

Decision Rule Driven Human Activity Recognition

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Abstract

Human activity recognition has many real world applications such as surveillance, assistive robotics and simulation systems. Several human activity recognition systems incorporate analysis of static features and posture based co-ordinates to detect activity. There is additional information in the movement based features and temporal series of frames which can be leveraged to identify a certain action. This paper uses dynamic, temporal data to compare with decision rules and templates for activity recognition. The human shape is extracted using geometric model across multiple frames. The extracted shape is transformed to binary state using eigen space mapping and parametric canonical space transformation. The image data frames are down sampled using activity templates to a single candidate frame. This candidate frame was compared with the decision rule driven model to associate with an activity class label. The decision rule driven and activity templates method produced 64% recognition accuracy indicating that the method was feasible for recognizing human activities.

Introduction

Automatic recognition of human activity has gained attention of researchers in the past decade. The study by Poppe [1] examined the relation of motion and certain human activities. The study analyzed the movement of extracted features and shapes. Bobick and Davis [2] also used dynamic features and compared them with temporal templates developed using a key reference frame. Hamid et al [3] used graphical models to represent activity and used this graphs to recognize human actions. Carisson and Sullivan [4] used shape extracted from images and matched them with a reference shape. Human behavior analysis was done using probabilities in a study [5]. Researchers [6] used real time evaluation of human actions to check the recognition accuracy of the automated systems. Human gait and facial expression shape analysis was done by Huang and Nixon [7]. The study used canonical space representation for dimensionality reduction. Study by Yamato et. al [8] used HMM in sequential images to detect human actions. Techniques such as fuzzy rules and view-invariant analysis has been done in studies [9], [10] for recognition of human actions. In addition to human activity recognition several studies have focused on recognition of emotions from body display [11], [14], [17], [18], [19], [22], [23]. Additional studies in the last decade have also focused on multimodal emotion recognition instead of unimodal or bimodal data [25],[26],[27],[28] and [35]. Many research studies [36] to [57] have also focused on 3D, sensor based human activity recognition, and

effective software implementations to support real time processing. This paper focused on using decision rule based evaluation of extracted features by comparing against a candidate human activity shape.

Method

For the purpose of this study, 7 participants enacted the action of walking in a room and picking up objects. The actions were recorded using 1 camera for the frontal view and another camera for the side view. The human shape was then extracted using geometric model across multiple frames. The extracted shape was transformed to binary state using eigen space mapping and parametric transformation in the canonical space. The image data frames were then down sampled using activity templates to a single candidate frame. This candidate frame was finally compared with the decision rule driven model to associate with an activity class label. For the decision rule driven comparison the window of 16 x 16 was used. For each superimposed frame on the extracted shape image, the pixel intensity and the color was compared with the reference frame. The window was then moved to the next 16 x 16 block on the image. For each comparison the rule was evaluated to see if the difference in the intensities was above or below threshold and the Euclidean distance between colors was above or below the threshold. The results of the 2 rule evaluation was coded into a true = 1 and false = 0 value. Thus a binary matrix consisting of 1s and 0s was obtained. The total of 1s was counted to calculate a similarity score for the image mesh. If the score was higher than the threshold then the activity was recognized as walking in the room and picking up objects else it was classified as the activity of neutral standing pose.

Result

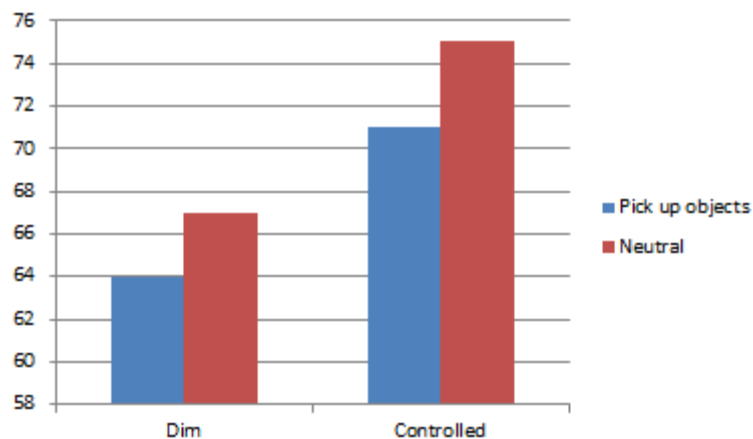


Fig. 1. Comparison of Recognition accuracy in dim and controlled lighting for individual person

The recognition accuracy for neutral was better (67% and 75%) as compared to the candidate activity of picking up objects (64% and 71%) for both lighting conditions (dim and controlled). The accuracy was lower for dim lighting conditions for both the neutral standing pose and the walking and picking up object action.

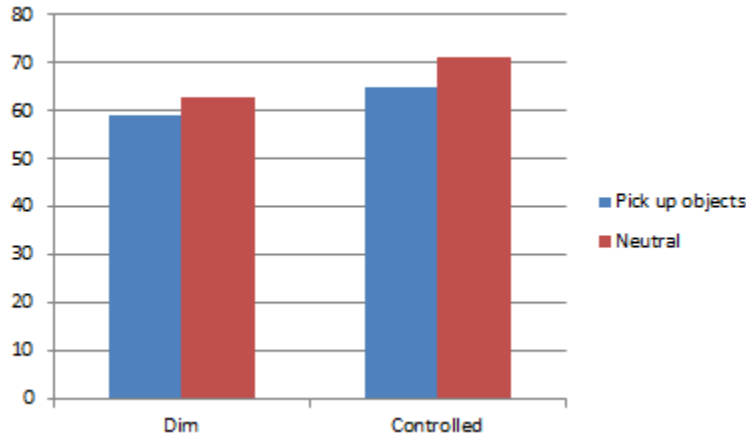


Fig. 2. Comparison of Recognition accuracy in dim and controlled lighting for group of people.

We also evaluated the recognition accuracy for a group of people performing the neutral standing pose and pick up objects actions under dim and controlled lighting. In this scenario the recognition accuracy for neutral was better (63% and 71%) as compared to the candidate activity of picking up objects (59% and 65%) for both lighting conditions (dim and controlled). The accuracy was lower for dim lighting conditions for both the neutral standing pose and the walking and picking up object action. But overall there was a drop in the recognition accuracy when compared with individual's performing the same actions instead of a group of people.

Conclusion

We did not find conclusive evidence that the decision rule based pixel analysis inside a 16 x 16 window was better for human activity recognition. The neutral pose recognition accuracy was better than picking up object accuracy. This was expected because the neutral position does not contain noise whereas the picking up object action involves a lot of movement which if not captured in the rule based evaluation may result in lower recognition accuracy. As a future scope other techniques such as HMM, 3D RGB-D sensor based tracking and image processing will be explored and compared with the method in this study to improve recognition accuracy.

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