Automated Video Lifting Posture Classification Using Bounding Box Dimensions

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Abstract. A method is introduced for automatically classifying lifting postures using simple features obtained through drawing a rectangular bounding box tightly around the body on the sagittal plane in video recordings. Mannequin postures were generated using the University of Michigan 3DSSPP software encompassing a variety of hand locations and were classified into squatting, stooping, and standing. For each mannequin posture a rectangular bounding box was drawn tightly around the mannequin for views in the sagittal plane and rotated by 30 º horizontally. The bounding box dimensions were measured and normalized based on the standing height of the corresponding mannequin. A classification and regression tree algorithm was trained using the height and width of the bounding box to classify the postures. The resulting algorithm misclassified 0.36% of the training-set cases. The algorithm was tested on 30 lifting postures collected from video recordings a variety of industrial lifting tasks, misclassifying 3.33% of test-set cases. The sensitivity and specificity, respectively were 100.0% and 100.0% for squatting, 90.0% and 100.0% for stooping, and 100.0% and 95.0% for standing. The algorithm was capable of classifying lifting postures based only on dimensions of bounding boxes which are simple features that can be measured automatically and continuously. We have developed computer vision software that continuously tracks the subject's body and automatically applies the described bounding box.

Keywords: Computer vision · Musculoskeletal disorders
Exposure assessment

1 Introduction

Computer vision was previously used for evaluating hand activity level [1], exertion frequency and duty cycle [2], and visualizing repetitive motion task factors [3]. The current study investigates automatic classification of lifting postures using simple features extracted from video. Rather than measuring joint angles, we take a practical approach that is insensitive to challenging workplace conditions, such as poor illumination, poor vantage points, and obstructions, by relaxing the need for high precision. We explore if features of a simple sagittal plane "elastic" rectangular bounding

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box encompassing the entire body while continuously tracking the subject in a video, can classify standing, stooping and squatting while lifting.

2 Methods

Mannequin postures were systematically generated using the University of Michigan 3DSSPP software to encompass the range of hand locations (20 ACGIH TLV lifting zone boundary points [4]) and anthropometries (5th, 50th, and 95th percentile height for males and females). After excluding locations that smaller mannequins cannot reach, 105 cases (training-set) were generated for analysis. Based on torso (40º) and knee angles (130º), there were 43 squats, 13 stoops, and 49 standing postures.

A bounding box was drawn tightly around the subject for each training-set case for views in the sagittal plane as well as rotated by 30º with respect to the sagittal plane. The stature normalized height and width were measured. After randomly ordering the data, a classification and regression tree (CART) algorithm was trained [5] to classify the postures [6]. Decision trees for splits ranging between 1 to 10 were generated to determine the optimal thresholds based on cross validation error. To test the classifier, ten industrial video clips [7–12] in each class, totaling 30 cases (test-set), were randomly selected if the full body during lifting was visible in the sagittal plane.

3 Results

The resulting tree had four levels and four splits, misclassifying 0.36% training-set cases. For the test-set, the algorithm correctly classified 10 of 10 squats, 9 of 10 stoops, and 10 of 10 stands, misclassifying 3.3% cases. The sensitivity and specificity, respectively was 90.0% and 100.0% for squat, 90.0% and 100.0% for stoop, and 100.0% and 95.0% for standing.

4 Discussion

These posture classifications, which are related to hip and knee angles, were identified without direct angle measurements, instrumentation, markers, or fitting the image to a skeletal model. Although this study was limited to the sagittal plane, future work will investigate additional views. We have developed software to track a worker using this bounding box approach which may be used for continuously quantifying the frequency and duration postures are assumed during work. It is anticipated that this simple algorithm can be implemented on a hand-held device such as a smart phone, making it readily accessible to practitioners.

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