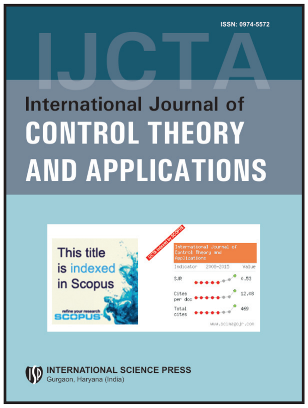

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Image-based Human Fall Recognition Using Gaussian Mixture Model and Support Vector Machine

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Abstract: This paper discusses an image-based approach for human fall recognition (HFR) where Gaussian Mixture Model (GMM) is being utilized for foreground detection and pixel modelling. The extracted feature vectors of GMM are being entered into two classifiers to compare the fall recognition performance that are Support Vector Machine (SVM) and Adaboost. This research is applicable in health care industry and elderly as they are highly exposed to the risks of injuries due to falls which may lead to death. A dataset of various series of falls and Activities of Daily Living (ADL) that include standing, walking and running, has been constructed. The experimental results indicate that SVM has a better fall recognition performance compared to Adaboost.

Keyword: Adaboost, Fall Detection, Gaussian Mixture Models, Support Vector Machine.

1. INTRODUCTION

The application of Human Fall Recognition (HFR) can facilitate and enhance the rehabilitation process of patients [1]. According to [2], the main cause of death among senior citizen is fall. However, one should be aware that falls cannot be completely prevented but the detection and recognition of falls can be performed to provide immediate and critical treatment to the injured persons [3]. Hence, this has led to the rising interests as well as demands for surveillance system that supports fall detection, especially in the healthcare industry due to the rising population of the elder ones.

The fall detection approach can be grouped into two types, namely wearable sensor-based [4][5] and image-based [6][7]. Usually, the autonomous wearable sensors are attached under the armpit or around the waist. The problems with wearable sensors are that the old people need to remember to wear them and these devices require batteries that need to be replaced for efficient performance [6]. Thus, this research investigates image-based approach for human fall recognition where only a video surveillance camera is required to be installed in the space needed without having to have the elderly to wear any sensors.

This paper is structured as follows. Section II explains the relevant studies on human fall recognition. Methodology of this research is discussed in section III while result and analysis are discussed in section IV. Section V concludes this paper and briefly explains the future work.

2. RELATED WORK

Advances in computer vision have increased research in image-based approach for human fall recognition (HFR) and one of the popular features utilized is Gaussian Mixture Model (GMM). The novel adaptive Gaussian background mixture models was first introduced by [8] for pixel modelling, to handle the issue of variable lighting conditions which was encountered by previous single Gaussian pixel modelling. A survey was conducted on various vision-based fall detection techniques using single RGB camera, 3D-based approach with multiple RGB cameras, and depth cameras [9]. Various types of falls make fall recognition a very challenging task and constructing a publicly available benchmark dataset of falls is important for better performance evaluation.

[10] design a fall detection system that extracts foreground using adaptive GMM. The foreground is represented in 5-dimensional feature vectors using the ellipse model, and applies Hidden Markov Model (HMM) for fall recognition. A statistical vision-based approach that uses the Weizmann dataset as features with Support Vector Machine (SVM) is proposed for keeping the extracted features simple and relatively small, and to be faster and easier in computation for real time applications [11]. SVM has also being applied for human behaviour classification where star skeletonization is the feature in the application of abnormal human behaviour for crowded urban monitoring environment [12]. [13] propose an activity recognition system that uses Histogram of Oriented Gradient Pattern History (HOGPH) with SVM.

[14] propose GMM super-vectors kernel function in SVM framework towards fall detection by using acoustic audio signal. Background subtraction or frame differencing is known as the easiest and direct method for foreground segmentation. A learning constant parameter is used to preserve the background frame with accordance to frame differencing, which allows foreground with large changes in the frames to be detected [15].

Single Gaussian is suitable for modelling pixels from a specific surface under particular lighting. However, in reality, various lighting conditions and multiple surfaces appear all the time. Thus, it is more appropriate to use adaptive Gaussian per pixel [15]. Foreground is recognized as pixel values that do not match the distribution of the background and this will be determined whenever sufficient and consistent information is obtained for the detecting foreground [8]. The well-establishment of GMM has provided strengths in terms of data adaptability, modelling flexibility and robustness [16].

One has to recognize the importance of machine learning in the development of human activity recognition system. [17] has provided a comprehensive research on the basic concepts and various applications of various kernel-based machine learning algorithm, such as Kernel Fisher discriminant (KFD), Support Vector Machine (SVM), Kernel Fisher discriminant (KFD) analysis, and kernel principal component analysis (KPCA). SVM is one of the commonly used classifiers due to its outstanding generalization and high paradigm accuracy [11]. Adaboost is utilized in various research related to object recognition and has shown good results [18] and [19]. Since SVM and Adaboost are two popular classifiers being applied in fall recognition applications, this research attempts to investigate their performance.

A. Gaussian Mixture Model (GMM)

A parametric representation model Gaussian Mixture Model (GMM) is a model that is based on probability frequency function, where it is trained to represent the distribution of a feature vector [20]. The basic concept of GMM is to model the pixel values as mixture of Gaussians, which correspond to the colours of the background based on persistence and variance.

Density models that are made up of a number of component functions (Gaussian) are known as mixture models. A mixture of K Gaussians distribution represents every single pixel, where the probability of perceiving the pixel value is presented in equation 1.

$$p(\omega \mid x) = \sum_{k=1}^{K} \alpha_k G(x; \mu_k, \sigma_k)$$

$$p(\omega \mid x) = \sum_{k=1}^{K} \alpha_k \cdot \frac{1}{(2\pi)^{d/2} \left| \sum_k \right|^{1/2}} \exp\left\{ -\frac{1}{2} (x - \mu_k)^T \sum_k^{-1} (x - \mu_k) \right\} \qquad (1)$$

where, αk is the mixing parameter that fulfilling G(x; αk, μk) is the probability density function (p.d.f) with correspondence to k-th Gaussian component [21].

B. Support Vector Machine (SVM)

The main purpose of SVM is to reduce misclassification error by maximizing the margin width. The simplest case of classification consists of two different classes. Based on the unknown distribution of possibility P(x, y), independent identically distribution generated from the input and output training data pairs is used for the estimation [17]. Linearly separable SVM classification is described as the separation of high dimensional data into two groups, $y_i = \{+1, -1\}$ with no overlap or misclassification. The maximum margin width and minimum margin width are subjected to constraint is shown in equation 2.

$$y_i(w_1 x_{i1} + w_2 x_{i2} - b) \geq 1 \text{ for } i = 1, 2, ..., m \qquad (2)$$

Therefore, weight vector (w), bias (b), number of support vectors (m) are critical parameters for classification. SVM can be categorized into 3 categories which is linearly separable, linearly inseparable and non-linearly separable.

C. Adaboost

"Adaptive boosting" also known as Adaboost is a subsequent weak learner is adjusted in assitance of those instances misclassified by preceding classifiers. Let ht (x)…"weak" or basis classifier, hypothesis, "feature" and H(x) is equal to sign ($f(x)$)… absolute classifier/ hypothesis or "strong". Adaboost adjusts adaptively the errors of the weak hypotheses by Weaklearn, which is a weak learning algorithm to be boosted. The preceding weak learners have only 50% accuracy over new scattering instead of sampling and re-weight. The ultimate classification is based on the weighted vote of weak classifiers [22].

3. METHODOLOGY

An overview of the GMM-SVM fall detection system is illustrated in Figure 1. The first phase of the methodology is foreground detection where the object is detected by using GMM. Each pixel in the sample image is modelled with 3 Gaussian numbers. Hence, the foreground pixel was not identified by a blob. GMM modelled pixels containing colour features which are affected by lighting conditions.

In the feature extraction phase, the colour features of each image is represented as the mean vectors by averaging the pixel values of every column obtained from the extracted features, and converted them to 1×360 matrix, which is later being used as input for the fall recognition phase. The mean vectors are being compared with the standard deviation vectors computed from the same features. This is to investigate whether the mean or standard deviation is better for fall recognition.

In the final recognition phase, the input datasets are grouped into two types which is training and testing on SVM and Adaboost. The activity is classified into two classes: Fall and Not Fall. Lastly, the accuracy of fall recognition performance is computed according to the number of correctly assign to fall and not fall activities divided by the sum of testing samples. The average is computed based on the results produced from 5 sets of training and testing data that have been constructed randomly. Since the performance of SVM is influenced by the kernel function, the same sets of samples are experimented with different kernel functions namely Polynomial, Radial Basis Function (RBF), Linear and Multilayer Perceptron (MLP) kernel to compare the effect of kernel functions in fall recognition.

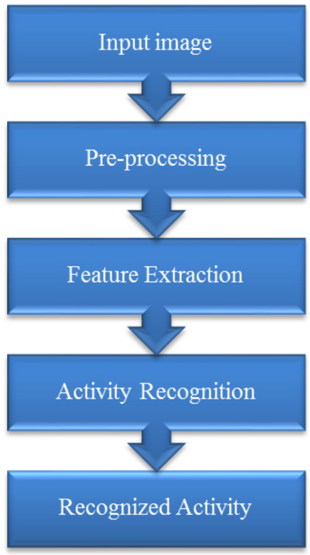

Figure 1: Overview of fall detection approach

Since the experiment focus on offline activity recognition, static images are used as input instead of video frames. Static images are captured by having the human models acting for ADL like standing, walking and running samples, while various types of falling images are captured to be used as falling samples. Figure 2 illustrates some sample images of falling while Figure 3 shows some sample images of ADL. 60 images of falling and 60 images of ADL have been captured. The training data set consist of 50 images for each activity while the testing dataset consist 10 images for each activity. 5 sets of training and testing data have been constructed by randomly chosen from the captured images and the average accuracy is computed based on the results produced by the 5 sets of data.

Figure 2: Sample images of different types of falling

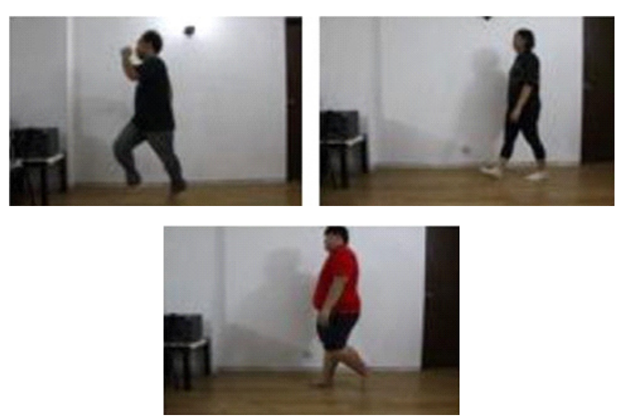

Figure 3: Sample images of non-falling or ADL

4. RESULT ANALYSIS

Experiments have been conducted using Matlab software. Table 1 shows the outcomes produced by different kernel functions for SVM with mean and standard deviation. By referring to Table 1, it is found that standard deviation is better than mean with polynomial kernel function. Adaboost only produced about 60% fall recognition accuracy with both mean and standard deviation. Thus, this study shows that GMM and SVM with polynomial kernel function are feasible to be utilized for human fall recognition. Adaboost is sensitive to noisy data that is due to illumination changes like shadows as can be seen from Figure 2 and Figure 3. Thus, since there are various types of falls, Adaboost's performance is very poor for these variations.

Table 1
Comparison of SVM performance based on different kernel functions

	Mean	*Standard Deviation*
Linear	73.0%	85.5%
Polynomial = 3	65.0%	90.8%
Quadratic	70.0%	87.5%
MLP	48.5%	68.0%
RBF	50.0%	50.0%

5. CONCLUSION

In this paper, the application of GMM with SVM and Adaboost for human fall recognition is demonstrated. SVM is more suitable than Adaboost for indoor fall recognition since it is not sensitive to illumination changes like shadows. In health care industry, elderly and patients are highly exposed to the risks of injuries that caused by falls, either indoor or outdoor. Thus, the outcome of this research is hoped to be able to assist in developing fall recognition application in healthcare. For future work, this research will explore other features that require less memory space and processing time, and other human activities.

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