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Visualizing stressful aspects of repetitive motion tasks and opportunities for ergonomic improvements using computer vision

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A R T I C L E I N F O

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A B S T R A C T

Patterns of physical stress exposure are often difficult to measure, and the metrics of variation and techniques for identifying them is underdeveloped in the practice of occupational ergonomics. Computer vision has previously been used for evaluating repetitive motion tasks for hand activity level (HAL) utilizing conventional 2D videos. The approach was made practical by relaxing the need for high precision, and by adopting a semi-automatic approach for measuring spatiotemporal characteristics of the repetitive task. In this paper, a new method for visualizing task factors, using this computer vision approach, is demonstrated. After videos are made, the analyst selects a region of interest on the hand to track and the hand location and its associated kinematics are measured for every frame. The visualization method spatially deconstructs and displays the frequency, speed and duty cycle components of tasks that are part of the threshold limit value for hand activity for the purpose of identifying patterns of exposure associated with the specific job factors, as well as for suggesting task improvements. The localized variables are plotted as a heat map superimposed over the video, and displayed in the context of the task being performed. Based on the intensity of the specific variables used to calculate HAL, we can determine which task factors most contribute to HAL, and readily identify those work elements in the task that contribute more to increased risk for an injury. Work simulations and actual industrial examples are described. This method should help practitioners more readily measure and interpret temporal exposure patterns and identify potential task improvements.

1. Introduction

Occupational ergonomics job analysis for hand-intensive repetitive manual tasks is rooted in the industrial and systems engineering approach, derived from traditional work measurement and time and motion study involving the systematic breakdown of tasks into their constituent elements (Armstrong et al., 1986; Dempsey and Mathiassen, 2006). This approach is central for work designers and engineers because it inherently relates specific aspects of the job to the risk factors of physical stress exposure for controlling their undesirable effects, including onset of fatigue or an injury. A limitation of this approach is that it is often subjective and time intensive for the analyst.

The development of quantitative upper extremity job assessment instruments and tools for evaluating physical stress exposure and associated risk, however, often trades quantification of risk for the ability to directly identify specific job elements that contribute to the risk of injury, thus making it difficult for designers and engineers to identify the most hazardous job attributes and opportunities to apply interventions for reducing or eliminating the risk. Such instruments include the American Conference of Governmental Industrial Hygienists (ACGIH® Worldwide, 2001) Threshold Limit Value® (TLV®) for Hand Activity Level (HAL), and the Strain Index (Moore and Garg, 1995), to name a few. Parameters involved in such instruments typically include evaluation of frequencies, duty cycles and speed of movements.

Conventional job analysis involves either observations or sometimes measurements using instruments attached to a worker's hands or arms. Observational exposure assessment is convenient, but is considered subjective, inaccurate, unreliable (Brodie and Wells, 1997), and subject to considerable intra- and inter-observer variability (Bao et al., 2009). Furthermore, observational methods are not well-suited for evaluating temporal exposure patterns such as duration and frequency (Wells et al., 2007),

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especially for long-term viewing or for quantifying risk factor interactions, relying on tedious frame-by-frame video data extraction.

Kazmierczak et al. (2006) studied the agreement between observers analyzing assembly work patterns from video and found that although there was good overall agreement on the proportion and duration of activities, observers disagreed substantially on the results for a particular video recording. Disagreement between two observers on the time history of activity categories showed notable differences. Instruments offer more accuracy and precision, but are often cost prohibitive, unsuitable for the workplace environment, invasive and interfere with operations, difficult to interpret and require technical expertise, and are impractical for routine applications by occupational health and safety professionals in industry who have limited time and resources at their disposal (David, 2005).

Video has become an indispensable tool in ergonomics practice. The advent of video technology has greatly facilitated this approach and has allowed engineers, and often the workers themselves, an opportunity to observe and review the tasks in slow motion or one frame at a time in order to identify the hazards and opportunities for ergonomics improvements. A survey of Certified Professional Ergonomists conducted by Dempsey et al. (2005) reported that not only was a video camera the most used basic tool (96.1%), it was rated “very useful” by most (68%) of the participants, only second to a tape measure.

Computer vision has impacted a diverse field of applications, ranging from industrial robotics, intelligent and autonomous vehicles, security surveillance, manufacturing inspection, and human-computer interaction. Furthermore, digital imaging technologies are advancing ever smaller in size, finer in granularity, and faster in processing, while becoming less expensive and thus more accessible to businesses, organizations, and individuals in devices such as smart phones and tablets. New computer vision methods are now being researched and developed for occupational ergonomics applications. It is anticipated that these new tools will profoundly impact the future of occupational ergonomics and provide a variety of new instruments and techniques for design, analysis and evaluation in the practice of ergonomics.

Our laboratory at the University of Wisconsin-Madison is using computer vision for evaluating repetitive motion tasks for hand activity level (Chen et al., 2013), time and motion, duty cycle and maximum acceptable exertions (Akkas et al., 2016), and skill acquisition (Glarner et al., 2014; Azari et al., 2016), utilizing conventional 2D videos. The approach we developed is made practical by relaxing the need for high precision, and by adopting a semi-automatic approach whereby the analysts interactively selects a region of interest such as a hand or arm to track relative to a stationary region, rather than imposing an a priori model of the tracked activity (Chen et al., 2014). Consequently, the analysis complexity is greatly reduced and more tolerable of the numerous variations encountered in field video recordings of occupational tasks.

In this paper, a new method for visualizing task factors comprising HAL using computer vision is demonstrated. This method displays the spatiotemporal characteristics of task factors for the purpose of identifying patterns of exposure as well as suggesting task improvements. The technical principles for capturing video and deconstructing and displaying the frequency, speed and duty cycle components of tasks that are part of the TLV for hand activity from the tracked hand kinematics are first described. Then visualization techniques used to create displays for the ergonomics analyst to identify patterns of exposure associated with the specific job factors are described. Finally examples are provided using work simulations and actual workplace applications.

2. Methods and results

2.1. Nomenclature and video coordinate system

The method utilizes conventional video of a worker performing a repetitive task. Video segments are selected that contain a clear view of the hands throughout the task, made from a viewpoint aligned with the plane of motion, and contain stable camera movement. A cross-correlation template matching algorithm is used to track the worker's hand while performing a repetitive task. A region of interest (ROI) centering on the hand is indicated by the analyst to initialize the marker-less video tracking algorithm, which is fulling described in Chen et al. (2014). The ROI location is tracked for each video frame using the algorithm. The result is a time series of points tracking the motions of the hand across the video clip.

The coordinate system used in this paper is shown in Fig. 1. For each video frame i of the N frames in a video segment, the algorithm calculates the horizontal location (x_i) and vertical location (y_i) of the center of the ROI within the video frame in pixels, and calculates speed for each frame.

The ROI speed was calculated using the equation:

$$S_i = \frac{r}{2} * \sqrt{(x_{i+1} - x_{i-1})^2 + (y_{i+1} - y_{i-1})^2} \ \frac{pixels}{second};\ 2 \le i \le N-1,$$

where r is the video frame rate (typically 30 frames per second), and N/r is the period (seconds) of a video frame. Associated with each (x_i, y_i) is a label of *exertion* $e_i \in \{0, 1\}$. $e_i = 1$ indicating if the hand location at the *i*th frame is part of an exertion, and $= 0$ otherwise. This label was obtained manually using MVTA software (Yen and Radwin, 1995) for the purposes of this analysis. The sequence $\{e_i;\ 1 \le i \le N\}$ consists multiple cycles of consecutive 1's followed by consecutive 0's, representing the when exertions are made by the worker during the task. The total number of exertions during the entire video clip is denoted by *M*. Ideally, with periodic hand movements, the duration of every cycle should be identical. In practice, however, some variations will occur. Since in one frame the hand movement can only belong to one cycle, the length of the cycle (in units of number of frames) that frame i is in is denoted as T_i. This is also manually labeled in the MVTA software for the current study.

Since speed was measured using the tracking algorithm in pixels per second, it had to be calibrated against physical dimensions. An object of known dimensions was chosen in the video, and the length was measured using the MVTA software. The data was calibrated based on the dimension of an object in the video in relation to its known dimension. When a reference object was not available, the hand breadth was measured in pixels and average hand breadth (9.04 mm for males and 7.04 mm for females) from the 1988 US Army Anthropometry Survey (Greiner, 1991) was used to convert from pixels to millimeters.

2.2. Video parameters

Using the *x*, *y* location and hand kinematics obtained from the video tracking algorithm, we can calculate global statistics for the entire video clip, be defined as follows:

Average exertion frequency (*F*) is:

$$F = \frac{\text{total number of exertion cycles}}{\text{total duration of video clip}} = \frac{M}{(N/r)} = \frac{M \cdot r}{N} \cdot \frac{\text{cycles}}{\text{second}}$$

Duty Cycle (*D*) is:

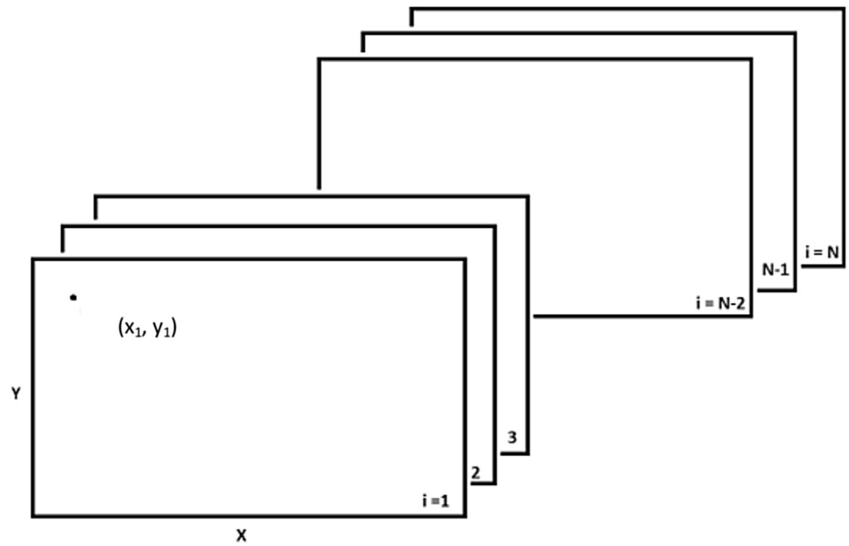

Fig. 1. Video coordinate system. Each video frame {i … N} contains unique pixels (x_i, y_i).

$$D = \frac{100}{N}\sum_{i=1}^{N} e_i$$

RMS exertion speed (S) is:

$$S = \sqrt{\frac{\sum_{i=2}^{N-1}\left(e_i{*}S_i\right)^2}{\sum_{i\in I(x,y)} e_i}}$$

We also defined *localized* versions of these parameters for each pixel location (x, y), that will be used for data visualization. First, we computed the spatial distribution of the ROI trajectory:

$$I(x,y) = \{i|(x_i,y_i) = (x,y), 1 \le i \le N\}$$

where $I(x, y)$ gives the frame numbers when the trajectory passes through the location (x, y). As long as the ROI remains within the video frame:

$$\bigcup_{x,y} I(x,y) = \{i|1 \le i \le N\}$$

With these, we may proceed to define the averaged exertion frequency ($F(x,y)$) in units of cycles per second) as:

$$F(x,y) = r{*}\frac{\left(\sum_{i\in I(x,y)}\frac{e_i}{T_i}\right)}{\left(\sum_{i\in I(x,y)} e_i\right)}$$

Where: $\sum_{i\in I(x,y)} e_i \neq 0$. $F(x, y)$ is the average frequency of those exertion cycles that passes through (x, y). If the origin and destination locations of the hand movement are fixed, a shorter trajectory of exertion may lead to shorter cycle time and hence higher frequency provided the speed remains unchanged. By labelling the trajectory points (x_i, y_i) with $F(x_i, y_i)$, one may visualize the portion of the trajectory where higher exertion frequencies are exhibited. Such a segment of trajectory may represent a short cut of the trajectory. It can be verified that

$$F = \frac{\sum F(x,y){*}\sum_{i\in I(x,y)} e_i}{N}$$

Now we may define a localized version of duty cycle, $D(x,y)$:

$$D(x,y) = \frac{1}{N}\sum_{i\in I(x,y)} e_i$$

It is easily verified that

$$D = \sum_{x,y} D(x,y).$$

Similarly, one may define root mean squared (RMS) exertion speed at a position (x, y) as:

$$S(x,y) = f(x) = f(x) = \begin{cases} \sqrt{\frac{\sum_{i\in I(x,y)}\left(e_i{*}S_i\right)^2}{\sum_{i\in I(x,y)} e_i}}, & \sum_{i\in I(x,y)} e_i > 00, \\ & \sum_{i\in I(x,y)} e_i = 0 \end{cases}$$

Therefore

$$S = \frac{\sum\left(S(x,y)\right)^2{*}\sum_{i\in I(x,y)} e_i}{\sum_{i=2}^{N-1} e_i}$$

These global measurements can be used to measure hand activity level (HAL) using the equation developed by Radwin et al. (2014) for frequency (F) and duty cycle (D):

$$HAL = 6.56 \ln D\left[\frac{F^{1.31}}{1 + 3.18\, F^{1.31}}\right]$$

or the equation developed by Akkas et al. (2015) for speed (S) and duty cycle:

$$HAL = -1.16 + 0.0047S + 0.053D.$$

where $F = \left(\frac{\text{exertions}}{\text{work time}}\right)$, $D = 100\left(\frac{\text{work time}}{\text{work time+rest time}}\right)$, and $S =$ RMS of exertion speed.

2.3. Video parameter visualization

The localized variables are plotted as a heat map distributed over the x-y coordinates that define a video frame. The more intense the color appears in a region, the greater are the values. These heat map plots may be superimposed over the video frame and displayed in the context of the task being performed. Based on the color distribution and intensity of the specific variables used to calculate HAL, we can determine which factors most contribute to HAL for a task, and readily identify those work elements in the task that contribute more to increased risk for an injury.

The adjusted frequency $F_{x,y}$, is the average number of exertions, adjusted by the video frame rate, *r*. We calculate the adjusted frequency in frame i by dividing each exertion state record (e_i) by the period of the cycle in record *i* (T_i). The calculation of $F_{x,y}$ is shown in Fig. 2(a). For each $F_{x,y}$, we take the average of the adjusted frequency for all frames in which the tracked ROI location is *(x, y)*. Plots of $F_{x,y}$ distributed over the video x-y coordinate axes, cross-referenced with a video segment, can be used to identify where certain the aspects of the task contribute to the exertion frequency.

Localized duty cycle $D_{x,y}$ is the percent exertion time at pixel (*x*, *y*) relative to the total task time. We divide the exertion record e_i by the length of the analyzed video segment to obtain the exertion percentage in frame i, which is the ratio of exertion time in this frame, to the length of the video segment. As shown in Fig. 2(b), to calculate the localized duty cycle at location *(x, y)*, we sum up all the exertion percentage of frames in which the tracked ROI location is *(x,y)*. A plot of localized duty cycle distributed over the video *x-y* coordinate axes visualizes how the spatial distribution of exertion time contributes to duty cycle.

RMS exertion speed $S_{x,y}$ is the root mean squared speed when the hand is exerting force in pixel (x, y). In each frame we calculate the instantaneous exertion speed by multiplying the tracked ROI speed by the binary variable of hand state e_i ($1 = $ exertion, $0 = $ rest). As shown in Fig. 2(c), we calculate $S_{x,y}$, the RMS exertion speed at location *(x, y)* by calculating the square root of the mean of squares of all instantaneous exertion speeds of video frames with tracked ROI location of *(x, y)*. A plot of localized RMS exertion speed displays the distribution of speed during hand exertions, across the video *x-y* coordinates, where the color intensity helps identify regions of high exertion speed.

The information extracted from these plots can be used to localize actions in the task that contribute to increased hand activity and potentially identify possible interventions for improving the task. Proposed interventions can be evaluated through the same visualization technique by performing "what-if "analyses. This paper will demonstrate how these visualizations are interpreted and applied using selected representative jobs. Due to the proprietary nature of the jobs studied, the video frames for actual jobs were obscured. We will start out with a laboratory simulation, so that all the aspects of the analysis associated with the job can be demonstrated.

2.4. Examples using a laboratory simulated task

We simulated and videoed packing tasks in the laboratory, and performed the analyses described above. A conveyor belt ran continuously so boxes arrived at a controlled rate. A worker standing in front a work table gets the boxes from the right side, and repeatedly packs them into a crate until it is full. The four steps of packing each box are shown in Fig. 3.

Three packing tasks were selected to demonstrate our method. The setting was identical for all three tasks, while the rate at which the boxes arrived was varied by changing the distance between boxes on the conveyor belt. The arrival time of boxes was the slowest for Task A, and was fasted for Task C. A summary of RMS speed of exertion frequency, duty cycle, and HAL calculated using the frequency-duty cycle equation by Radwin et al. (2014) and speed-duty cycle equation by Akkas et al. (2015) for the three tasks is presented in Table 1.

The kinematics of the ROI was first measured using the video tracking algorithm and then we calculated $F_{x,y}$, $D_{x,y}$, and $S_{x,y}$ for each *x* and *y* location in the video frame. Each of the three local variables $F_{x,y}$, $D_{x,y}$, and $S_{x,y}$ were plotted using the 640 by 480 pixel axes, defined by a video frame.

The high exertion frequency of 0.85 exertions per second for Task C indicates that an opportunity to reduce HAL is by controlling exertion frequency. The adjusted frequency plots for task A, B, C is shown in Fig. 4. The plot for Task C (Fig. 4 c) shows that the color is intense throughout the regions of hand movement and a large portion of that region has an average frequency of approximately 1 exertion per second. This indicates that the exertion frequency was evenly distributed over the region of movement. Consequently, in order to reduce exertion frequency, the overall pace of the job could be reduced.

The localized duty cycle plots for the three tasks are shown in Fig. 5. The plot for task C shows that the region on the upper left of the plot (encircled area) has a deeper color, indicating that the exertion time was more intensely distributed in this region where the hand lifts up boxes from the conveyor belt, as compared against the remaining regions of movement. One way to reduce the duty cycle is to therefore focus on this area where the operator grasps a box and starts moving it to the crate.

Exertion time can be reduced in this area by redesigning the task so that there are less exertions. For example, instead of having boxes arriving at the workstation one after another, two boxes could arrive at the workstation as a group for a lower frequency, and the operator could transfer the pair of boxes rather than one at a time. Since the individual weight of the boxes are not great, this increase in load should not necessarily cause much concern. By performing less exertions in the same amount of time, the ratio of exertion time to total time reduces and therefore duty cycle also reduces. In addition, the reduced number of exertions in the same amount of time, reduces exertion frequency for this task.

The exertion speed plots are shown in Fig. 6. The plot for task C shows that the upper portion of the region of movement where the hand moves to the crate with a box has intense color, indicating that the exertion speed in this area is higher than the rest of the region of movement. We can focus on this area of motion to reduce the exertion speed and therefore reduce HAL for the task. The exertion speed can be reduced by reducing the arrival time between the boxes in order to allow more time to transfer boxes into the crate. The arrival time between boxes are less in tasks A and B, and consequently the color of RMS exertion speed plots (Fig. 6 (a) and (b)) of these two tasks are lighter, as compared with task C.

2.5. Industrial examples

Three tasks were selected having high HAL ratings (HAL > 7) from tasks videoed and analyzed in Harris et al. (2011). An ROI was tracked for the most active hand and a kinematic record of the hand was obtained for these tasks. Each frame of the video segment was labeled as either exertion or rest using MVTA software. The RMS speed of exertion, duty cycle, and exertion frequency was calculated for each video based on this information. A summary of the three videos is presented in Table 2.

The first example (Task D) consisted of an operator getting boxes from a running conveyor belt and stacking them in crates. A plot for the adjusted exertion frequency is shown in Fig. 7(a). The overall color of the region of movement is mostly uniform in distribution,

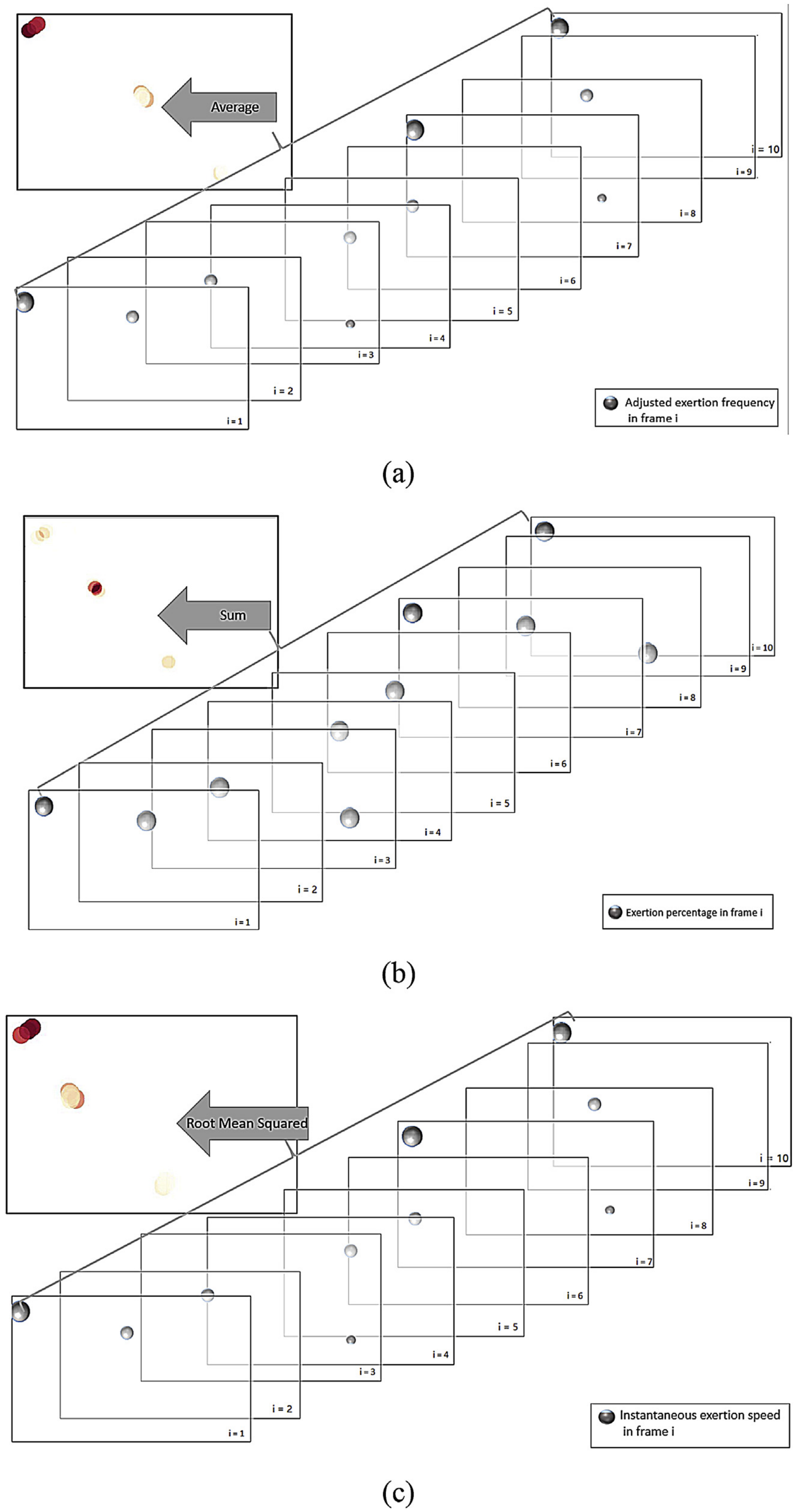

Fig. 2. Calculation of adjusted exertion frequency (a), Local Duty Cycle (b), and RMS Exertion Speed (c) from tracking data.

and the adjusted exertion frequency in these regions are approximately 1 Hz. It indicates a high frequency of exertion in the region of movement, which agrees with the overall exertion frequency of 0.96 Hz of this task. In order to reduce the exertion frequency of this task, we can start from the encircled region and reduce the number of exertions while stacking the boxes into the crate, or allow more time between cycles. The overall frequency can be reduced by reducing the pace of work.

Fig. 3. Packing tasks fabricated in laboratory.

Table 1
Summary of laboratory simulated tasks.

Task	Box Distance (cm)	RMS Exertion Speed (mm/s)	Duty Cycle (%)	Frequency (Hz)	Speed HAL	Frequency HAL
A	30.5	723.53	22.54	0.16	3.53	1.44
B	15.2	655.61	40.98	0.28	3.87	2.87
C	3.8	1256.43	65.70	0.85	8.18	6.22

A plot of localized duty cycle is shown in Fig. 7(b) where the color in the encircled region is most intense, indicating that a large proportion of exertion time occurs in this location. We can focus on this region to reduce the duty cycle and therefore reduce the HAL. In this region the operator picks up boxes from the conveyor belt. As an intervention, a mechanism might be introduced to replace the manual operation of grasping the boxes. This could drastically reduce the duration of exertion in this area where exertion duration is the most intensely distributed and the overall duty cycle could be reduced, resulting in a lower HAL of the job.

A plot of RMS exertion speed is shown in Fig. 7(c). The color of the plot is more intense along the path the hand traverses from the conveyor belt to the crate (encircled region). It indicates that this job can be further improved by reducing the exertion speed of hand. Based on the information in this plot, one way that the overall exertion speed can be reduced is by reducing the path distance.

The next example (Task E) consists of an operator continuously painting an object by dabbing it with a brush. A plot of adjusted exertion frequency is shown in Fig. 8 (a). The color is most intense throughout the regions of hand movement, indicating that the exertion frequency is highest throughout these regions. A large portion of the region is dark red. In these regions the average exertion frequency reached or exceeded 2.5 exertions per second. Since the color intensity is evenly distributed in the plot, the exertion frequency can be reduced by reducing the overall pace of the job.

Consider the equation $F = \left(\frac{\text{exertions}}{\text{work time}}\right)$ for calculating exertion frequency. The frequency can be reduced by replacing the highly frequent and short intense exertions with longer smaller exertions. Demanding less exertions in the same amount of time, the task can be improved by reducing exertion frequency. One way to accomplish this might be to use a spray gun for painting rather than a manual brush.

A plot of local duty cycle is shown in Fig. 8(b). The color in the encircled regions are more intense in comparison to the other regions, indicating where the exertion time is mostly concentrated. These should be considered when redesigning the task to reduce the duty cycle and therefore reduce the HAL. One way to improve this task might be to incorporate more rest time during the task. In the encircled regions where a large amount of exertion time occurs, rest time can be increased by reducing the pace of work when the hand travels to these locations.

A plot of RMS exertion speed is shown in Fig. 8(c). The color intensity is moderate and is evenly distributed in the majority of the regions of movement. This task might be further improved by reducing the exertion speed and therefore reducing HAL. Exertion speed for this job can be reduced by making the objects to be painted closer spaced. Methods for applying more paint in the same amount of time may help reduce the exertion speed.

The last example (Task F) involves packaging landscaping stones, in which an operator picks up bricks on the side, moves them into a deep crate, and sets them in a crate. A plot of adjusted exertion frequency is shown in Fig. 9(a). The color of the right side of the plot (encircled area) where the hand traveled from the edge of the workstation to the bottom of the crate has slightly more intense color in comparison to the remaining regions of movement, indicating where the adjusted exertion frequency is greater. This means there are more exertions per unit time in that occur at that location. Since the operator pick up bricks at a location on the upper right side of the plot, the region with deeper color is closer to where the bricks are located.

To reduce HAL from the perspective of frequency, this task can be redesigned by transferring more items during each cycle. For example, the bricks can be pre-packed into groups with a reasonable weight, and the worker can move each group of bricks into the crate in one motion. As a result, less exertions occur in the same amount of time, and therefore the exertion frequency is reduced. This allows the worker to exert less frequently without compromising the productivity.

A plot of local duty cycle is shown in Fig. 9(b). In the video analyzed, the hand moves across the video frame without a constrained region of movement. As a result, the motion of hand is distributed across the video frame, and therefore the amount of exertion time at each location is relatively evenly distributed, resulting in the generally light color in the plot. The cluster with relatively deep color (encircled area) is where the exertion time is most intensely distributed. In this area the worker places the bricks on the bottom of the crate. Reducing the exertion time in this area can have great effect on the global duty cycle, and this can also be accomplished by grouping the bricks and moving several bricks at the same time. This allows more rest time for the worker to accomplish the same productivity, and therefore reduces duty cycle.

A plot of average exertion frequency is shown in Fig. 9(c). Similar to the plot of adjusted exertion frequency, the right side of the plot (encircled area) where the hand was closer to the bricks to be picked up has deeper color, indicating that in this

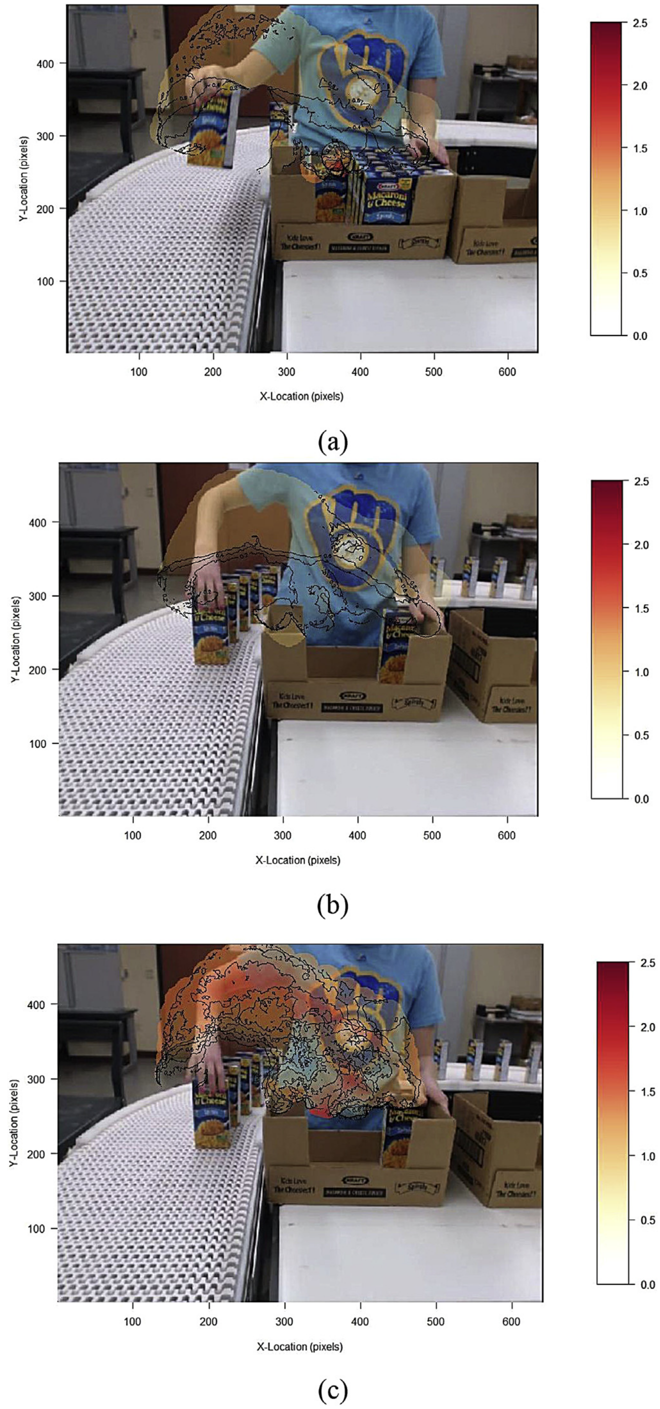

Fig. 4. Adjusted exertion frequency (exertions/s) of packaging tasks plotted over the x-y coordinates: (a) Task A, F = 0.16 Hz. (b) Task B, F = 0.28 Hz. (c) Task C, F = 0.85 Hz.

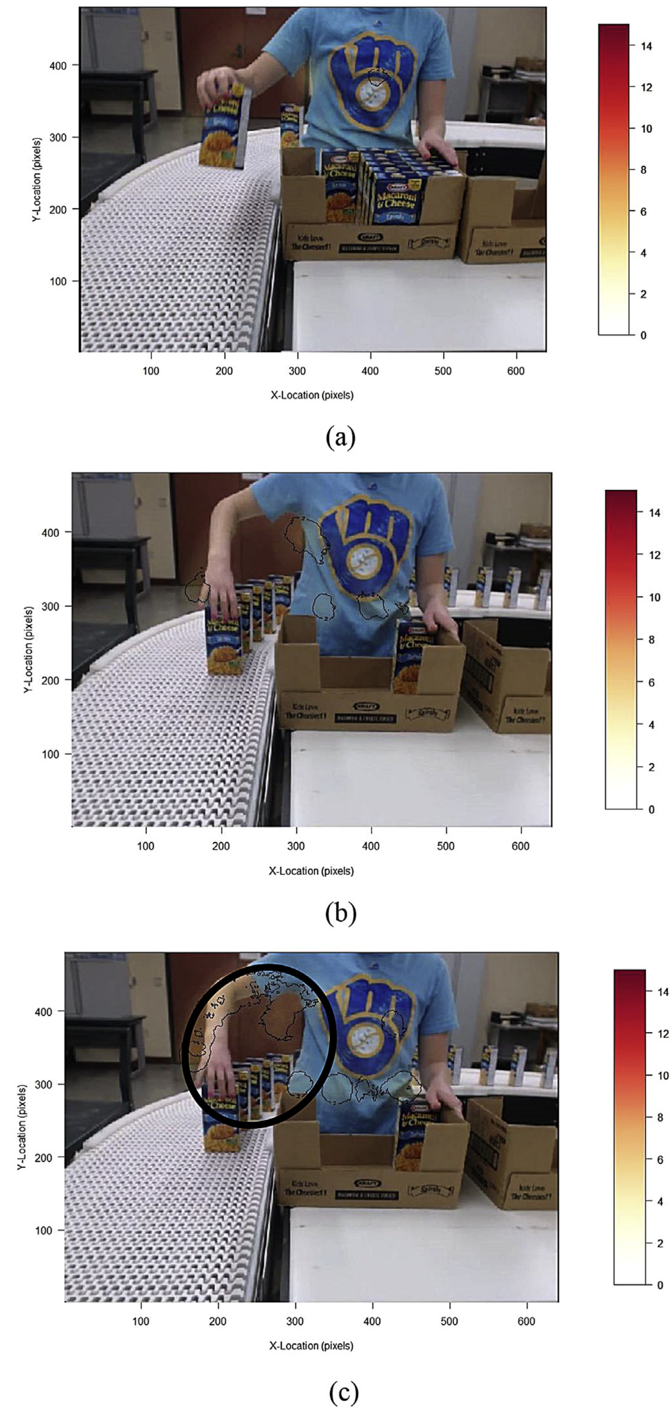

Fig. 5. Local Duty Cycle (%) of packaging tasks plotted over x-y axis: (a) Task A, D = 22.54%. (b) Task B, D = 40.98%. (c) Task C, DC = 65.70%.

region the hand was moving faster than the remaining regions of movement. The HAL for this task can be reduced by reducing exertion speed. Based on the information provided by this plot, we can reduce the exertion speed in the encircled area by reducing the distance that the hands travels. This may be accomplished by redesigning the workstation to raise the bottom of the crate or tilt the crate to reduce the distance between the bottom of the crate and the workstation. Shortening the distance that the hand needs to travel in the same amount of time, the average speed of hand is reduced.

3. Discussion

This paper describes a new computer vision method for visualizing physical stress parameters comprising the HAL, specifically exertion frequency, duty cycle and speed. Additionally, due to the numerous factors that contribute to variations, traditional manual observation for task analysis can be time consuming. Using conventional 2D videos and computer vision, this method provides efficient means for conducting ergonomics analysis. We have demonstrated that these parameters can be displayed relative to

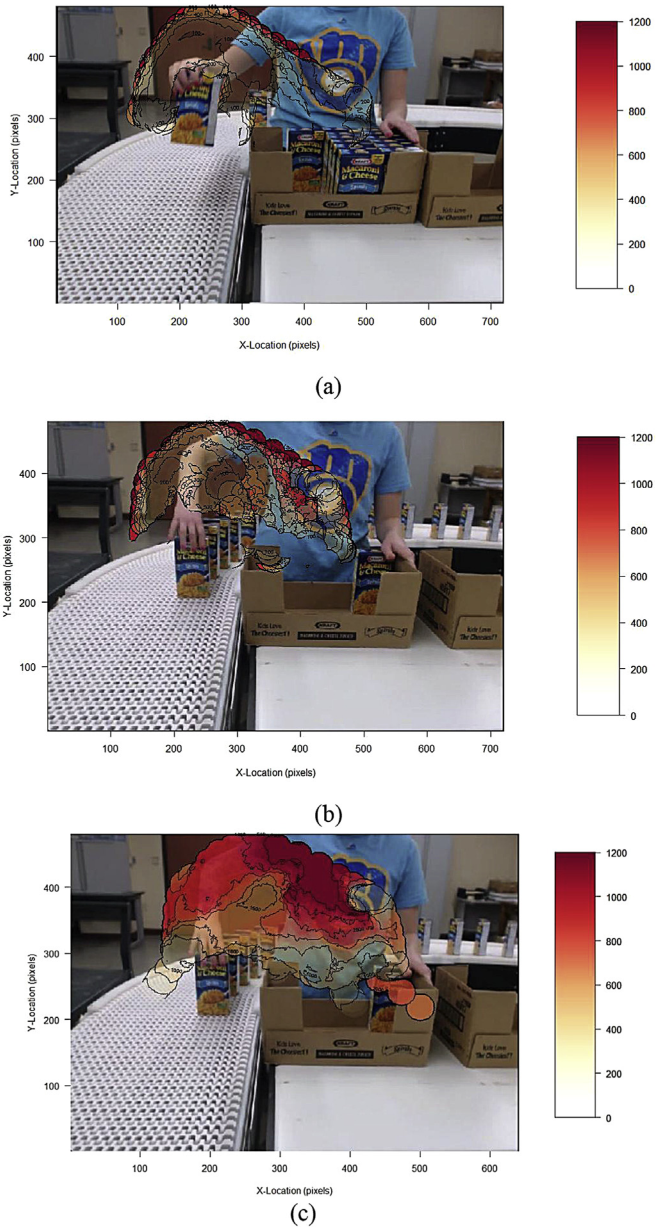

Fig. 6. Local RMS Exertion Speed (mm/s) of packing tasks plotted over x-y axis: (a) Task A, S = 723.53 mm/s. (b) Task B, S = 655.61 mm/s. (c) Task C, S = 1254.43 mm/s.

spatiotemporal characteristics of repetitive motion tasks using laboratory simulations as well as actual industrial jobs.

The method developed in this study obtains hand movement information through computer vision, breaks down the HAL for a task into separate factors used in the equations for predicting HAL, and then visualizes how each are distributed spatially to identify possible improvements focusing on the areas where these factors are intensely distributed. Patterns of exposure variation are typically difficult to measure and the metrics of variation and techniques for identifying them is an underdeveloped area of occupational exposure assessment (Dempsey and Mathiassen, 2006). This method should help practitioners more readily measure and interpret temporal exposure patterns and identify potential task improvements.

Conventional ergonomics job assessment tools, such as the TLV for hand activity, provide information on the exposure to risk of tasks and limits of exposure, but do not directly suggest corresponding ergonomic interventions other than reducing HAL. The TLV for hand activity is dependent on the NPF and the HAL, which are affected by a wide range of job-specific factors. Consequently, the TLV for HAL does not provide sufficient information about what factors of the task directly contribute to the increased risk for an injury, or suggest specific ergonomic interventions that should be considered in order to reduce the risk.

The new method visualizes the spatiotemporal distribution of task factors comprising the HAL which includes frequency, duty cycle, and hand speed. The color intensity of the heat map directly indicates the magnitude of each task factor at a given location. Therefore for the visualization of each task factor, the locations or aspects of the work where the color is the most intense should alertthe analyst when a task factor is most stressful, and consider ergonomic improvements for a particular this task factor. Once ergonomic improvements are identified, this method can be applied to perform what-if analyses on the effectiveness of the proposed improvements, and the results can be readily obtained by comparing the color intensity of the visualization of the task factor with and without the ergonomic intervention. Providing straightforward visualization on task factors, this method can also serve as a straightforward tool in the communication of ergonomic improvement plans to engineers as well as workers.

In the current study, each video frame was manually classified using MVTA as depicting either an “exertion” or “rest” based on observed hand activity. An automatic method for classifying exertion and rest in currently being developed in our laboratory, and it is anticipated that this analysis will be automatically, or semi-automatically conducted by the algorithm, and is described for laboratory simulations of repetitive tasks in Akkas et al. (2016). These algorithms performed well in predicting duty cycles automatically in paced, laboratory simulated tasks. The current study used manually classified hand status for the purpose of precisely demonstrating the visualization. In the future, a fully automated algorithm for predicting exertions and duty cycles could be incorporated so that this method can be more readily used bin practice. Using conventional 2D videos to analyze tasks, this method can only assess motions that are on the same plane as the video. Currently this method provides information on task improvements from the perspective of HAL by identifying the components of the task that contributes to HAL, and redesigning the task with focus on these components results in effective reduction of hand and wrist injuries. Since the TLV for hand activity is intended to measure the risk of single, short-cycle tasks, the method is currently less suitable for assessing more complex, multi-task jobs. Though limited in analyzing complex motions, 2D videos provide sufficient information of single, short-cycle tasks which users can easily find a camera

Table 2
Summary of industrial tasks.

Task	Description	RMS Exertion Speed (mm/s)	Duty Cycle (%)	Frequency (Hz)	Observed HAL	Speed HAL	Frequency HAL
D	Dairy packing	1362.42	58.2	0.96	8	8.2	6.3
E	Painting	696.91	100	2.04	7.3	7.0	8.5
F	Packing stones	1102.53	64.4	0.55	7.5	7.7	5.1

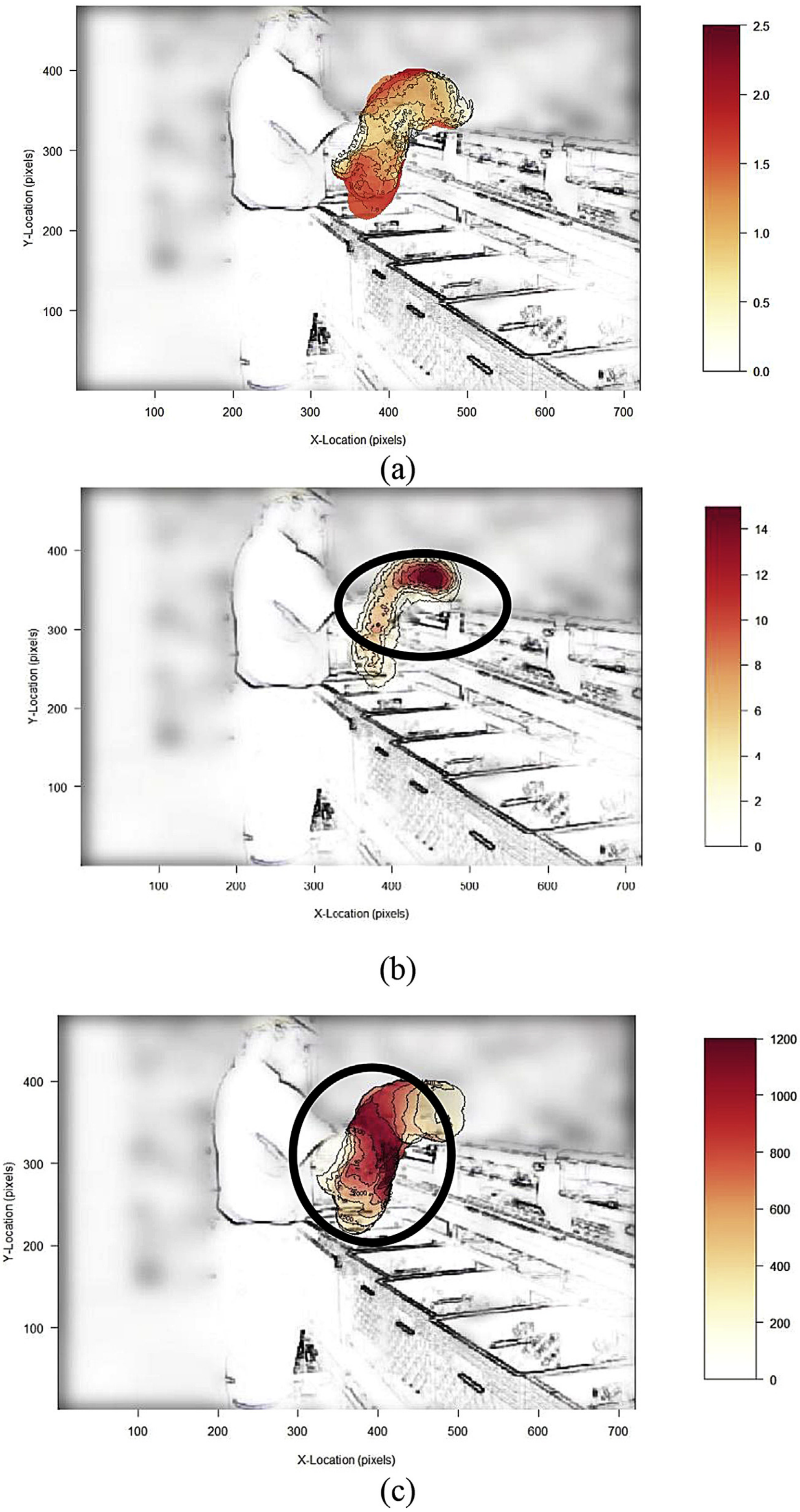

Fig. 7. (a) Adjusted exertion frequency (exertions/second), (b) localized duty cycle (%), and (c) RMS exertion speed of sour cream task, plotted over x-y axis. The video image is intentionally obscured for confidentially.

location to optimize the video captured. Since it focuses on task analysis and improvement using the task factors comprising HAL, the limitation that the method is limited to motions within or near 2D planes. The method does not take into account the effort of the hand and wrist, which is another factor contributing to the risk of injuries. In order to further improve this method, the information on exertion force should be combined with the current information used in this analysis.

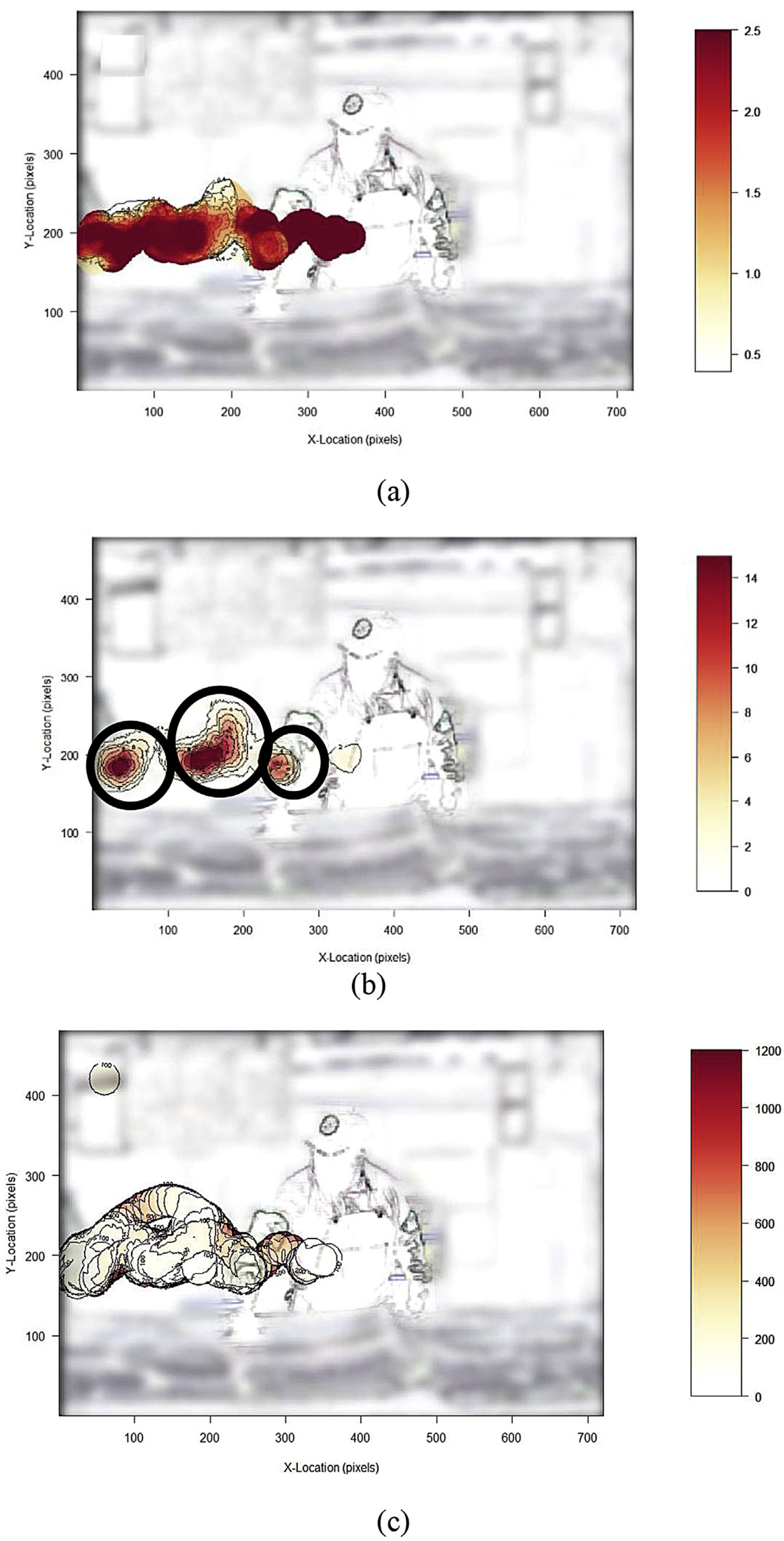

Fig. 8. (a) Adjusted exertion frequency (exertions/second), (b) localized duty cycle (%), and (c) RMS exertion speed of painting task, plotted over x-y axis. The video image is intentionally obscured for confidentially.

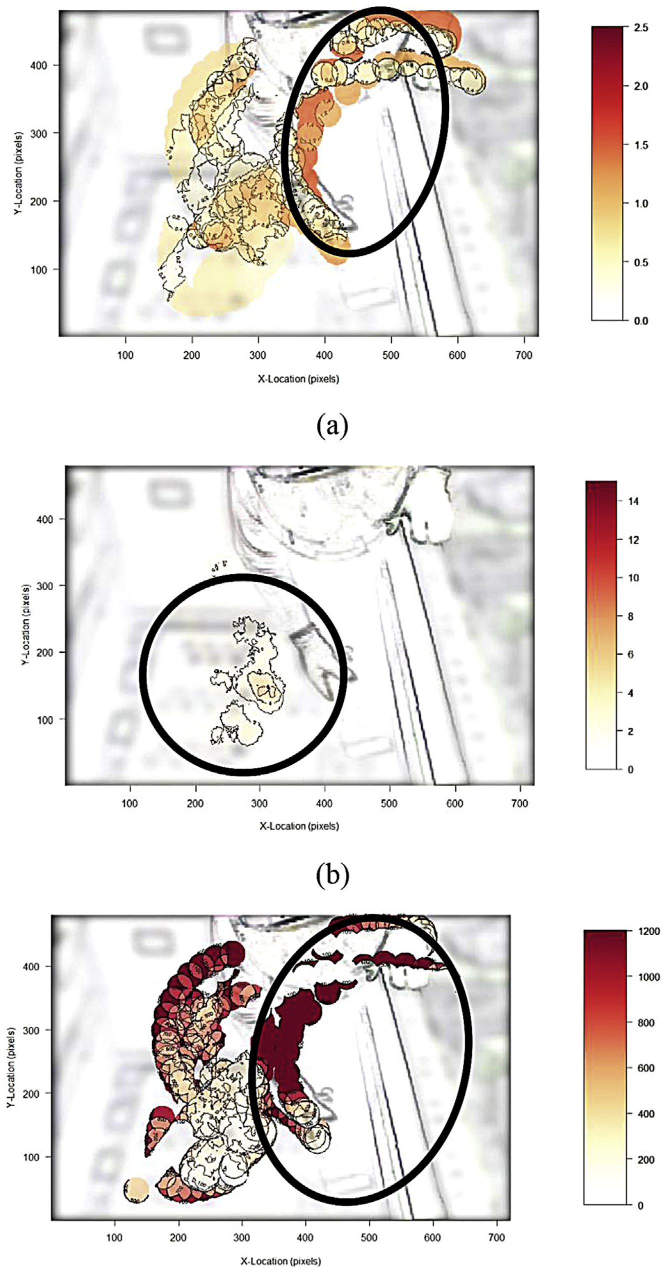

Fig. 9. (a) Adjusted exertion frequency (exertions/second), (b) localized duty cycle (%), and (c) RMS exertion speed of stone packing task, plotted over x-y axis. The video image is intentionally obscured for confidentially.

There are numerous tools that can be readily used to estimate the exertion force. The Borg Psychological Assessment of Effort is a simple tool that is widely used for assessing the physical effort of the worker performing the task. Hull et al. (2008) utilized the Borg scale as a measure to assess the usability of steel bucking bars which is a frequently used tool of aircraft manufacturers. In the study of Waye et al. (2013), the Borg scale was used to measure and compare the effort of single-person cardiopulmonary resuscitation (CPR) terrestrial gravity and in simulated microgravity. Once the data on exertion effort is obtained, it can be readily incorporated into the current method and visualize the information accordingly. Attempts for visualizing the risk of job elements against spatiotemporal relationships of the work have been previously attempted. Garg and Kapellusch (2011) used temporal plots of the Borg CR-10 hand force rating and posture for the dominant hand in order to visualize changes in the strain index rating and RULA scores.

Although useful for quantifying risk, the TLV for HAL is unlike some ergonomics analysis tools that can suggest task improvements in addition to identifying the risk of injuries. Composed of six multipliers based on factors of a task, the 1991 NIOSH Lifting Equation (Waters et al., 1993) is commonly used to calculate the recommended weight limit (RWL) for the task as nearly all healthy workers could perform for an extended period of time without increasing the risk of lower back pain. The RWL itself provides guidelines on how heavy the load should be in a lifting task; if the actual load is heavier than the RWL, the task can be improved by reducing the load to below the RWL. In addition, the six multipliers also provide information on which factors of the task are compromising the RWL. Redesigning the task based on this information could increase the RWL so that the risk of injury can be reduced without compromising productivity.

Similarly, the Strain Index (SI) proposed by Moore and Garg (1995) also predicts risks of work-related distal upper extremity disorders with multiplicative interactions of task variables. For each hand every risk factor of the task is evaluated and is given a rating based on the provided scale, and the SI is calculated by obtaining the product of these rating multipliers. The SI is then compared against a given range to determine the risk of disorders of the task. The individual multipliers are also indicators of which task factors are contributing to the increased risk of distal upper extremity disorders, and these factors should be focused on for task improvements. Such ergonomic analysis tools provide information that is useful for task improvements. Visualizing task factors in these ergonomic tools with the method described in this paper potentially elucidates how the task factors are distributed spatially, and therefore provides more insights on improving these factors from the spatial perspective.

Observational methods have been favored for ergonomic assessment of jobs due to their relatively ease of use. Today an increasing number of low-cost, easily-operated technologies are becoming available for ergonomic analysis and are especially useful for direct measurement. Methods that utilize accelerometers to assess postures and motion have arisen in the past decade and used in wearable systems to measure physical activities (Yang and Hsu, 2010). Dahlqvist et al. (2016) validated a model of triaxial accelerometer with integrated data loggers, stating that the device is suitable for evaluating motion and posture of human. Korshøj et al. (2014) proved the validity of inclinometer measurements by an inexpensive model of accelerometer. Inertial sensors are useful in direct measurement. Vignais et al. (2013) described a work evaluation system for the upper body using inertial sensors combined with RULA to provide real-time ergonomic assessment. The synchronization of video and sensor data is applicable to the visualization methods introduced in the current paper.

The method described in this paper provides a new way of presenting and comprehending a wide range of task factors, and when incorporated with data from such direct measurement devices synchronized with video, can display more diverse information on the job. Visualizing the spatiotemporal distribution of magnitude of task factors, this method can provide abundant information with solely video recording of a task at minimum cost. Unlike direct measurement methods, it is not invasive which would have minimum disruption on the working operations. Furthermore, such analyses can conceivably be implemented on a hand-held device like a smartphone, already containing high definition video cameras, high speed processors, and the ability to do cloud computing, making it broadly accessible. Since the current method obtains kinematic data from 2D videos, the method lacks precision compared with direct measurements. However high precision may not be needed in many applications and is certainly more precise than observation.

The current paper illustrates how heat maps of spatiotemporal representations job analysis factors can be superimposed over video images of the task being performed in order to localize aspects of the work associated with greater risk. Due to the static constraints of a printed publication, it is not possible to fully illustrate here, but we envision that these analyses will be superimposed over video clips while they play, fully depicting the task in motion. These heat maps may be displayed for the entire video clip, or they might be displayed so that the map is localized to specific regions associated with the location of the hands depicted in the current video frame. We anticipate that such animated visualizations will provide the practitioner with even greater insight as to the quantification of risk factors associated with the work.

4. Conclusions

This paper illustrates how computer vison may be used for providing occupational ergonomics practitioners with more quantitative tools for analyzing and improving jobs. The video and computing platform for the algorithms developed in this paper are inherently inexpensive, broadly available, and based on conventional technology. This method should help practitioners more readily measure and interpret temporal exposure patterns and identify potential task improvements.

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References

Akkas, O., Azari, D.P., Chen, C.-H.E., Hu, Y.H., Ulin, S.S., Armstrong, T.J., Rempel, D., Radwin, R.G., 2015. A hand speed and duty cycle equation for estimating the ACGIH hand activity level rating. Ergonomics 58 (2), 184–194.
Akkas, O., Lee, C.H., Hu, Y.H., Yen, T.Y., Radwin, R.G., 2016. Measuring elemental time and duty cycle using automated video processing. Ergonomics 1–12.
Armstrong, T.J., Radwin, R.G., Hansen, D.J., Kennedy, K.W., 1986. Repetitive trauma disorders: job evaluation and design. Hum. Factors J. Hum. Factors Ergon. Soc. 28 (3), 325–336.
Azari, D.P., Pugh, C.M., Laufer, S., Kwan, C., Chen, C.H., Yen, T.Y., et al., 2016. Evaluation of simulated clinical breast exam motion patterns using marker-less video tracking. Hum. Factors J. Hum. Factors Ergon. Soc. 58 (3), 427–440.
Bao, S., Howard, N., Spielholz, P., Silverstein, B., Polissar, N., 2009. Interrater reliability of posture observations. Hum. Factors J. Hum. Factors Ergon. Soc. 51 (3), 292–309.
Brodie, D., Wells, R., 1997. An evaluation of the utility of three ergonomics checklists for predicting health outcomes in a car manufacturing environment. Proc. 29th Annu. Conf. Hum. Factors Assoc. Can.
Chen, C.H.E., Hu, Y.H., Yen, T.Y., Radwin, R.G., 2013. Automated video exposure assessment of repetitive hand activity level for a load transfer task. Hum. Factors J. Hum. Factors Ergon. Soc. 55 (2), 298–308.
Chen, C.H., Hu, Y.H., Radwin, R.G., 2014, July. A motion tracking system for hand activity assessment. In: Signal and Information Processing (ChinaSIP), 2014 IEEE China Summit & International Conference on (pp. 320–324). IEEE.
Dahlqvist, C., Hansson, G.Å., Forsman, M., 2016. Validity of a small low-cost triaxial accelerometer with integrated logger for uncomplicated measurements of postures and movements of head, upper back and upper arms. Appl. Ergon. 55, 108–116.
David, G.C., 2005. Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. Occup. Med. 55 (3), 190–199.
Dempsey, P.G., Mathiassen, S.E., 2006. On the evolution of task-based analysis of manual materials handling, and its applicability in contemporary ergonomics. Appl. Ergon. 37 (1), 33–43.
Dempsey, P.G., McGorry, R.W., Maynard, W.S., 2005. A survey of tools and methods used by certified professional ergonomists. Appl. Ergon. 36 (4), 489–503.
Garg, A., Kapellusch, J.M., 2011. Job analysis techniques for distal upper extremity disorders. Rev. Hum. Factors Ergon. 7 (1), 149–196.
Glarner, C.E., Hu, Y., Chen, C., Radwin, R.G., Zhao, Q., Craven, M., Wiegmann, D., Pugh, C.M., Carty, M.J., Greenberg, C.C., 2014. Quantifying technical skills during open operations using video-based motion analysis. Surgery 156 (3), 729–734.
Greiner, T.M., 1991. Hand Anthropometry of US Army Personnel (No. TR-92/011). Army Natick Research Development and Engineering Center MA.
Harris, C., Eisen, E.A., Goldberg, R., Krause, N., Rempel, D., 2011. 1st place, PREMUS best paper competition: workplace and individual factors in wrist tendinosis among blue-collar workers – the San Francisco study. Scand. J. Work Environ. Health 37 (2), 85–98.
Hull, S.S., Chaparro, B.S., Jorgensen, M.J., 2008. Perceived usability of ergonomic interventions for steel bucking bars. Proc. Hum. Factors Ergon. Soc. 52nd Annu. Meet. 3, 1458–1462.
Kazmierczak, K., Mathiassen, S.E., Neumann, P., Winkel, J., 2006. Observer reliability of industrial activity analysis based on video recordings. Int. J. Ind. Ergon. 36 (3), 275–282.
Korshøj, M., Skotte, J.H., Christiansen, C.S., Mortensen, P., Kristiansen, J., Hanisch, C., Ingebrigtsen, J., Holtermann, A., 2014. Validity of the Acti4 software using ActiGraph GT3X+ accelerometer for recording of arm and upper body inclination in simulated work tasks. Ergonomics 57 (2), 247–253.
Moore, J.S., Garg, A., 1995. The strain index: a proposed method to analyze jobs for risk of distal upper extremity disorders. Am. Ind. Hyg. Assoc. J. 443, 56.5(1995).
Radwin, R.G., Azari, D.P., Lindstrom, M.J., Ulin, S.S., Armstrong, T.J., Rempel, D., 2014. A frequency-duty cycle equation for the ACGIH hand activity level. Ergonomics 58 (2), 173–183, 2015.
Vignais, N., Miezal, M., Bleser, G., Mura, K., Gorecky, D., Marin, F., 2013. Innovative system for real-time ergonomic feedback in industrial manufacturing. Appl. Ergon. 44 (4), 566–574.
Waters, T.I.L., Putz-Anderson, V., Garg, A., Fine, L.J., 1993. Revised NIOSH equation for the design and evaluation of manual lifting tasks. Ergonomics 36, 7.
Waye, A.B., Krygiel, R.G., Susin, T.B., Baptista, R., Rehnberg, L., Heidner, G.S., de Campos, F., Falcão, F.P., Russomano, T., 2013. Evaluation of upper body muscle activity during cardiopulmonary resuscitation performance in simulated microgravity. Adv. Space Res. 52 (5), 971–978.
Wells, R., Mathiassen, S.E., Medbo, L., Winkel, J., 2007. Time—a key issue for musculoskeletal health and manufacturing. Appl. Ergon. 38 (6), 733–744.
ACGIH Worldwide, 2001. Hand Activity Level TLV®. Cincinnati, OH.
Yang, C.C., Hsu, Y.L., 2010. A review of accelerometry-based wearable motion detectors for physical activity monitoring. Sensors 10 (8), 7772–7788.
Yen, T.Y., Radwin, R.G., 1995. A video-based system for acquiring biomechanical data synchronized with arbitrary events and activities. IEEE Trans. Biomed. Eng. 42 (9), 944–948.