How Do Computer Vision Upper Extremity Exposure Measures Compare Against Manual Measures?

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BACKGROUND

Various quantification methods have been used to measure exposure to risk factors for musculoskeletal injuries, including observation, video-based frame-by-frame analysis, and direct measurements. Each technique has advantages and disadvantages.

The American Conference of Government Industrial Hygienists (2017) Threshold Limit Value® (TLV®) uses the hand activity level (HAL) rating scale, a 10-point visual analog scale based on hand speed and rest pauses. HAL may be determined subjectively by an observer or from a lookup table, or an equation by measuring exertion frequency (*F*) and percent duty cycle (*D*).

This study compares task level physical exposure variables measured manually and using video computer vision for jobs selected from a selected subset of the Upper Limb MSD Consortium prospective study. We compared *F* and *D*, calculated both using manual single-frame MVTA analysis and automatic computer vision (Akkas et al., 2015, Akkas et al., 2016, Akkas et al., 2017, Greene et al., 2017).

METHODS

This study utilized exposure data from prospective studies conducted by the National Institute for Occupational Safety and Health (NIOSH), the Safety & Health Assessment & Research for Prevention (SHARP) in the State of Washington, and the University of California -San Francisco (UCSF). Some data from these prospective cohort studies had been previously pooled and analyzed as part of the Upper Limb MSD Consortium, a group of seven prospective cohort studies (Bao et al., 2015; Harris-Adamson et. al., 2013a, 2013b; Harris-Adamson et. al., 2014; Kapellusch et al., 2013, 2014; Fan et al., 2015).

Because the videos were created for a different purpose, not all were suitable for computer vision analysis. We selected 1001 videos where we applied hand tracking and data checking to date. Thus, not all study sites are equally represented.

The occurrence of each exertion was first identified in all the videos by human analysts for manually calculating the frequency (exertions/ second) and duty cycle (percent exertion time/ cycle time). The hands were tracked using marker-less video tracking and a feature vector training (FVT) algorithm (Akkas et al., 2016 Akkas et al., 2017) was trained using the first cycle exertions identified by an analyst, for automatically estimating subsequent exertions in the videos. We then applied the FVT algorithm to the 1001 videos clips and automatically identified video frames representing exertions of the dominant hand. As a result, we counted total frames of exertions as well as the total number of exertions to calculate *F* and *D*.

RESULTS

The calculated *D* (%) and *F* (Hz) errors were the average difference between the manual frame-by-frame and the computer vision estimates. We found an average error of 12.7% (SD=36.8%) for *D* and 0.06 Hz (SD=0.38 Hz) for *F*. The average HAL error was 1.3 (SD=2.2), which is considered negligible.

CONCLUSIONS

The results indicate that computer vision can reliably estimate important exposure variables for many tasks. Since the videos used in this study were taken for a different purpose, we anticipate the algorithms will perform better when videos are recorded specifically for computer vision analysis.

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