Information of detected lifting events was used to continuously compute the lifting frequency $\omega_{Lift}(t)$ defined as

$$\omega_{Lift}(t) = \frac{N_{Lift}(t)}{t - t_0} \tag{2}$$

where $N_{Lift}(t)$ is the number of detected lifting events at time t, and the time difference $t - t_0$ is the total trial duration expressed in minutes that started at time t_0. In addition, we compute instantaneous frequencies ω_i of the individual lifting events defined as

$$\omega_i = \frac{1}{t_i}, \quad for\ i = 1, \ldots, N_{Lift} \tag{3}$$

where t_i is the duration of the ith lift defined as the duration between the starts of the two consecutive lifts and N_{Lift} is the total number of lifts.

Carried Load Estimation. The load carrying events during walking were analyzed between the heel strike on the second consecutive force plate and the toe off at the second to last force plate. Such timing configuration guaranteed capturing GRF fully supported by the force plates. A GRF normal force threshold of 50 N was set to detect the heel strike and toe off events on those two force plates that defined the time interval used for estimating the carrying load. Trials where the subject did not step on all six force plates consecutively were not considered in the analysis.

We summed the normal GRF measurements of all the force plates and applied second-order Butterworth filter with a 1 Hz cut-off frequency to suppress the effects of body and load dynamics in the GRF signal. Additionally, we computed a continuous average over the last 0.5 s time window of the filtered signal to even further suppress the GRF oscillations due to walking dynamics.

3 Results

3.1 Lifting Event Detection

Estimations of object weight, frequency and duration of the lifting tasks were possible using only the normal component of the GRF measurements and trunk dynamics. Figure 2 shows the results of the estimated lifting load. Compared to the actual load, the average estimated load mass was within 3.9% (5.1 ± 0.5 kg) considering whole body dynamics and within 9.7% (4.8 ± 0.5 kg) considering trunk only dynamics.

Figure 3 shows the results of the lifting frequencies. The calculated average continuous lifting frequencies from the GRF data were both 9.7 ± 1.4 lifts/min

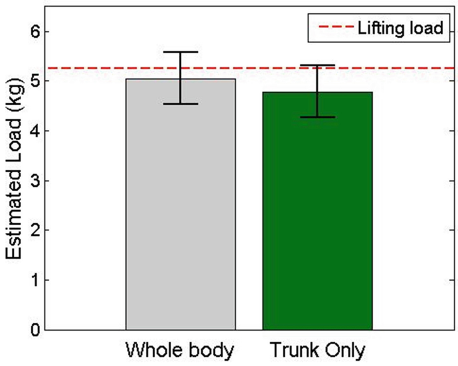


Fig. 2. Estimated lifting load considering whole body dynamics and trunk only dynamics.

considering whole body or trunk only dynamics. Compared to the frequency determined from the box marker velocity data they both deviated less than 0.2%. In addition, we present the instantaneous frequency results ω_i presented as discrete events after each lift. The instantaneous frequency results show greater variations compared to the continuous frequency measurements for both methods. In Fig. 3, we intentionally plot the average lifting frequency over the whole trial as computed in the RNLE (average over 15 min) to show the discrepancies compared to the instantaneous frequency estimation.

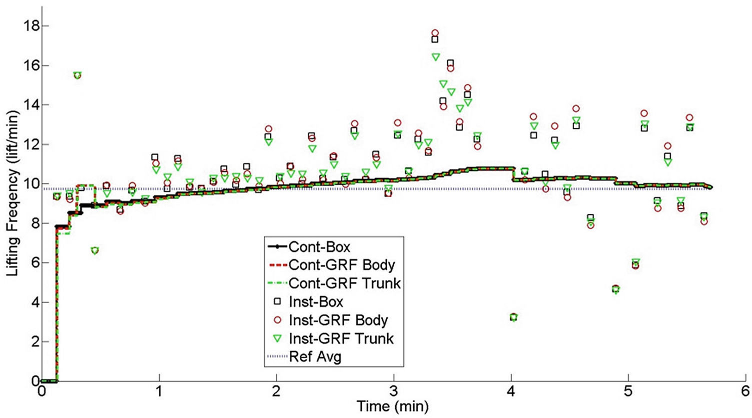


Fig. 3. Estimated lifting frequency results as continuous measurement (lines) and discrete instantaneous values (dots) determined from the box marker position data and GRF considering whole body dynamics or trunk only dynamics. A reference value represents the average lifting frequency during the whole trial.

Figure 4 shows the results of the lifting/lowering durations for the motion capture and GRF data. The average lifting duration estimated from the box marker data was

2.2 ± 0.4 s and was taken as a reference. The lifting durations from the GRF considering whole body and trunk only dynamics were 2.3 ± 0.6 s and 2.5 ± 0.7, respectively, deviating 1.4% and 13.3% from the lifting duration for the box marker data. The results obtained from both methods during fast squat or stoop lifting events show a high correlation, while the lifting durations from GRF data during squatting slow lifts overestimated those obtained from the box marker velocity data. These lifting duration estimates considering trunk only dynamics show greater discrepancies compared to the data considering whole body dynamics.

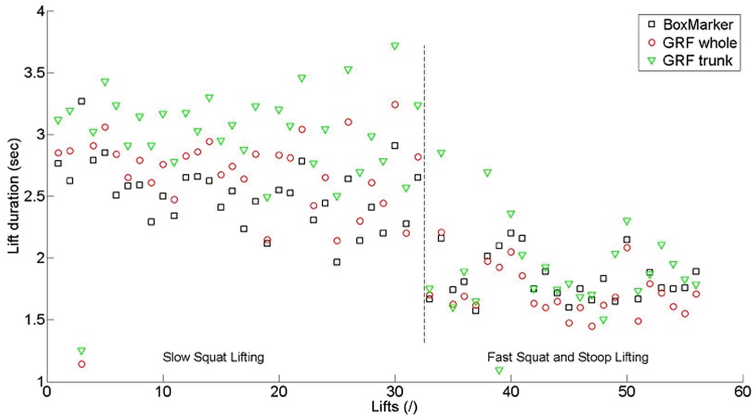
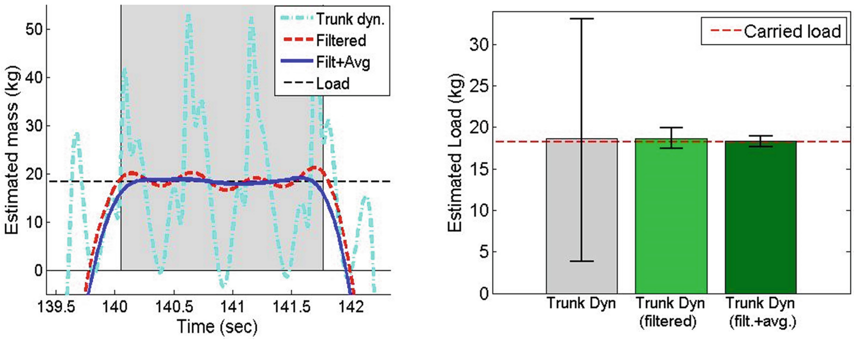


Fig. 4. Estimated lifting duration of an individual lift determined from the box marker position data and GRF considering whole body dynamics or trunk only dynamics.

3.2 Load Carrying

Figure 5(a) shows the results of three individual signals of continuous carried load estimations for a representative trial considering the subject's body mass and trunk dynamics. The subject mass and trunk dynamics subtracted from the initial signal shows large oscillations indicating a larger contribution of limb and heavy carrying load dynamics. After applying filtering and averaging the signal, our estimation closely matches the actual load mass. The average load estimation results of the initial, filtered and averaged filtered signals during the carrying event are 18.4 ± 14.6 kg, 18.7 ± 1.2 kg and 18.3 ± 0.6 kg, respectively, see Fig. 5(b). The mean load estimations of all three signals accurately estimated the actual load, however, the large standard deviation of the initial signal makes it impossible to use for instantaneous and continuous load estimation. The standard deviation decreases with the applied signal filtering and averaging which provides instantaneous and accurate information about the carrying load during the entire carrying duration (1.6 s–4 steps).

We further confirmed the results by comparing the estimations considering trunk only and whole body dynamics. Figure 6 shows average load estimation results during load carrying. The mass estimation of the carried load during walking was overestimated by 0.3% (18.3 ± 0.6 kg) considering whole body dynamics and underestimated



(a) (b)

Fig. 5. (a) Comparison of initial, filtered and averaged filtered signals during carrying event (shaded area). (b) Estimated mean and standard deviation of carried load estimation results for a representative lifting trial considering trunk only dynamics.

by 0.2% (18.2 ± 0.6 kg) for trunk only dynamics when compared to the actual carried load mass.

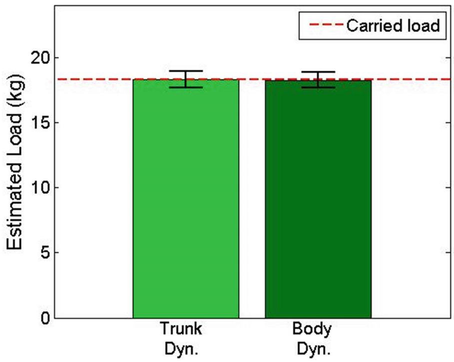


Fig. 6. Estimated average carried load considering whole body or trunk only dynamics.

4 Discussion

The purpose of this paper was to identify lifting events and extract parameters associated with injury risk, such as the weight of an object, lifting frequency and lift duration during MMH. The ability to identify lifting events primarily using GRF data represents an important step towards eliminating the need of motion capture systems used to detect these events. Signal processing of the normal component of the GRF vector, such as filtering and averaging, was necessary to suppress the dynamics of the upper and lower limbs. Processing the GRF signal using low frequency filters smoothens out the signal and allows for reliable extraction of the load information, however it introduces a limitation of not allowing detection of very short lifts or short load carrying events. The recommended duration of detecting lift and carry events when applying a filter with 1 Hz cutoff frequency should not be shorter than 1 s. The detection and load estimation of fast lifting and short carrying events (<1 s) is out of the scope of this paper as it would require the use of different data processing techniques and an additional validation study.

The signal processing parameters were selected based on our primary goal to detect all of the lifting events with 100% accuracy and to achieve the best accuracy of the lifting load estimation as the secondary goal. We tried to maintain the same parameters for lifting load estimations considering whole body and trunk only dynamics for comparison purposes. However, due to the large signal oscillations in the data considering trunk only dynamics, we had to choose a different averaging time interval window between the two to guarantee detection of all of the lifting events.

In our study we used the instantaneous frequencies ω_i as an additional validation of the computed continuous frequency. The results of the instantaneous frequency measurements show greater variations compared to the continuous frequency measurements for both methods. A similar observation was made when comparing to the reference frequency value. These observations show the importance of the continuous frequency measurements compared to the traditional approaches and suggest that such measurements can be used to improve monitoring of workers during MMH to obtain more complete exposure information.

An interesting observation from the study was also that the estimated lifting durations of the slower squat lifts at the beginning of the trial were largely overestimated compared to the faster, jerky and stoop lifts at the end of the trial. Potential reasons for the overall overestimations could lie in how the GRF signal was filtered and averaged. More accurate event detection and duration estimation of the faster lifting events could be due to greater instantaneous force generation, since we used a force threshold-based approach.

The limitations of this study include a small sample size and handling a single object during lifting and carrying. Further testing is required to identify the minimum weight of an object that the algorithm can reliably detect. We speculate, that for the average population, the performance of the algorithm's load estimation would improve, since the weight of the subject in our study was well above the average male. A lower subject's weight would lower the dynamics contributions from the limbs and would result in proportionally smaller GRF oscillations. Consequently, the algorithm would be more sensitive to the object weight and provide improvements in the load estimation.

The importance of the results in this paper lies in being able to sufficiently estimate risk parameters using a reduced number of measurements. Identifying the minimum number of sensors that still provide sufficient accuracy is particularly important and desirable for practical applications. Future work will use these results to develop a wearable system to track exposure to lifting related hazards and improve risk estimates during MMH.

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