ERGONOMICS

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ARTIFICIAL INTELLIGENCE for Injury Prevention

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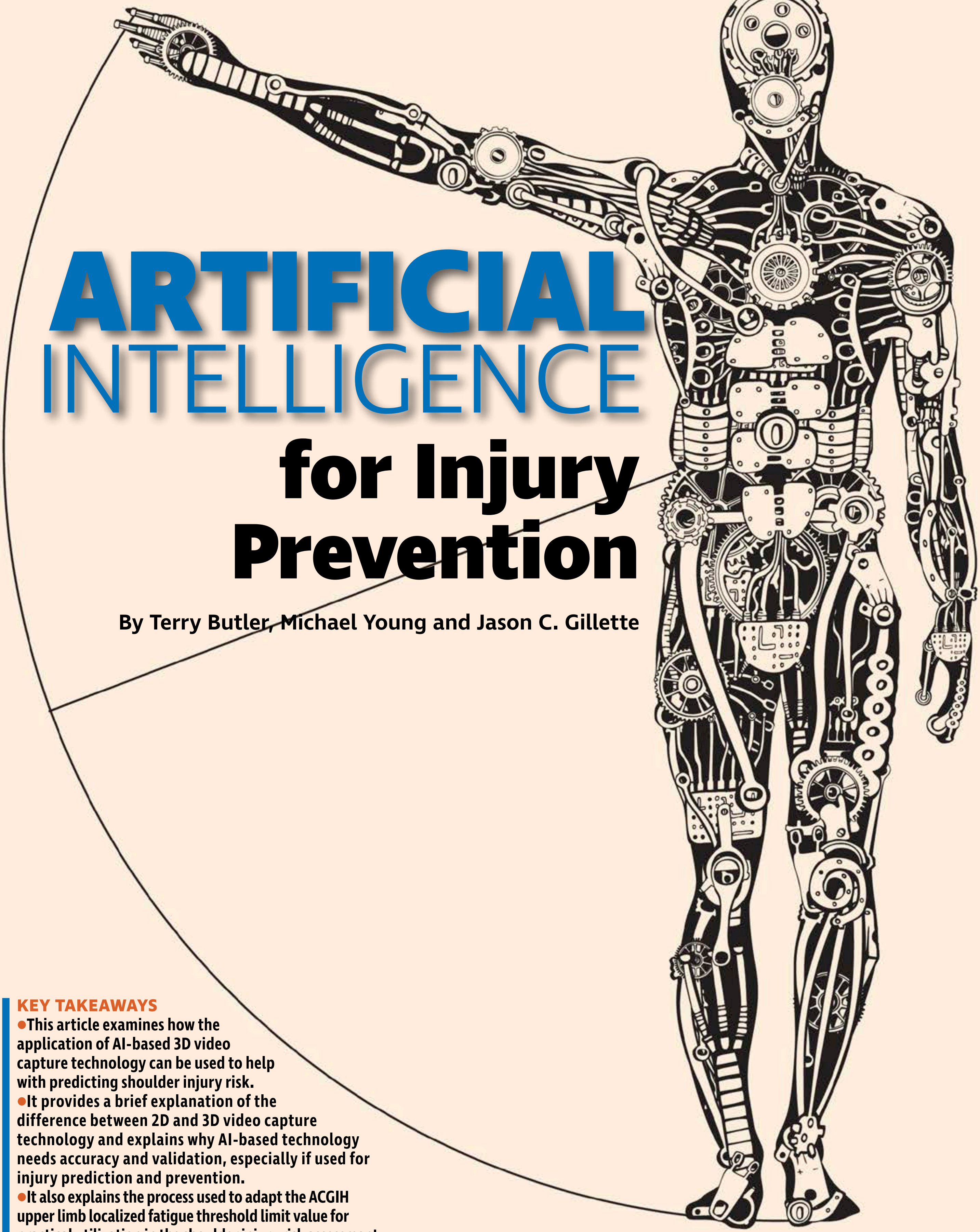

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KEY TAKEAWAYS

- This article examines how the application of AI-based 3D video capture technology can be used to help with predicting shoulder injury risk.
- It provides a brief explanation of the difference between 2D and 3D video capture technology and explains why AI-based technology needs accuracy and validation, especially if used for injury prediction and prevention.
- It also explains the process used to adapt the ACGIH upper limb localized fatigue threshold limit value for practical utilization in the shoulder injury risk assessment.

MOST ERGONOMIC RISK ASSESSMENTS are completed by watching a person work, making measurements, performing calculations, and comparing the results against a checklist, index or published standard. In addition to being time-consuming, these observational assessments are prone to inaccuracy and inconsistency due to interoperator variance. If 10 different practitioners perform an ergonomic risk assessment on the same job using observational techniques, it is unlikely that they would produce identical results. The results would vary because everyone perceives what they see a little differently when using the standard observational methods deployed today. This is an ideal opportunity to apply artificial intelligence (AI) to objectively measure the performance of a work task and assist the practitioner with ergonomic risk assessments.

This article focuses on the use of AI for identification of ergonomic risk associated with upper-limb fatigue in jobs requiring raised and extended arm postures. AI is increasingly applied to real-world problems in industry to perform tasks that require visual perception, speech recognition, decision-making and in-process quality checks. Advances in AI are combined with advances in mobile devices such as smartphones to incorporate processing power, advanced cameras and inertial measurement unit sensors. Inertial measurement unit sensors are worn on the body to measure and report acceleration and angular velocity as a person's limbs are in motion.

This article explains the use of AI to characterize a worker's 3D motion to assist practitioners in providing accurate, repeatable and objective assessments. Without AI assistance, comparable upper-limb fatigue studies would take a practitioner countless hours to complete and require potentially error-prone subjective decisions. This article also describes the enabling technologies, background research and development of a new shoulder injury risk assessment (SIRA) methodology for ergonomic analysis.

AI-Based 3D Motion Capture

A significant advancement of this project is the implementation of AI-based 3D motion capture from single-camera task videos. Moving from current 2D motion capture technology to 3D motion capture is a leap in technology and needed for increased accuracy of ergonomic risk assessments. The limitations of 2D and the importance of 3D motion capture can be illustrated with a simple example using the lifting posture as shown in Figure 1 (p. 26). The 2D joint angle calculation of trunk flexion angle (illustrated by dotted lines) is dependent upon the viewing plane of the camera. In 2D, the back angle when viewed from the side is interpreted differently than the angle when viewed from the front. Imagine walking around the stick figure and the calculated 2D trunk flexion angle varies dramatically, from near zero to 67° in this example, depending upon the view of the camera. This effect is much less prominent for 3D motion capture systems, and the resulting 3D joint angles provide more accurate inputs to posture-based ergonomic assessments.

Research Background

Electromyography (EMG) data, video, and subjective surveys with workers in the field and participants in controlled laboratory settings were collected in a series of studies (e.g., Alabdukarim & Nussbaum, 2019; Gillette & Stephenson, 2018; Iranzo et al., 2020). Wireless EMG sensors were placed on the skin over muscles and measured neural stimulation as an electrical signal and a measure of muscle activity (Hermens et al., 2000). The lab environment provided precise data collection, with choreographed task sequences, precisely measured work areas and a 12-camera video capture system. On-site data collections involved valuable real-world examples of workers performing elevated work tasks in various challenging environments. This field and lab data acquisition process produced hours of video and billions of EMG data points. Analysis of this dataset led to the ability to quantify muscle activity and to predict fatigue risk of different job tasks (see "The TLV Curve" section for further details). One objective of this analysis was to develop models of fatigue risk while working with and without a shoulder exoskeleton. For example, EMG data were used to determine whether a shoulder exoskeleton reduced muscle fatigue risk during automotive assembly (Gillette et al., 2022).

These datasets will be used to inform the development of an ASTM F48 standard test method for shoulder exoskeleton assessment using EMG. The test method documents how EMG data can be utilized with the American Conference of Governmental Industrial Hygienists (ACGIH, 2016) upper limb localized fatigue threshold limit value (TLV). This ASTM F48 standard will benefit from insights gained during these research projects, along with feedback from industrial and academic partners. The research findings also led to the development of a practical application of this methodology via the SIRA.

A New Ergonomics SIRA Methodology

Worksite data collected during automotive assembly, warehouse construction and tunnel construction informed the development of the AI-driven SIRA. During lab testing, EMG and multicamera video data were combined to understand how posture, posture duration and tool weights could be used to predict risk of muscle fatigue. During field testing, EMG data were successfully collected, but motion tracking using inertial measurement units or standard video proved to be challenging and time consuming. It became apparent that there would be advantages (increased safety, reduced work disruption and improved accuracy) to finding an alternative means to collect workers' motion data.

The answer came from recent advances in single-camera motion capture that use computer vision and machine learning of human movement datasets to generate 3D postures. In general, AI-based motion capture extracts what it detects as human movement from a video and matches it to an anthropometric model while learning from previously collected movements. Interestingly, this motion capture technology is driven in large part by the requirements of movie and game developers for fast and accurate 3D human motion capture. Early work to streamline the SIRA into an app technology utilized a combination of open-source and proprietary software as the motion capture pipeline. Given the current limitations of AI motion capture technology, such apps require continued development but are promising as a future ergonomic tool. The 3D SIRA methodology is shown as a schematic diagram in Figure 2 (p. 27).

The process begins with acquiring one or more digital videos of a work task ("job") and uploading the video for processing. The processing is completed on a dedicated server for computing and storage resources that people refer to as "the cloud." The video is uploaded to the cloud, then transcoded and formatted for input to the AI motion capture server. SIRA uses a simple application programming interface (API) for setting the motion capture and file output parameters. The video is processed frame by frame to identify the individual's 3D pose. Once the video is processed, the 3D joint angle data are retrieved via the API and used to generate datasets that are compared to the ACGIH TLV curve.

The TLV Curve

The ACGIH upper limb localized fatigue TLV is a logarithmic curve relating muscle exertion (maximum voluntary contraction, or %MVC) and duration (duty cycle percent). This curve shows the intuitive relationship between muscle exertion and time to fatigue. An exertion level held longer than the threshold duty cycle percent on the curve (i.e., a point "above the curve") will lead to predicted fatigue (Figure 3, p. 28). For example, high muscle exertion can be held only for a short duration before being considered above the acceptable fatigue TLV and an increased risk for shoulder injury. When analyzing lab or field data, the fatigue risk value is calculated as the EMG amplitude minus the TLV as determined by the measured duty cycle (Gillette & Stephenson, 2018).

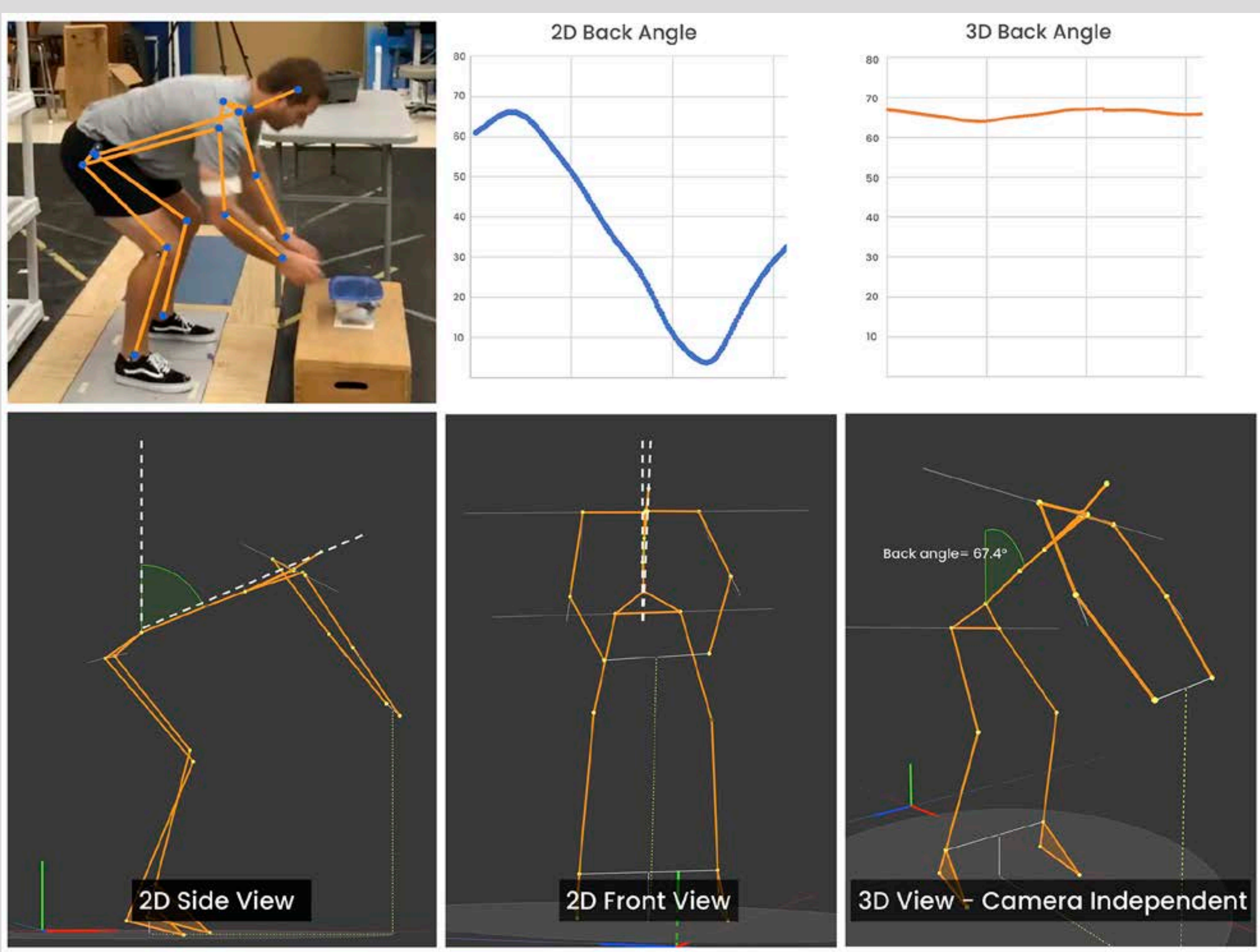
When using EMG sensors, maximum isometric muscle contractions are first collected to normalize the EMG signals to %MVC. Next, the %MVC required to move to combinations of shoulder and elbow angles while using different tool weights is determined utilizing EMG data from lab studies (Figure 4, p. 28). This mapping of postures and tool weights can then be combined with duty cycle data (percent of total work time held in a particular posture) to determine whether the TLV is exceeded. For example, it was found that repetitively moving to a 135° shoulder flexion position with a 5-lb tool required 30.8 %MVC. According to the ACGIH TLV curve, this combination of posture and tool weight would be predicted to cause fatigue at or above 18.4% of the duty cycle (see Figure 3, p. 28).

The guidelines for taking video are straightforward: frame and follow the worker in the video field or select a fixed camera position, if possible. Obtain a clear shot of both of the worker's hands, often at an approximately 45° camera angle from the front of the worker. In addition, minimize other workers in the background so as to not confuse AI processing. The requirements for the video length and content vary according to the job task. For example, if a worker is performing automotive assembly with 1- to 2-minute repetitive cycles over a 2-hour shift, then a single 1- to 2-minute video may be sufficient. If the work is variable like construction or agricultural equipment assembly, it would be more representative to take multiple videos of the various parts of the job task.

FIGURE 1

CALCULATED TRUNK FLEXION ANGLES

Example of calculated 2D and 3D trunk flexion angles as the camera view starts with a side view and rotates around the worker.



AI motion capture data from the job video are used to identify intervals when the shoulder and elbow angles are within a posture range. Duty cycles for each arm posture are the relative time durations within the posture ranges. Arm postures while using a specified tool weight are mapped to previous lab data to determine %MVC values. With %MVC and duty cycle values, a point on the ACGIH graph can be plotted and it can be determined whether the fatigue TLV is exceeded. For example, when considered separately, none of the arm postures involved in this job task exceed the fatigue TLV, as indicated by the crosses in Figure 5 (p. 28). However, cumulative fatigue of the shoulder also must be considered. This is determined using a weighted average based on duration in each of the arm postures and the total time in the arm postures. In this example, the combined effect of the arm postures is above the fatigue TLV as indicated by the red diamond. Thus, the shoulder is at risk of fatigue and an ergonomic intervention is recommended.

Methodology to Application

Early prototypes of the SIRA were created in a spreadsheet before developing a prototype desktop and mobile app. The prototype SIRA app is used to capture field and lab videos that are automatically processed using AI. The methodology schematic shown in Figure 2 provides the basis for how data are collected, uploaded and processed using AI. Within the prototype app, the motion data are analyzed to identify the arm postures and intervals that are used as inputs to the fatigue TLV predictive model. Figure 5 (p. 28) shows the results of a video processed by the AI. The prototype SIRA app was developed for easy identification of the at-risk postures and understanding which postures are contributing to that risk. The prototype SIRA app outputs a summary of the arm postures and fatigue risk for the analyzed job task.

Methodology Application Accuracy Validation

Research requires data that provide empirical evidence and quantitative results that achieve statistical significance. Data can be collected in the lab or in the field. Because an app like SIRA can be used anywhere, accuracy testing and validation of the methodology started in the lab and then later in the field. Since the prototype SIRA app is focused on elevated shoulder postures, a lab protocol was designed to capture data from three types of simulated work tasks. The lab stations mimic a standing assembly job ("standing task"), a sitting assembly job ("sitting task"), and a load, transfer or stow material handling job ("shelf task"). Testing in a biomechanics lab allows researchers to simultaneously collect mobile-based video data for the AI system, lab-based multicamera video motion capture, and EMG data. Comparing AI motion capture to lab motion capture provides a

FIGURE 2

AI PROCESSING & SIRA

The AI video processing and SIRA consists of five phases: acquire the video, upload the video, generate tracking skeletons, calculate 3D angles and perform TLV assessment calculations.

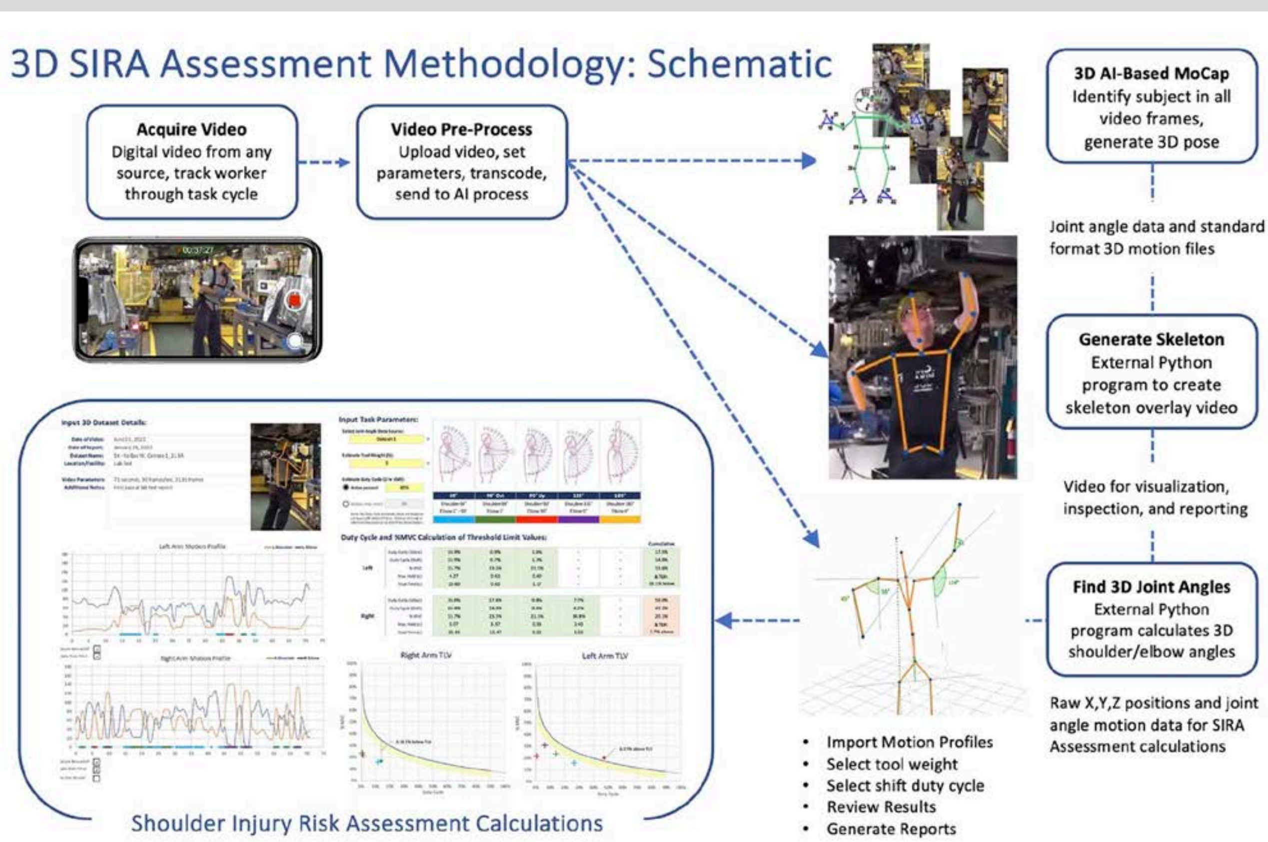
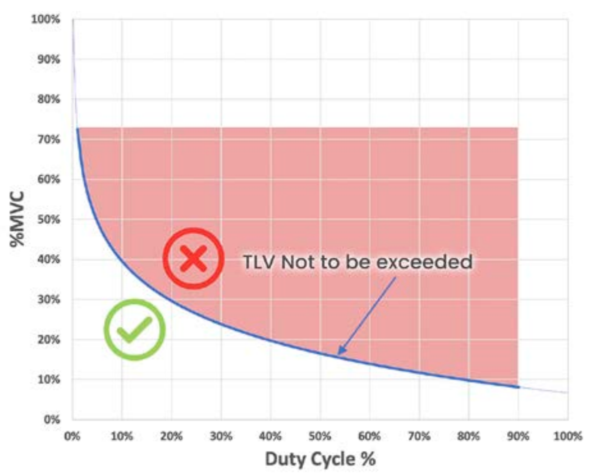


FIGURE 3
UPPER LIMB LOCALIZED FATIGUE TLV CURVE

The ACGIH upper limb localized fatigue TLV curve. Combinations of %MVC and duty cycle above the curve are predicted to cause fatigue.



Note. Adapted from *Upper Limb Localized Fatigue: TLV Physical Agents 7th Edition Documentation*, by ACGIH, 2016.

FIGURE 5
RIGHT ARM SIRA RESULTS

SIRA right arm output for a job task that involved use of a 5-lb tool and 100% duty cycle. Points on ACGIH graph for each arm posture (crosses) as well as the cumulative effect of the arm postures (red diamond) relative to the fatigue TLV (blue curve). The cumulative effect of all postures indicated by the diamond shape shows fatigue is predicted in the right shoulder.

FIGURE 4
SHOULDER & ELBOW JOINT ANGLES

Examples of shoulder and elbow joint angles that are involved in the standing assembly task. Note that the participant moved to all postures with a 3-lb drill and without a tool in hand.

1) shoulder 130°, elbow 5°, drill placed on upper target
2) shoulder 100° elbow 10°, precision threading nut
3) shoulder 90°, elbow 20°, drill socket tightening nut
4) shoulder 90°, elbow 75°, precision threading nut
5) shoulder 70°, elbow 70°, drill placed on mid target
6) shoulder 125°, elbow 5°, precision threading nut
7) shoulder 120°, elbow 5°, drill socket tightening nut
8) shoulder 75°, elbow 15°, precision touch target
9) shoulder 90°, elbow 80°, precision touch target
10) shoulder 130°, elbow 5°, precision touch target

FIGURE 6
SITTING TASK POSTURE EXAMPLE

Example of a posture assumed during the sitting task with the original video (left), stick figure from the AI motion capture (center), and joint angles calculated from the stick figure (right).

measure of accuracy, while comparing the SIRA app fatigue prediction to EMG data provides a measure of validation.

Job task stations were built for initial pilot testing of the experimental protocol. These job task stations were adjusted to set the arm elevation angles for the participant. The participant completed the three job tasks while wearing EMG sensors and retroreflective markers for the lab-based motion analysis. The participant was fitted with two shoulder exoskeletons for comparisons between working with and without an exoskeleton and between the exoskeleton designs. The standing task was completed with a 3-lb drill (Figure 4), the sitting task with a 5-lb drill (Figure 6) and the shelf task with 7-lb containers (Figure 7). Three synchronized smartphones mounted in different locations were used to capture videos of the task being performed to check if camera position impacted AI motion capture accuracy (Figure 8, p. 30).

Summary Discussion

Just like understanding how a confined space multi-gas detector works, how it is checked for accuracy and the steps for calibration, it is critical that safety professionals understand AI as a tool for injury prevention.

The focus of this article is on the methodology, application, and accuracy testing of objective AI motion capture and the prototype SIRA app. The article describes the progression of lab and field research on shoulder fatigue risk assessment to practical application. The approach leverages a large dataset from studies of workers in lab and real-world conditions performing physically demanding tasks requiring overhead work. A methodology was developed that allows for the direct utilization of the ACGIH TLV for upper limb localized fatigue, a widely accepted standard for evaluating risk. Using AI motion capture from a job task video enables quick, repeatable task assessments that may significantly reduce the inaccuracies of interoperator deviation. The limitation on using AI motion capture rests with obtaining a clear, unobstructed view of the worker without other workers in the video frame. A benefit is that AI enables ergonomics assessments without requiring a tape measure, pen or calculator.

Lab-based studies benefit from systematic manipulation of posture conditions, additional measurement capabilities and accuracy comparisons. However, it is difficult to simulate industrial work conditions, and the participants may not be skilled at the tasks of interest. On-site studies benefit from real-world task conditions and skilled participants but are potentially limited in motion capture as noted and require coordination to minimize job disruption. AI-based motion capture in real-world environments allows on-site assessments without requiring wearing of sensors and without disrupting the work process. In fact, all that is required to initiate the assessment process is permission to video record a job task, allowing ergonomics professionals to focus on utilizing the results for injury mitigation.

FIGURE 7
SHELF TASK POSTURE EXAMPLE

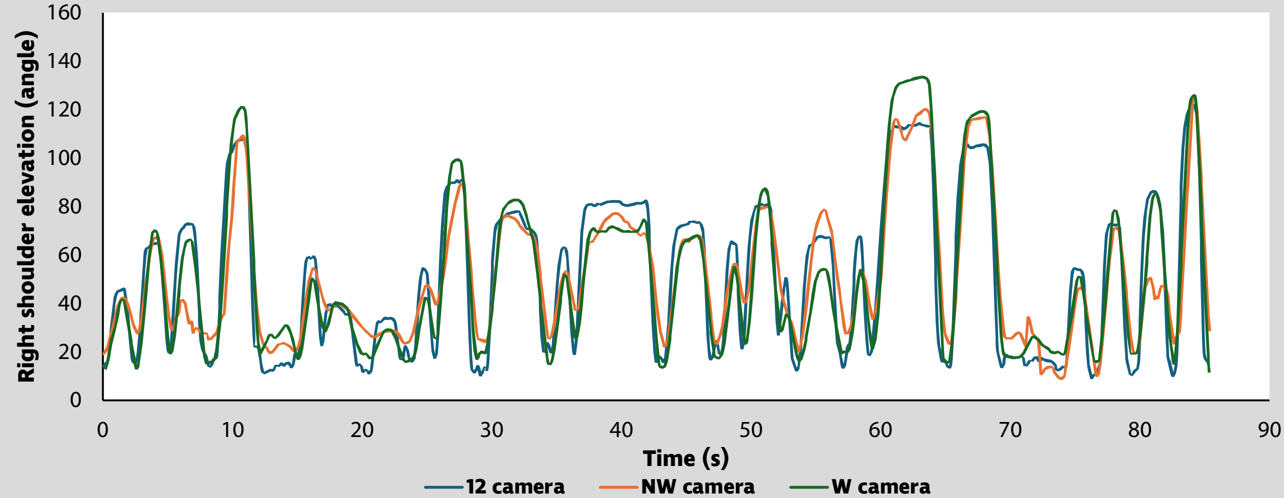
Example of a posture assumed during the shelf task that requires packing, transporting, and lifting or lowering containers and involves twisting, turning, bending, reaching out and walking.

AI-based video capture can be extended to standard ergonomics assessments used to evaluate lifting and lowering such as the NIOSH Lifting Equation, rapid upper limb assessment and rapid entire body assessment, Bureau of Workers' Compensation/Ohio State University Lifting Guidelines, Liberty Mutual Manual

FIGURE 8

STANDING WITHOUT EXOSKELETON, TRIAL NO. 2

Example of accuracy testing comparing shoulder elevation angles from the 12-camera lab motion analysis system to AI motion capture from two smartphone locations.



Materials Handling guidelines, and Exo-LiFFT (Zelik et al., 2022). These assessments utilize information about posture, which could be analyzed by AI-based video, and lifted load, which could be entered by the safety professional to estimate injury risk. Accurate full-body posture and motion data can also facilitate more sophisticated biomechanical assessments, such as energy expenditure and low back compressive forces. The possibilities for using this technology to reduce worker injury risks holds great promise, but feedback from safety professionals using the technology is essential to making it more accurate and overcoming some of the limitations with capturing video. When considering AI-based technology for injury prevention, one principle to remember is "In God we trust, but all others bring data." AI-based injury risk assessments require thorough accuracy testing, validation of analysis and usability trials. This is especially important when decisions are being made for protecting worker safety and health. Safety professionals who are considering the use of an AI-based risk assessment tool are encouraged to request a trial of the technology and test it at their workplace environment.

Researchers and practitioners are optimistic that AI motion capture will make it possible to use tools like the prototype SIRA app to assess whether work tasks are likely to lead to shoulder injuries. This automated assessment would assist in identifying situations where workers may benefit from ergonomic interventions such as an exoskeleton. Further lab and field AI motion capture accuracy validation research is being sponsored by a National Safety Council grant awarded to Iowa State University. The goal is to publish findings of this expanded AI accuracy study to assist safety professionals when considering AI-based assessment tools. **PSJ**

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