Drunken Abnormal Human Gait Detection using Sensors

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***Abstract*— Several studies have examined human activity and gait detection. But relatively fewer studies have looked specifically into abnormal gait or how drunken person walks. This paper uses markers based tracking to train an SVM classifier for recognizing various abnormal actions while walking such as tripping, swaying, walking side-ways, falling, dragging and walking with support vs normal gait. 5 subjects participated in enacting drunk behaviour from a list of actions representing abnormal gait. The classification results indicated x% accuracy under controlled lighting. The accuracy was lower by 3.1% in dim indoor lighting and natural outdoor setup.**

***Keywords*— Drunken, Abnormal, Human Activity, Gait, Sensor, SVM, 3D tracking, Emotion, Hand, Body, Face, Legs.**

I. Introduction

The study by Holien [1] examined how the manner in which people walk affect authentication. The study used accelerometer sensor to find patterns in walking and recommended possible application in security. The study only tracked gait using sensor on the left hip. Hayfron-Acquah [2], [3] evaluated generalized symmetry operator instead of relying on shapes and borders. The study used discrete Fourier transforms and nearest neighbour approach to find similarities in gaits of same person. In a study on human gait recognition Huang et. al [4] used spatio-temporal templates to identify human gait. The study used reference templates to compare the temporal changes in features and detect gait. Wang [5] used statistical shape dynamics to recognize human gait. The study discussed focussing on gait from the front making it view-dependent and only analysing static shapes leaving an opportunity for exploring impact of dynamic information. Researchers Zeng and Wang [6] used time-invariant representation of time-varying dynamical pattern to detect gait. The study used angular velocities and joint angles as features. Research by Wang et. al [7] examined gait recognition in non-frontal position and used features such as distance between legs and height. Results in study by Ismail [8] indicated left and right thigh features were significant in improving detection rate. The study focused on abnormal gait patterns like dragging and drunken walk. Studies [9], [10], [11], [12], [13], [14], [15] have used 3D data for real time detection using probabilistic approaches such as hidden markov model (HMM) and view invariant techniques. Researcher in [16] through [36] have analysed emotions in detail using multiple modalities and temporal and pose based techniques. The studies also discuss efficient software implementation methods for real time image processing and human activity detection. Research done in [37] through [54] contain surveys and comparisons of state of the art human activity recognition mechanisms.

II. Method

A total of 5 participants were used to enact from a list of 10 actions and 1 normal walking activity. Markers were applied to participants tracking points on the face, hand, body and legs. The data was annotated using 1 class labels associated with each of the 6 actions. The data was split into 80% for training and 20% for test. The SVM classifiers for each action was trained using 10-fold cross validation. A total of 20 markers on the body and 20 on the face were used to track the drunken human gait. The feature vector consisted of movement of each tracked point for 3 second window measured in terms of velocity, the x,y,z co-ordinates of each point and the distance of each point from the reference point on the back. The participants were shown the 10 actions as reference and spontaneously moved as if they were drunk.

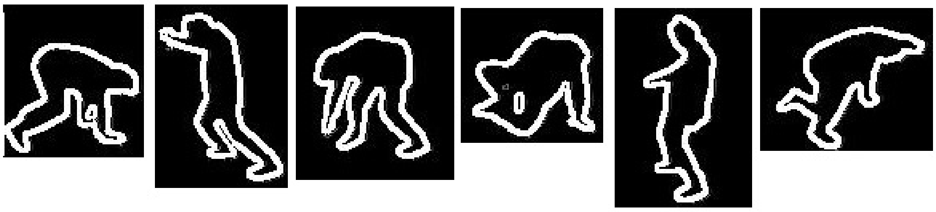

Fig. 1. The six actions with limited movement and more activity on the spot.

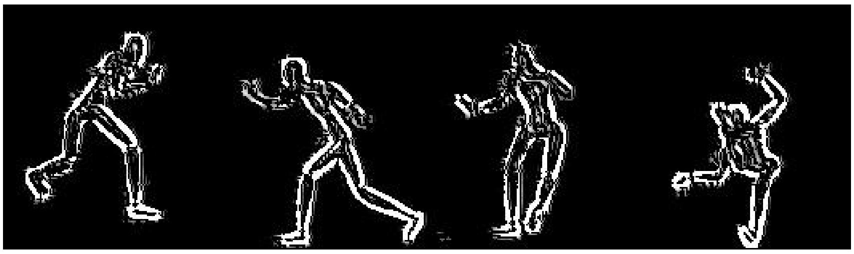

Fig. 2. The four actions involving drunken walking.

III. Results

0.697	0.022	0.02	0.066	0.068	0.078	0.048	Drunk action 1
0.126	**0.775**	0.004	0.034	0.032	0	0.03	Drunk action 2
0.166	0.025	**0.69**	0.031	0.046	0.028	0.014	Drunk action 3

0.026	0.043	0.247	**0.562**	0.047	0.047	0.029	Drunk action 4
0.02	0.039	0.046	0.085	**0.735**	0.032	0.043	Drunk action 5
0.056	0.015	0.048	0.02	0	**0.672**	0.189	Drunk action 6
0.088	0.044	0.07	0.027	0.019	0.025	**0.728**	Normal walk

Fig.1. Confusion matrix for controlled lighting.

The overall accuracy for the drunken and abnormal gait detection was 69.4%. Action 6 had a relatively higher rate of misclassification with normal walk compared to other actions. Normal walk was classified incorrectly mostly as drunken action 1 (8.8%).

0.644	0.021	0.054	0.064	0.08	0.076	0.061	
0.129	**0.77**	0.004	0.035	0.033	0	0.031	
0.174	0.026	**0.677**	0.032	0.048	0.029	0.014	
0.023	0.038	0.216	**0.547**	0.065	0.054	0.057	
0.035	0.035	0.127	0.077	**0.66**	0.028	0.038	
0.054	0.015	0.046	0.019	0.034	**0.649**	0.182	
0.084	0.042	0.067	0.025	0.063	0.024	**0.695**	

The overall accuracy for the abnormal human gait detection decreased under dim indoor lighting and natural outdoor settings. The accuracy dropped from 72.8% to 69.5% in terms of recall rate for normal gait. The overall accuracy of drunk action recognition recall rates dropped by 3.1%.

IV. Conclusions

The system performed at a higher accuracy level under controlled lighting compared to accuracy levels in indoor dim lighting or outdoor naturalistic settings. This showed that more features need to be explored and the classifier needs to be trained with more data before the results can be generalized. The number of participants 5 was less and as a future scope higher number of participants in more natural lighting would need to be used for training the recognition system.

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