iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 4 **Issue:** IX **Month of publication:** September 2016

DOI:

www.ijraset.com

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Volume 4 Issue IX, September 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Background Removal Using RGB-D Data for Fright Recognition

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Abstract— This research paper evaluates the automatic recognition of various human activities while moving inside a lobby using depth data for background removal and using the surrounding walls as reference lines of frame. The study examines detection of panic and fear as the subject of focus in the process of activity recognition. Many times, humans escape from danger and threat, try to evade, run to a secure spot because of fear caused by ambush, violence, presence of life threatening incidents such as shooting or because of natural calamity such as cyclone, hurricane, flash floods, earthquake and tornado. The research first uses a sequence of image to extract the human blob, shape form using image filtering. A background to foreground subtraction approach is taken to eliminate non-interesting regions. The blob, shape form is then normalized using a reference frame of lobby, room, followed by edge enhancements and then features are extracted by repeated application of a mesh with varying thresholds. Finally, a support vector machine (SVM) classifier was used to detect activity that represented fright. The results showed recognition accuracy of 74.8% for continuous, automatic, real time unconstrained video image series.
Keywords— Fear, Evade, Human Activity, Threat, Surveillance, Sensor, SVM, 3D tracking, Emotion, Hand, Body, Face, Legs.

I. INTRODUCTION

More and more incidents of violence in public are being reported. Sometimes there are natural calamities such as tornado, earthquake, flash floods, tsunamis. In such life threatening scenarios humans take evasive actions. They panic and run to take shelter and express fear. Surveillance systems equipped with detection of such behaviour can provide alerts and notify the authorities to take immediate action to resolve the issue. This paper examines detection of human activities in the hallway specifically during the event of some threat. Haritaoglu et. al [1] have implemented a surveillance system to detect human activity in outdoor environments. The study used infrared sensing and grey scale image processing for object detection. In a research by Stauffer [2], similarities in activities was examined to find patterns in real time. Elgammal et. al [3] used kernel density estimation to separate background from foreground. Researchers [4], [5], [6], [7], [8] have analyzed view independent human gait detection, using view calibration, multi-view recording, shape and motion features. The studies [9], [10], [11], [12], [13], [14], [15] on human activity recognition have used various techniques such as probabilistic classification, HMM and model based approaches. Readers are directed towards studies [16] through [36] for surveys, unimodal, bimodal and multimodal emotion recognition techniques as well as software strategies for real time implementation of such systems. Researchers [37] through [53] have focused on capturing data using sensors, motion based human activity recognition, 3D feature creation and using color and depth data (RGB-D) for segmentation and action recognition.

II. METHOD

In this research 28 participants were asked to enact actions (7 action categories in total) representing fear and normal walk through the hallway. The video footage was captured using an infrared sensor and video camera to store the color and depth data. The sessions were repeated under different lighting conditions, clothes color, wall color. The data was then fed to the automatic background subtraction system (AUBSS). The background subtraction used two channels for the data. The first channel was the depth frame and the second channel was the color frame. In the first step the total available depth information was calculated. Then the depth was split into 1000 sub divisions. Then the frame which was farthest was processed first.

Each pixel in the frame was analysed for similarity in color in the HSV space with the threshold of 20. This resulted in blobs of pixel with similar colors. This was repeated for each sub division of the depth frame. Once a collection of blobs was obtained the images were superimposed with a reference frame. The reference frame was constructed by first performing edge detection to detect the walls in the hallway. Then the reference frame was used to eliminate the blobs which were outside the frame boundaries. A grid image was applied on each blob and the 3-D co-ordinates and color of the intersecting point were taken as the feature for the particular frame. A feature vector was constructed from all the depth sub divisions. This was used for training the SVM based classifier for each class of action. The slack variable was set to 0.3 and optimized using grid forward search. The data was split into 80% training data and 20% test data. The training was done using 10-fold cross validation. The radial basis function was used as the

Volume 4 Issue IX, September 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

kernel for the training.

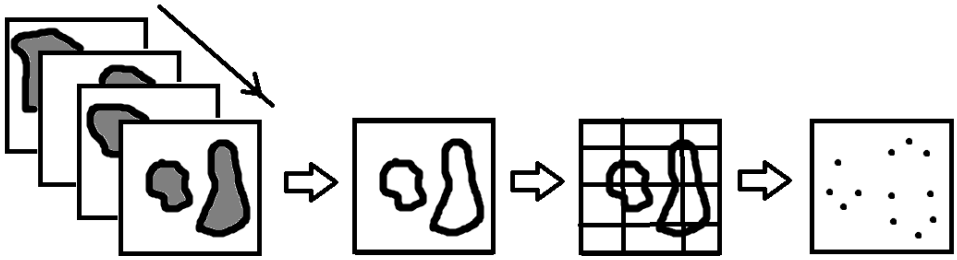

Fig. 1. Blob extraction and grid based feature co-ordinate extraction.

Fig. 2. Edge detection on the background subtracted human shapes.

III. RESULTS

Results for classification of actions in controlled lighting.

0.789	0.025	0	0.063	0	0.088	0.034	Run Forward
0.128	**0.79**	0.004	0.034	0.033	0	0.011	Duck
0.15	0.028	**0.771**	0	0.052	0	0	Crawl
0.016	0.05	0.086	**0.651**	0.054	0.054	0.09	Run Away
0.027	0.038	0.03	0.021	**0.879**	0	0.005	Push against doors
0.068	0.019	0	0.025	0	**0.866**	0.023	Push against wall
0.022	0.051	0.009	0.013	0.022	0.029	**0.853**	Normal walk

The overall accuracy of the activity recognition system under controlled lighting was 80%.

Results for classification of actions in dim lighting.

0.698	0.022	0.02	0.066	0.068	0.078	0.047	Run Forward
0.126	**0.775**	0.004	0.034	0.032	0	0.03	Duck
0.139	0.025	**0.713**	0.032	0.048	0.029	0.014	Crawl
0.031	0.052	0.09	**0.679**	0.056	0.056	0.035	Run Away
0.028	0.039	0.032	0.086	**0.74**	0.032	0.043	Push against doors
0.066	0.018	0.057	0.024	0	**0.795**	0.04	Push against wall
0.022	0.05	0.009	0.031	0.022	0.029	**0.838**	Normal walk

The overall accuracy of the activity recognition system was 74.8% which was lower than the accuracy in controlled lighting.

IV. CONCLUSIONS

The drop in the accuracy in activity recognition under dim lighting showed a limitation in the system and more work needs to be done to make the system more generalizable and robust. The research provided benchmark fear detection results data for further analysis. The processing performance of the implementation was real time which indicated that the method proposed was not computationally intensive as initial thought. As future scope some improvements in the mesh based feature extraction techniques need to be explored to improve the classification accuracy and discriminatory power of the feature vectors.

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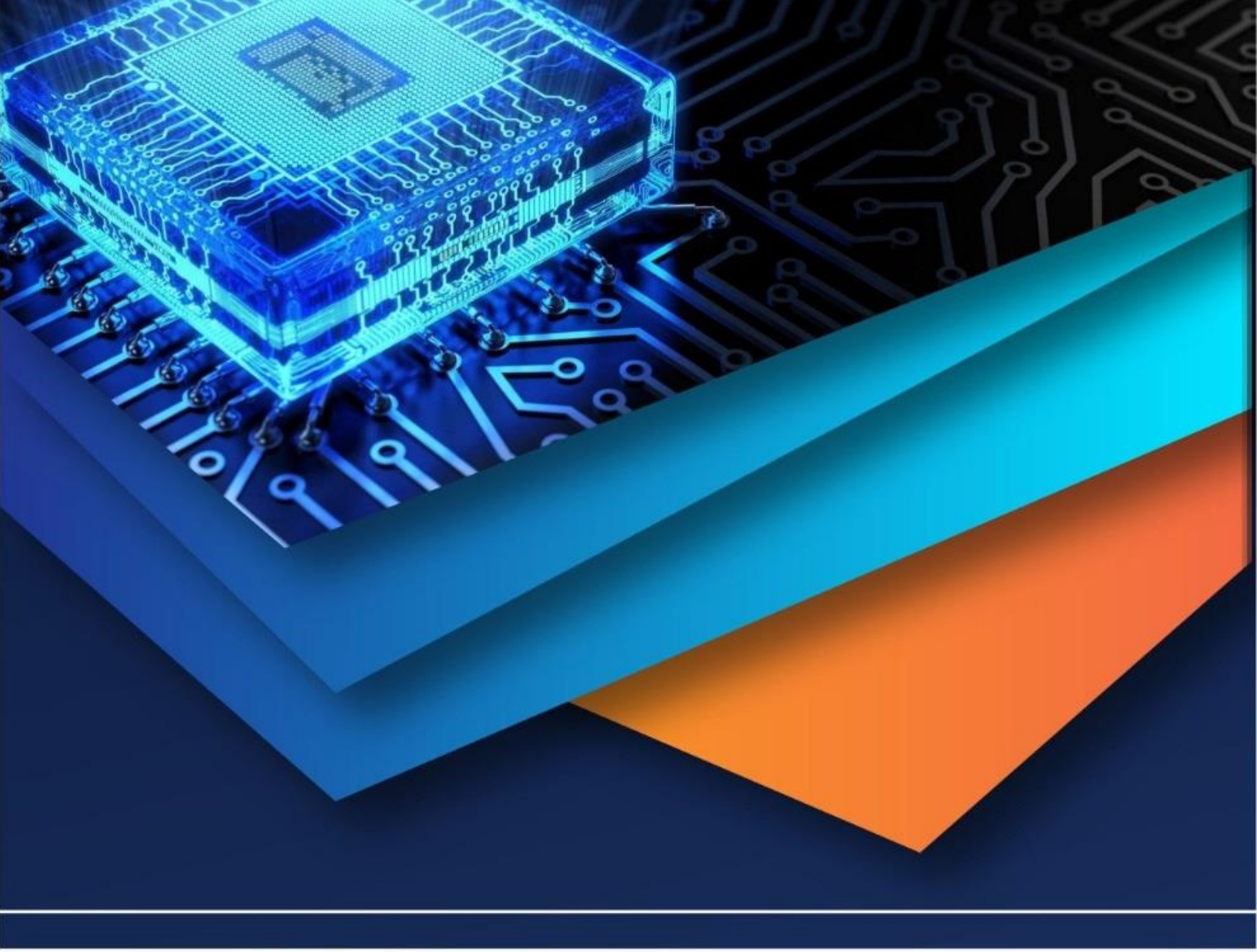

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