Automated Video Exposure Assessment of Repetitive Hand Activity Level for a Load Transfer Task

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Objective: A new method is described for automatically quantifying repetitive hand activity with the use of digital video processing.

Background: The hand activity level (HAL) is widely used for evaluating repetitive hand work. Conventional methods involving either a trained observer on- or off-site or manual off-site video analysis are often considered inaccurate, cumbersome, or impractical for routine work assessment.

Method: A cross-correlation-based template-matching algorithm was programmed to track the motion trajectory of a selected region of interest across successive video frames for a single camera to measure repetition frequency, duty cycle, and HAL. A simple, paced, load transfer task was used to simulate a repetitive industrial activity. A total of 12 participants were videoed performing the task for varying HAL conditions. The automatically predicted HAL was compared with the manually measured HAL with the use of frame-by-frame video analysis.

Results: Predicted frequency, duty cycle, and HAL were in concert with the manually measured HAL conditions. The linear regression slopes of the automatically predicted values with respect to the manually measured values were 0.98 (R^2 = .79), 1.27 (R^2 = .63), and 1.06 (R^2 = .77) for frequency, duty cycle, and HAL, respectively.

Conclusion: A proof-of-concept for automatic video-based direct exposure assessment was demonstrated.

Application: The video assessment method for repetitive motion is promising for automatic, unobtrusive, and objective exposure assessment, which may offer broad availability with the use of a camera-enabled mobile device for helping evaluate, prevent, and control exposure to repetitive motions related to upper-extremity injuries in the workplace.

Keywords: biomechanics, hand activity level, repetitive motion, upper extremity injuries, work-related musculoskeletal disorders

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INTRODUCTION

Upper-extremity injuries are prevalent in repetitive hand-intensive work (Fan et al., 2009; Harris, Eisen, Goldberg, Krause, & Rempel, 2011; Hegmann et al., 2009; Silverstein et al., 2010). A variety of observational and self-report methods are available to help assess exposure to repetitive hand motion (Burt & Punnett, 1999; Garg & Kapellusch, 2009; Homan & Armstrong, 2003; Ketola, Toivonen, & Viikari-Juntura, 2001; Paquet, Punnett, & Buchholz, 2001; Spielholz, Silverstein, Morgan, Checkoway, & Kaufman, 2001). Instruments for direct measurement are also available (Buchholz & Wellman, 1997; Jonsson & Johnson, 2001; Marras & Schoenmarklin, 1993; Marshall, Mozrall, & Shealy, 1999; Schoenmarklin & Marras, 1993).

A commonly employed observational method for quantifying the degree of repetition is the Hand Activity Level (HAL), which is based on the 10-point visual-analog scale originally proposed by Latko et al. (1997). It is one of the factors in ascertaining the threshold limit value (TLV) for repetitive manual tasks (American Conference of Governmental Industrial Hygienists [ACGIH], 2009). The HAL scale (Figure 1) quantifies repetitive motion, ranging from *idle hand activity* (0) to *rapid steady motion with difficulty keeping up* (10). The degree of repetition can be determined by a trained observer using the scale in Figure 1 or a table of objective measurements of frequency and duty cycle from stopwatch time study or frame-by-frame video analysis.

HAL is based on duty cycle and exertion frequency. For many tasks, these measures are associated with hand and arm movements and static exertions. The frequency is the rate of repetition in cycles per second or Hz. The duty cycle is the percentage ratio of hand exertion time to the total cycle time of the activity (i.e., exertion time/cycle time). Consequently, a 100% duty cycle refers to repetitive work whereby force is exerted for the entire time, and a 50% duty cycle occurs when force is exerted half of the time.

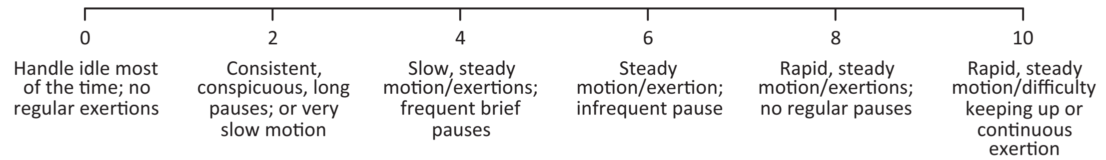

Figure 1. Hand Activity Level visual-analog scale (Latko et al., 1997).

Several researchers have attempted to automate the analysis of repetitive motion measurement in the workplace (Bhattacharya et al., 1999; Person, Hodgson, & Nagy, 2001). Spectral analysis of electrogoniometer data was proposed as an efficient method for quantifying repetitive joint motions that agreed closely with, and was more precise than, observational or frame-by-frame analysis (Juul-Kristensen, Hansson, Fallentin, Andersen, & Ekdahl, 2001; Radwin & Lin, 1993; Yen & Radwin, 2000). Radwin, Lin, and Yen (1994) devised an approach analogous to a sound level meter using frequency-weighted filters based on psychophysical data for equivalent discomfort levels resulting from instruments measuring repetitive wrist movements of different amplitudes and frequencies (Lin & Radwin, 1998a, 1998b; Lin, Radwin, & Snook, 1997).

Direct measurements have been mostly limited to research studies, and both observations and direct measurements are often considered impractical for routine industrial analysis. Compared with instruments, observation is noninvasive but lacks precision and accuracy, is not suitable for long observation periods, and requires considerable analyst time (Lowe, 2004). Alternatively, attaching sensors on working hands is time-consuming (Yen & Radwin, 2000), and sensors may interfere with normal working operations. Not only is instrumentation use resource intensive, but the required technical knowledge often makes this approach inaccessible to general industry. Considering these limits, the protocols for the National Institute for Occupation Safety and Health multi-institutional musculoskeletal research consortium mostly involved indirect observational data related to motion and exertions (Garg & Kapellusch, 2009).

In this article, we describe a new approach that involves digital video processing for automatically measuring repetitive motion exposure with the HAL metric. A direct video assessment method has several advantages to commonly used observational and instrumentation methods: It is objective, can automatically perform the analysis in real time, requires minimum human intervention, and is determinate for a given video segment.

Despite advancements in image processing, there are no previous developments that address automatic video analysis of repetitive hand activity for occupational health and safety assessment. Related bodies of work are rooted in video tracking and, more recently, vision-based control. Traditional methods used for tracking monocular image sequences normally require prior knowledge of a scene (Frade, Marroquin, Perez, & Moreno, 1997) or complex stochastic cues of the foreground-background model (Sidenbladh & Black, 2001). Similar assumptions are impractical and unacceptable for our purposes since the background activity of occupational settings is usually very busy and, depending on the workplace, may vary considerably. Furthermore, the computational complexity of a stochastic model is high and is not ideal for real-time mobile computing, for which low-power signal processors are needed.

Some previous video-based cyclic motion analysis methods (Allmen & Dyer, 1990) require complex analysis and recovery of spatiotemporal (ST) surfaces and ST curves for different scale space. Tsai, Shah, Keiter, and Kasparis (1993) present an approach to performing cycle detection using autocorrelation and Fourier transform techniques. The approach we developed is made practical by relaxing the need for the high precision normally important for ST motion tracking of joints and body linkages, by emphasizing temporal patterns, and by adopting a semiautomatic approach whereby

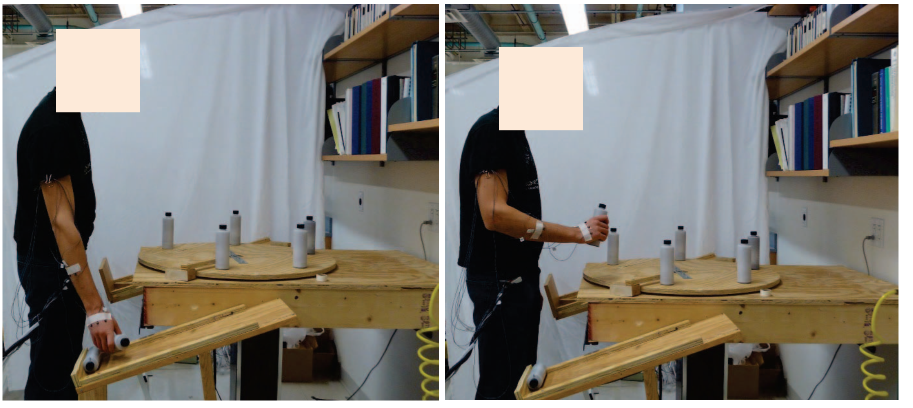

Figure 2. Laboratory repetitive motion task in which a participant gets loaded bottles from the tray (left) and moves them onto the turntable (right).

the analyst uses human discretion to interactively select a region of interest associated with the repetitive task, such as a hand or arm, to track rather than imposing an a priori model of the tracked activity.

We propose an algorithm that operates by identifying and tracing the pixel pattern that best resembles the selected region of interest as it changes location in successive video frames. The velocity of this pixel area, relative to a stationary pixel region, is used to estimate the rate of repetition and pauses needed to calculate HAL. Consequently, the analysis complexity is greatly reduced and may be more tolerable of the numerous variations encountered in field video recordings of occupational tasks.

METHOD

Participants

We recruited 12 young, healthy volunteers from within the University of Wisconsin–Madison. Their ages ranged from 18 to 32 years. There were 6 males and 6 females, all right-hand dominant, except 1 male. Before each session was scheduled, we conducted a short phone prescreening to help qualify candidates to ensure that they did not have any ongoing hand or elbow injuries that could prevent them from gripping and transferring weighted bottles for 1 hr. They were also asked to report basic demographic information. The protocol was reviewed and approved by the Institutional Review Board of University of Wisconsin–Madison prior to participant recruitment, and all participants provided informed consent.

Apparatus and Experimental Procedures

We implemented a laboratory mock-up of a simple load transfer task to simulate repetitive motion activities typically performed in an industrial setting (Figure 2). The loads were equally weighted plastic bottles filled with calibrated quantities of lead shot. The apparatus consisted of a 6-RPM turntable, driven by an electric motor, attached to a chute for the weighted bottles to drop into. The task involved reaching with the right hand for a weighted bottle (2.2 N) in a dispenser located at the end of a chute, grasping and moving it to the turntable, and continuously repeating the operation after the bottles returned to the chute. We paced the repetition frequency and duty cycle to achieve various levels of hand activity.

Each participant was required to perform seven paced tasks in one single session. Participants were given a practice period to become familiar and proficient with the pace. Each task contained 10 to 60 cycles and lasted 60 s to 200 s, depending on the specific condition. We provided 2 min of rest in between experimental conditions to prevent fatigue. The seven paced tasks that were performed in the laboratory varied in repetition frequency (Hz)

TABLE 1: Frequency and Duty Cycle Settings for Each Hand Activity Level (HAL) Condition

Frequency (Hz)	Duty Cycle (%)	Paced HAL	HAL by Equation (1)
0.125	25	1	0.1
0.250	10	2	2.1
0.250	20	2	2.4
0.500	20	4	3.7
0.500	30	4	4.1
0.500	50	5	4.7
1.000	50	5	5.4

and duty cycle (%) to produce HALs between 1 and 5. The frequency and duty cycle experimental conditions are described in Table 1.

A three-tone set of audio cues was used for pacing the task. The first tone signaled the participant to reach, grasp, and move the bottle from the dispenser to the turntable. The second tone signaled the participant to return the hand to the rest position. The third tone signaled the start of a rest period, during which the participant was instructed to remain at rest until the cycle repeated. Note that for the 50% duty cycle condition (HAL of 5), only two tones were used since there was no rest period in between cycles.

A JVC Everio GZ-MS230BUS video camera was positioned on the right, 3 m away from the participant. Each experiment was videoed and stored as a single MPEG video file with 720 × 480 resolution at the frame rate of 30 frames per second. The videos were each processed by the video algorithm, and HAL was calculated on the basis of the movement frequency and duty cycle. We also analyzed each video manually frame by frame using Multimedia Video Task Analysis™ (MVTA) software to measure the cycle time (i.e., 1/frequency) and hand exertion time to compute frequency, duty cycle, and HAL.

The automatic video algorithm measurements were compared against similar observationally measured properties. We timed the motions observed in each video clip using frame-by-frame analysis with the MVTA software tool. The analyst reviewed the videos and manually measured repetition frequency and duty cycle by annotating cyclic motions on a frame-by-frame basis.

A cycle in the laboratory task was defined by the elements (a) reach for a bottle, (b) grasp and move bottle, (c) release bottle and return to the starting position, and (d) rest (Figure 3). For this particular task, cycle time was the time elapsed between each repetition cycle (i.e., start of Element 1, reach for a bottle). Hand exertion time was the time elapsed between grasping a load and releasing it (i.e., Element 2, grasp and move bottle).

The HAL was estimated as a linear combination of the frequency of the movement time ($1/f$) and the duty cycle (D) according to the equation

$$\text{HAL} = 4.31 - 0.637 \times (1/f) + 0.034 \times D. \quad (1)$$

If the equation returned a negative HAL, the level was considered zero. The equivalent HAL values for corresponding combinations of frequency and duty cycle according to the HAL TLV (ACGIH, 2009) are included with the HAL values from Equation (1) in Table 1. We processed all 84 videos using the automated video analysis framework and manually using MVTA to measure the actual frequency and duty cycle. To reflect the true algorithm performance, the HAL values were not rounded to the nearest integer.

Video-Tracking Algorithm

An algorithm was programmed in C# with the open-source OpenCVSharp (.Net wrapper for the OpenCV) vision library. We initialized the cross-correlation-based tracking algorithm by designating a rectangular region of interest

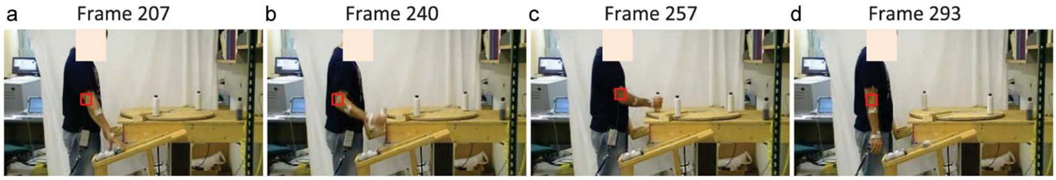

Figure 3. Selected video frames illustrating the task cycle: (a) reach for a bottle, Frame 207; (b) grasp and move bottle, Frame 240; (c) release bottle and return to the starting position, Frame 257; and (d) rest, Frame 293.

(ROI) on the upper limb to select the focal area on the hand or arm. The template-matching tracking algorithm tracked the ROI motion trajectory across successive video frames. A cyclic motion analysis algorithm estimated the movement time on the basis of zero crossings of the ROI relative to a stationary gating region.

To elaborate, we denote $\mathbf{r}_i$ to be a vector of intensity values of all pixels within the ROI at the ith frame and $\mathbf{r}_{i+1}(w)$ to be a candidate ROI at the $(i + 1)$th frame with a displacement of $w \in \Omega$ in a prespecified search area. Ω is determined on the basis of prior knowledge of the speed of arm movement (pixels per frame). The cross-correlation between $\mathbf{r}_i$ and $\mathbf{r}_{i+1}(w)$ is defined as the angle between these two vectors ($\|\mathbf{r}_i\|$ is the magnitude of the vector $\mathbf{r}_i$, $\mathbf{r}_i^T$ is the transpose of $\mathbf{r}_i$):

$$R(w) = \mathbf{r}_i^T\mathbf{r}_{i+1}(w) / \|\mathbf{r}_i\| \cdot \|\mathbf{r}_{i+1}(w)\|. \quad (2)$$

The displacement $w^* = \text{arg. max.}_W R(w)$ determines the updated position of the ROI at the $(i + 1)$th frame, $\mathbf{r}_{i+1} = \mathbf{r}_{i+1}(w^*)$. The sequence of w^* is recorded as the ROI displacement between these two frames, and the new position of the ROI yields the motion trajectory at the $(i + 1)$th frame.

In this design, our approach for computing the cycle time was to monitor the crossing of the moving ROI and a stationary gating region in the video frame. A cycle was defined as the time elapsed between consecutive gating region crossings from the same direction. The recorded video data pixel location values x_{vid}, y_{vid} were low-pass filtered with the use of a Butterworth filter. The velocity (v_x, v_y) and acceleration (a_x, a_y) vectors at each time stamp were calculated as follows:

$$\begin{aligned} v_{p,i} &= (p_{i+1} - p_{i-1}) / 2\Delta \\ a_{p,i} &= (p_{i+1} - 2 \times p_i + p_{i-1}) / \Delta^2, \end{aligned} \quad (3)$$

where $p \in \{x, y\}$, $i \in \{2, 3, \ldots\}$, and $\Delta = 1/30$ s, which is the sample rate of the video. The video velocity and acceleration magnitude were determined by the following:

$$\begin{aligned} v_{xy,\,video} &= \sqrt{(v_x)^2 + (v_y)^2} \\ a_{xy,\,video} &= \sqrt{(a_x)^2 + (a_y)^2} \end{aligned}. \quad (4)$$

An algorithm was developed to automatically detect when the hand was loaded on the basis of velocity and acceleration of the ROI. It was observed that the peak ROI acceleration was greater when participants were moving the load than when they were reaching and resting. This finding is illustrated by the histogram in Figure 4. A representative single-cycle velocity and acceleration curve from the video analysis is illustrated in Figure 5. The period between two consecutive local minima points on the velocity curve was considered loaded if more than one point on the acceleration curve exceeded a threshold value. The hand was considered still loaded if more than one acceleration point exceeded threshold for the adjacent pair of local minima (see Figure 5). The duty cycle D was then calculated as the average time when hand was loaded divided by cycle time. In our experiment, the threshold value was arbitrarily set by trial and error to the 85th percentile acceleration when the tracked ROI was in motion (see Figure 5).

To further comprehend the algorithm used to determine when the hand is loaded, refer to

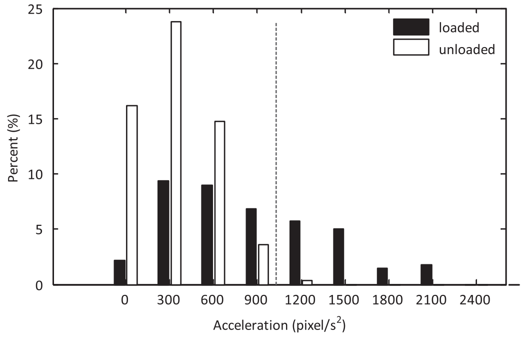

Figure 4. Histograms for acceleration corresponding to the example in Figure 5. The dashed vertical line represents the acceleration threshold used as criterion for a loaded hand.

the example in Figure 3. The small red square represents the tracked ROI, which contains approximately 900 pixels (30 × 30). The stationary gating region was selected near the bottle dispenser. The local minima on the velocity curve are labeled 1 through 11 in Figure 5. The algorithm compares two consecutive local minima points sequentially and determines when the hand was loaded on the basis of the criteria described earlier. In the example shown in Figure 5, the algorithm detected that the hand was not loaded between local minima pairs 1-2, 2-3, and 3-4, whereas the hand was loaded between local minima pairs 4-5 and 5-6.

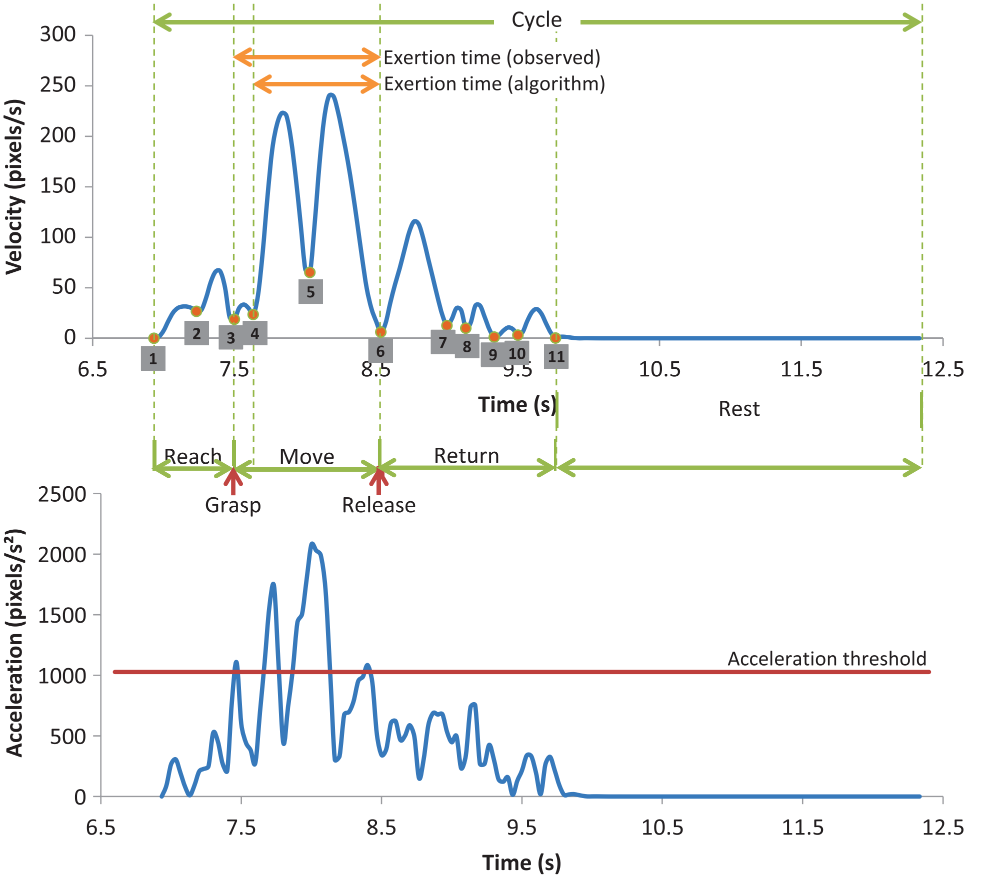

Figure 5. Representative single-cycle velocity and acceleration plots for the laboratory load transfer task. The exertion time is the period in which the load is grasped, moved, and released, and the cycle time is represented by the task period determined by the video-tracking algorithm.

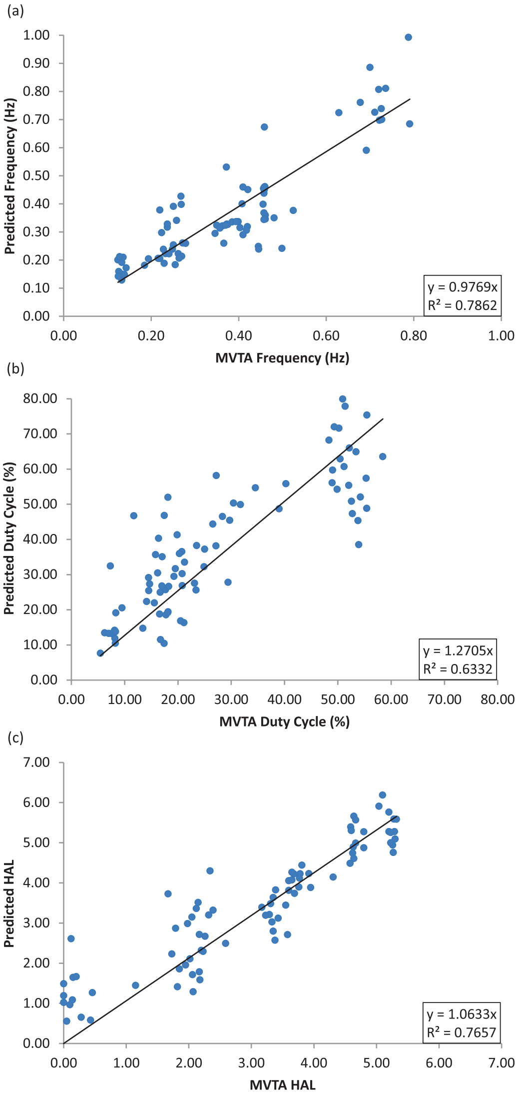

Figure 6. Algorithm-predicted result compared with MVTA manually measured result, showing (a) frequency, (b) duty cycle, and (c) hand activity level (N = 84).

RESULTS

The automatically predicted frequency, duty cycle, and corresponding HAL were estimated for the duration of each video clip and are plotted against the corresponding manually measured MVTA values in Figure 6. A linear regression line was estimated with the intercept set to 0. The slopes of these three plots were 0.98 (R^2 = .79), 1.27 (R^2 = .63), and 1.06 (R^2 = .77) for frequency, duty cycle, and HAL, respectively.

Summary statistics for predictions of HAL, frequency, and duty cycle are provided in Table 2. Averages are among the 12 participants for each HAL condition.

DISCUSSION

For the two paced conditions whereby HAL = 2 (0.25 Hz from Table 1), the difference between the average observed frequency and the paced frequency ranged from 0 Hz to 0.03 Hz, respectively. For a paced HAL = 3, 4, and 5 (0.5 Hz from Table 1), the differences between the average observed frequency and the paced frequency ranged from –0.2 Hz to –0.07 Hz. When HAL = 5 (1 Hz from Table 1), the difference was –0.24 Hz.

Although the aforementioned comparison seemed reasonable as a group, it does not fully account for individual variability. During the experiment, we found that each person responded somewhat differently to the audio cues, despite the fact that they were given the same oral instructions and same amount of practice period. Individuals also responded differently when dealing with fast and slow pacing.

The average predicted HAL was closest to the paced HAL when HAL exceeded 1. In the case of paced HAL = 1, the duty cycle was underestimated and the frequency was overestimated, resulting in higher predictions (Figure 4). This result was mainly attributable to the selection of the velocity magnitude threshold. For low HAL conditions, movement speed within the video frame was small. The slow movement speed was filtered out by the predefined threshold, which lowered the estimation of active time (hand motion time) and hence resulted in higher estimates of frequency.

Occlusion and disappearance of the ROI also pose challenges. When a hand is occluded by a foreign object, the video tracking may fail and the region being tracked may be "hijacked" by the foreign object. Self-occlusion is also possible when the person turns against the camera and therefore the hand region may be occluded by the body. Disappearance of the hand and arm is also possible, since the person shooting the video may underestimate the job activity region.

TABLE 2: Averages According to Automated Video Analysis

Paced HAL	HAL by Equation (1)	Predicted HAL	Frequency (Hz)	Duty Cycle (%)
1	0.1	1.2 (0.55)	0.17 (0.03)	23.97 (10.81)
2	2.1	2.1 (0.74)	0.25 (0.07)	15.30 (6.11)
2	2.4	2.9 (0.63)	0.28 (0.07)	29.48 (10.50)
4	3.7	3.2 (0.36)	0.30 (0.04)	31.58 (5.47)
4	4.1	4.1 (0.20)	0.37 (0.07)	45.06 (9.15)
5	4.7	5.0 (0.44)	0.43 (0.09)	64.80 (9.96)
5	5.4	5.4 (0.41)	0.76 (0.10)	56.74 (11.32)

Note. Standard deviations shown in parentheses. HAL = hand activity level.

When the hands reach beyond the field of view of a camera, there is a great chance that the tracking system will fail. Camera motion causes undesired video input, such as a blurry image and temporary disappearance of the ROI.

In practice, selection of a ROI that minimizes disappearance is highly dependent on the specific task, work layout, camera location, and other workplace conditions. Our methodology requires the analyst to carefully identify the specific location of the ROI on the body—whether it is hand, forearm, arm, or shoulder—by pinpointing a body part that is directly related to the hand-arm motion and is visible to the camera. In many cases in actual workplace conditions, these measures by themselves may be insufficient to fully eliminate disappearance. The camera angle and location are additional considerations. In future research, we will study the magnitude of these limitations and strategies for minimizing their effects.

To address these problems through image processing, it is crucial that the tracking system make use of the past trajectory history. By incorporating a suitable statistical state transition model, such as the Kalman filter, we may be able to predict the new ROI position. This predicted new position will be used as the reference position for the next tracking cycle. Every iteration, the state model location is updated and corrected to maintain the accuracy of the prediction.

One way to compensate for camera motion is to track background patches or strong corner points, in addition to tracking the ROI. The motion of these patches or corners can be averaged together and can provide an estimate of the camera motion (Adams, Gelfand, & Pulli, 2008). Another way to estimate camera motion is to obtain help from devices such as a gyroscope or accelerometer, which provides the orientation and motion information of the camera. The estimated camera motion information can later be used to correct the hand displacement quantity and to provide better estimates of the HAL value.

Different camera locations and angles can impose further limitations on the current method. One most obvious constraint is that when the participant is viewed from one side, the contralateral side is occluded by the body. Currently, our method has been tested in the laboratory for a task that was limited in field-of-view changes. We are investigating how the threshold selection affects the performance of the HAL estimates and whether additional variables, such as patch size, should be incorporated in the threshold selection process.

The measured velocity and acceleration in the two-dimensional video may be affected by participant movements outside of the plane. Different camera angles may also affect algorithm performance, including parallax, and this issue will be assessed and addressed in future studies. In future research, we will consider repetitive tasks that vary in body movements, directions, and exertions. The effect of ROI selection on HAL estimates based on various limb segments is another area of future research. Future improvements to the algorithm will involve a systematic method for differentiating between the active and inactive portion of a cycle. Currently, the threshold values were determined by experience and trial and error and were specific to the laboratory repetitive motion task performed in this study.

The ACGIH TLV involves measurements of normalized peak force in addition to HAL for assessing exposure limits. HAL is strictly related to frequency of motion and duty cycle. Exertions, whether static or dynamic, are independent of HAL and are considered separately in the TLV in the measurement of exertion levels. The methodology is limited to coordinated motions that are observed in the video recording, and hand exertions that may not be visible are not measured. The algorithm and the results of this study were limited to one particular load transfer task described in this proof-of-concept study. This study provides a starting point by which similar algorithms can be developed for other tasks. The algorithm has not yet been tested in alternative tasks, such as using a computer keyboard, or jobs that involve prolonged static postures. The algorithm does not measure static exertions, whereby forces are made without movements. For example, if an individual gains control of an object and then continues to grip it without motion, the action would extend the work time, the cycle time, and the duty cycle. In the future, researchers should address exertions and account for these types of activities.

For the task in this study, the peak ROI acceleration was greater when moving the load than when reaching and resting. This observation was used to segment the cycle. It is likely that other criteria might be needed (other than peak acceleration) for different tasks. Algorithms for detecting exertions based on ROI kinematics need to be further evaluated and developed and will be the subject of future research. In the current experiment, the threshold value was arbitrarily set to the 85th percentile acceleration when the tracked ROI was in motion. A general acceleration threshold algorithm should be developed for duty cycle detection. The method used in the current study sufficed for proof-of-concept purposes.

We conclude that the video-based direct exposure assessment method shows promise. The use of markerless video is unobtrusive and does not require attaching sensors to the bodies of workers, which often interferes with the job and, possibly, movement patterns and exertions. Furthermore, such an application might be ported to programmable, camera-enabled mobile devices, which could lower the instrumentation barrier and make routine analysis of upper-limb work-related occupational hazards more accessible to general industry.

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KEY POINTS

- The method is semiautomatic, whereby the human analyst interactively selects a region of interest associated with the repetitive task to track, rather than imposing an a priori model of the tracked activity.
- The markerless video algorithm emphasizes temporal patterns, rather than high precision normally important for spatiotemporal motion tracking, for measuring frequency of movements.
- Exertion time is estimated from video by the identification of changes in kinematic properties when a load is moved for duty cycle measurements.
- The approach is objective, unobtrusive, does not require attaching sensors to the body of workers, and suitable for a real-time, direct-reading exposure assessment instrument for hand activity level.

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