Performance of Random Forest and SVM in Face Recognition

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Abstract: *In this study, we present the performance of Random Forest (RF) and Support Vector Machine (SVM) in facial recognition. Random Forest Tree (RFT) based algorithm is popular in computer vision and in solving the facial recognition. SVM is a machine learning method and has been used for classification of face recognition. The kernel parameters were used for optimization. The testing has been comportment from the International Burch University (IBU) image databases. Each person consists of 20 single individual photos, with different facial expression and size 205×274PX. The SVM achieved accuracy of 93.20%, but when optimized with different classifiers and kernel accuracy among all was 95.89%, 96.92%, 97.94%. RF achieved accuracy of 97.17%. The approach was as follow: Reads image, skin color detection, RGB to gray, histogram, performance of SVM, RF and classification. All research and testing which were conducted is with aim to be integrated in mobile application for face detection, where application can perform with higher accuracy and performance.*

Keywords: *SVM, RF, face recognition.*

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1. Introduction

The facial recognition plays a role in computerized system and its aim is in recognizing individuals by using computerized system. Pattern recognition, machine learning, artificial recognition represents emerging approaches in training of smart mobile computers for human recognition. This is very complex issues, therefore it consist of various different features [2]. Kremic and Subasi [15] proposed implementation of Principle Component Analysis (PCA) for mobile recognition. This paper, discuss the novel results, whose purpose for the future study and exploration is to perform on mobile machine with much higher rate of accuracy. In here, we are presenting the result of Random Forest (RF) compared with Support Vector Machine (SVM). Human brains are highly capable of recognizing humans instantly [21]. Emphasize of this research is in training the machine system to be capable to learn and to recognize with the ability that will be closest in accuracy as human. Today, there exists higher need for artificial recognition using face, more than just a finger prints or other biometric features. In general, face recognition consists of feature vector matching as described in PCA [12, 15, 16]. In this study we have used 40 human faces and for each faces we used 20 different facial images for each person, which in total are 800 images of 205×274 sizes.

The purpose of this research is to bring well designed approach for face recognition; therefore it can be incorporated and tested on real time application for mobile security.

In studies conducted before, the images recognition has been done by applying the statistical model of PCA with feature vector extraction or SVM feature vector extraction. The methodology of this research is: Images were read from database, 3D color image RGB are read from database then is performed skin color detection, then RGB to gray, histogram, SVM/RF, classify and authentication. The results obtain by accomplishing these steps for SVM 97.94% and RF 97, 17%. This paper briefs on RF [11, 24] and SVMs, in section 2 it will present the performance of face recognition using these two approaches.

2. Random Forest and SVMs Background

2.1. Random Forest

Each learning method includes some methods of randomization. Such aim is to choose the best option at every step. Very famous is RF [19]. RF learns built randomized decision tree. For each iteration the algorithm often produces excellent predictors [25].

RF [4, 13, 25] basic idea is to find the average value of noise. Very complex interaction trees can capture, complex input space can be computed into simpler space and it's the aim of decision tree and RF are collection of decision trees [4, 13, 25]. In [4] has shown that the collection of RF, decision trees trained randomly. Therefore, available data reduces the over fitting in comparison [4, 13, 25]. Therefore, RF methodology is extension of bagging classification tree [4, 13 ,25].

It is a parallel learning process. It achieves a high accuracy and has fast training phase. The advantages of RF are [3]:

- Straightforward Learning.
- Local Representation.
- Classification with Occlusion.
- Parallelization.
- Fast Training Time.

It uses random selection methods, so it can perform a better, especially when there are many redundant features discrimination [1, 9].

The method that describes RF [1] follows: For b=1, …, B, sample n, observations with replacement from L [1, 8]. It refers [1]:

1. Node t, randomly sample m of the p independent variables
2. $\forall$ of the k=1, …, m sampled variable; among all splits of variable k^{th}, find the best split s_k.
3. In s*, choose the best split from among k=1, … , m; find the best split s_k for splitting node t; j^{th} variable is defined cut point c_{s*} that is used for splitting node t.
4. At this node, split the data by sending the i=1, …, n; observation with $x_{ij}< c_{s*}$ to the left descending node and all observation $x_{ij}\geq c_{s*}$ to the right descendant.
5. Repeat steps 1 to 4 on all descendant nodes for growing a maximally sized tree T_b.

2.2. SVMs

A SVM performs classification by constructing an N-dimensional hyper plane that optimally separates the data into two categories. SVM models are related to neural networks. In fact, a SVM model using a sigmoid kernel functions that is equivalent to a two-layer perceptron neural network. The classical neural networks are very similar to model of SVM. With usage of kernel, SVM's are alternative training methods. Those methods are for polynomial, radial basis function and multi-layer perceptron classifier, where the weights of networks are found and defined in problem of quadratic programming problem QP with linear constrains. Sloping a non-convex and unconstrained minimization problem as what is it standard in neural network training [22].

We are faced with many various descriptions in literatures that refer to the subject of SVM. Sometimes we will find a predictor variable that is called an attribute and transformed attribute that is used to define the hyper plane called a feature [7, 22]. The most suitable representation is known as feature selection. It describes row of predictor values called by vector. The model of SVM has found its purpose in finding the optimal hyper plane that separates clusters of vectors in such a way where cases with one set of variables on one side of the plane and cases with other sets of variables on the another side of the plane. The vectors near the hyper plane are the support vectors [7, 22]. Vapnik [7, 22] invented SVM in 1979. In its simplest, linear form, an SVM is a hyper plane that separates a set of positive example from a set of negative example with maximum margin. The SVM machines are the three-layer of Feed-forward Neural Network (FNN). Its implementation in the structural risk minimizes principle which roots in the implementation statistical learning theory. SVM's do not minimize the training error. Instead, the purpose of SVM is to minimize an upper bound of the generalization error and to maximize the margin between a separation hyper plane and the training data.

Nonlinear kernel functions are used to overcome the course of dimensionality. The space of the input examples, $x \subset R^n$, is mapped onto a high dimensional feature space so that the optimal separating hyper plane built on this space allows a good generalization capacity. A typical classification problem is in the separation positive member from negative members. Therefore, we are required to build a conventional classifier that separates positive members from negative members. If the data points in the training set are vectors of m numbers, the development of such a classifier is to find a hyper plane that is able to separate members. They are usually not ideal and they involve non–separable data. What it means? It means that may not exist a hyper plane allowing us to separate all positive members from the negative members. The beauty of SVM comes from its elegantly defined criterion for selecting a separating plane because there may usually be many high-dimensional candidate planes available for doing a similar job. SVM are able to select the plane that maintains a maximum margin in the training set. The reason why it is found as important is because statistical learning theory suggests that the choice of the maximum margin hyper plane will lead to maximal generalization when the result is used for predicting classification of unseen data.

For the linear case [7, 18] the margin is defined by the distance of the hyper plane to the nearest of the positive and negative examples. The formula for the output of a linear SVM is:

$$u=w \times x - b \tag{1}$$

Where w the normal vector to the hyper plane and x is the input vector [18]. The separating hyper plane is the plane u=0. The nearest points lie on the planes u=+1 and u=-1. The margin m is thus.

$$m=\frac{1}{\|w\|2} \tag{2}$$

SVM can be even further generalized to non-linear classifier. The output of a non-linear SVM is explicitly computed from the Lagrange multipliers:

$$u=\sum_{j=1}^{N} y_j \alpha_j K(\mathrm{x}_j, x) - b \tag{3}$$

Where K: Is a kernel function that measures the similarity or distance between the input vector x and the store training vector x_j [8].

2.3. Linear SVM

We will start with the simplest case [6]: Linear machines trained on separable data Figure 2 (as we shall see, the analysis for the general case-nonlinear machines trained on non-separable data-results in a very similar quadratic programming problem). Labeling the training data x_j, y_i, i=1, ..., l, y_i™{-1, +1}, $x_i \in R^d$, let assume some hyper plane separates the positive and the negative examples from each other's (a "separating hyper plane"). The points which lie on the hyper plane satisfy $w \times x + b = 0$, where w is normal to the hyper plane, $|b|/||w||$ is the perpendicular distance from the hyper plane to the origin and $||w||$ is the Euclidean norm of w. Let d_{mm} be the shortest distance from the separating hyper plane to the closest positive (negative) example. Define the "margin" of a separating hyper plane to be d_{mm}. For the linearly separable case, the support vector algorithm simply looks for the separating hyper plane with largest margin. This can be formulated as follows: Suppose that all the training data satisfy the following constraints [6]:

$$x_i \times w + b \geq for\ y_i = +1 \tag{4}$$

$$x_i \times w + b \leq for\ y_i = -1 \tag{5}$$

These can be combined into one set of inequalities:

$$y_i (x_i \times w + b) - 1 \geq 0 \forall_i \tag{6}$$

Now, consider the point for which the equality in Equations 4 and 5 holds parallel hyper planes. These points lie on the hyper plane. Hyper plane H_1:$x_i \times w + b = 1$ has normal w and perpendicular distance from the origin $|1-b|/||w||$. Similarly, the point within the equality Equation 5 hold the hyper plane H_1:$x_i \times w + b = -1$, with normal again w and perpendicular distance from the origin $|-1-b|/||w||$. Hence, $d_+ = d_- = /||w||$ and the margin is simply $2/||w||$. Note that, H_1 and H_2 are parallel (they have the same normal) and that no training points fall between them. Thus, we can find the pair of hyper planes which gives the maximum margin by minimizing $|w||^2$, subject to constraints Equation 6 [5, 6].

The training points for which the equality in Equation 6 holds (i.e., those which wind up lying on one of the hyper planes H_1 and H_2) and whose removal would change the solution found are called support vectors. They are shown in Figure 1 by the extra circles [5].

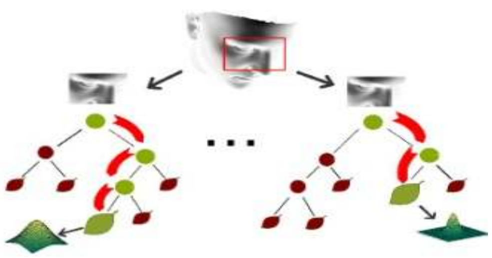

Figure 1. Example of regression forest for facial pose estimation [9].

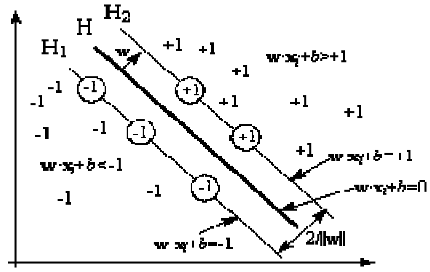

Figure 2. Linear separating hyper planes.

3. Discussion

3.1. Methodology

In different research methodologies researcher for face recognition were using altered approaches [2]. They have had used different statistical methods as: PCA, LDA, SVM, K-NN, etc., [2] they have been used edge detection methods, different algorithm approaches, comparing image to image directly. The aim of this research is to adapt to real time face recognition system. Moreover, we are presetting the best solution that will be implemented and incorporate in further study for mobile computer system. In [3] were dealing with detection and recognition of human faces using the RF. The approach they were using is object/face detection, segmentation, feature extraction RF and recognition. In [14] were performed SVM feature extractions for face recognition. Moreover, in [6, 15, 17] was performed PCA for face recognition.

For this study images were acquired via mobile phone, since the initial study was intend to develop the reliable mobile system with the face recognition application. The resolution of mobile phone camera is 5 px. In Figure 4 is represented the sample of data sets. It is the International Burch University (IBU) face image data set acquired for the research which takes implementation in facial recognition. The structure of the approach applied for facial recognition is presented in Figure 3. The following steps were:

- Read Image.
- Skin Color Detection.
- RGB to Gray.
- Histogram.
- SVM and RF.
- Classify.
- Authentication.

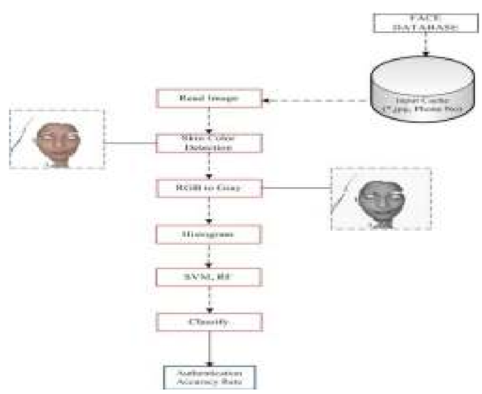

Figure 3. Diagram of approaches for face recognition.

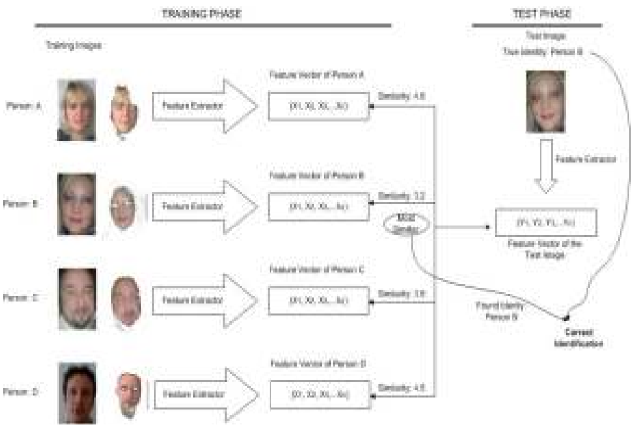

Figure 4. Training and testing Phase.

The images were read into machine from database. The database consists of images in file system. Dataset consist of images with various poses. The poses which were taken into testing were: Pose, presence of structural components, facial expression, occlusion, image orientation and image condition [16]. After considering all those images, we have performed skin color detection. The skin color detection we can express as follows:

$$S_n(x, y) = \sum_{i,j=1}^{1} I(x+i, y+j) \quad (7)$$

In expression Equation 7, we remove the noise from the image as skin pixels and then we have binary image from RBG to gray scale image $I(x, y)$ in a neighboring area. Then we perform histogram values for $S_n(x, y)$, would be in a set of number for example of {0, 1, 2, ..., 200}. Then, we can perform the machine learning algorithm or tree (in our case SVM and RF), where we performed the recognition and accuracy rate. In Figure 3 visually is presented the process of training and testing phase.

Figure 4 shows schematic diagram of training phase where we read imaged for training then we see skin color detection, in between are feature vectors and test phase where is perform recognition. The SVM and RF we performed in Weka. The authentication consists of verification and identification [15, 16]. Therefore, the machines need to be able to learn, comprehend the process and to identify the matching input data with all samples from the dataset.

4. Results and Discussion

4.1. Performance Evaluation

For performing the analysis based on image dataset of face poses is very interesting in predicting the people. Very different techniques can be applied. We have compared two methods: RF and SVM [10, 20]. For performing testing we have dataset consisting of face images, training data for training classifier and test data for testing used for evaluation of final methods.

All data were selected independently. In training data were different images from those in testing data set. Overall error estimation is the 10 error [23]. Cross Validation Accuracy (CVA) Equation 8 is the average of k individual accuracy measures:

$$CVA = \frac{1}{k} \sum_{j=1}^{k} A_i \quad (8)$$

Where k (represent number of folds in use) and A_i for accuracy measure for each fold i=1, …, k [23]. Accuracy we measure by calculating True Positive (TP) Equation 9 and False Positive (FP) Equation 10 rate that are used for evaluating the performance Therefore sensitivity and specificity more known as TP Rate (TPR) and FP Rate (FPR) are used in diagnosing the testing results. *TPR* is referred for those people, who have positive test results:

$$TPR = \frac{TP}{TP+FN} \times 100\% \quad (9)$$

While, *FPR* Equation 10 refers to the group of people who have negative recognition rate where 1-FP is defined as:

$$FPR = \frac{TN}{TP+FN} \times 100\% \quad (10)$$

Accuracy Equation 11 is used to represent the overall measure and is represented as:

$$Accuracy = \frac{TPR+FPR}{2} \times 100\% \quad (11)$$

The ROC is used to show the evaluation of discrimination of the classifier’s ability. The curve of ROC denotes the performance of classifier. In [23] is presented the calculation of ROC. The ROC is described on plot with representation of sensitivity vs. 1-specificity. On Y-axis are plotted *TPR* and on X-axis are plotted *FPR*. In the above equation are described *TPR* and *FPR*. By calculation of ROC we are able to measure the highest achievable detection accuracy to allowed number of *FP* [3, 23]. One more measure which we have performed in here is *F-measure*. *F-measure* is described as:

$$F\text{-}measure = \frac{2TP}{2TP+FP+FN} \times 100\% \quad (12)$$

4.2. Experimental Results

The results presented in this study have demonstrated that SVM recognition rate is improved by extracting feature vectors from face images and using the histogram, where accuracy for RF has improved. In order to perform all calculations data is divided into training and test phase. We performed SVM Puk kernel, SVM Linear kernel with different number of k folds and RF. The k number was 10 and 20 used for SVM linear kernel. This testing was done by using Weka 3.6 on desktop computer with 2GB RAM and 3GHz. In this study we have evaluated the face recognition for RF and SVM. We applied first skin color detection, then RBG to Gray, after we have performed SVM and RF and we added some classifier. From face images we have extracted feature vector and histogram values. In this research in IBU face database images we have used 20 poses for each 40 people. Images were in JPEG format 205×274 pixel sizes. Dataset consisted of males and females.

4.3. Experiment 1, 2 and 3: SVM with Puk Kernel and Linear Kernel

The parameter of images that were applied in SVM was histogram values retrieved from facial images as we have described in methodology. During the training phase SVM parameters were selected according to k-fold procedure [23]. Depending on k times of training and accuracy computation the average accuracy was represented respectively by SVM In SVM classification we have used Weka and parameter for "*c*" value we have used 100. For polynomial vector we have used 1. We have used Puk kernel. As training we have perform 20 poses for 40 persons. Also, we have used in Weka Poly Linear Kernel. In SMO linear kernel increasing numbers of folds we have used are: 10 and 20. In SVM recognition rate we have obtained is 97, 94%. The database consisted of male and females as in Figure 5. In the experiment were included 800 images. In research study [12] SVM was 97.5% where in here we have 97.94%. In Tables 1, 2 and Figures 6, 7 are shown results. The results were better for face recognition then presented in [3]. The methodology used for face recognition in here performs higher accuracy than methodology described in [7] therefore we can see significant improvements. F-measure for SVM puk kernel is 95%, 0.95 respectively and F-measure for Linear kernel with k=10 is 0.97; k=20 is 0,971, 97% respectively. Moreover in here is confirmed by this experiment is the preeminence as observed in other application field, i.e., in [2, 14, 23]. The results provided for SVM linear kernel in further research can be improved these interesting results, since facial image are complex set of data with various features.

Figure 5. IBU sample of facial data set.

Table 1. Results of RF and SMO.

	Correctly Classified Instance	Incorrectly Classified Instance	Time Taken to Build Model
RF	97,17	2,82	0,84
SMO Puk Kernel	95,89	4,1	3,08
SMO Linear Kernel	96,92	3,07	4,14
SMO Linear Kernel (a)	97,94	2,94	3,96

Table 2. ROC, F-measure and TP for RF and SVM.

	RF	SVM Puk Kernel	SVM Linear Kernel	SVM Linear Kernel (a)
ROC	0,998	0,996	0,997	0,997
F-Measure	0,972	0,959	0,97	0,971
TP	0,972	0,959	0,969	0,971

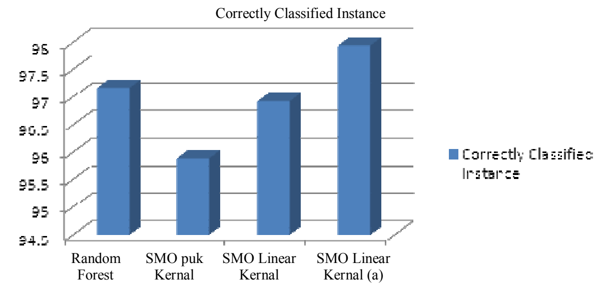

Figure 6. Graphical representation of results.

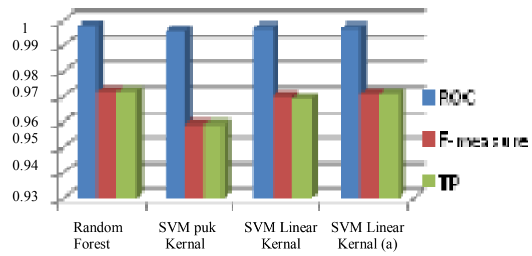

Figure 7. Graphical representation of ROC, F-measure and TP.

4.4. Experiment 4: RF

The proposed RF methods show an improvement in facial recognition where further such methodology will incorporate with application model for human recognition application. RF performs with 97.17% accuracy, with 2.82% incorrectly classified instance. During the testing RF constructed 30 trees, each constructed while considering 9 random features. RF constructed 30 trees considering 9 random features. The results are shown in Tables 1, 2 and Figure 7. For evaluation of RF the number of cross validation folds k=10. F-Measure of RF is 97%, 0,972 respectively. The results of performing the RF by using skin color detection and histogram has shown substantial improvements from the results of performing the detection and recognition of human faces in [7]. The ROC area (AUC=0,998) and is higher than in SVM.

Based on the evaluation of data and study of presented work of face classification problems we can highlight the following:

- The performance of histogram values of face images performed on SVM linear kernel performs well accuracy.
- For training the SVM the appropriate classifier C were selected and the optimal values of C where results perform better is C=100.
- We can see that Random Forest Tree (RFT) performs nearly good as SVM linear kernel.
- Beside all the above mentioned such model incorporated with real time face recognition system for expert system may be improved with such

higher accurate results via incising the versatile number of parameters.

Very high results in this study were obtained by testing this with RF algorithm for performance of face recognition. The main novelty in this paper is the proposed SVM and RF approach where we have first read image from the database, then we have performed skin color detection, converted RGB to grey scale, than histogram value of facial images after those histogram values were optimized with SVM and RF, then we have used classify and retrieve the accuracy as described in this paper. Another advantage is that RF performs high accuracy by constructing the 30 trees. Therefore, both SVM and RF succeeded with interpretation of the values retrieved from the feature vector extraction and histogram values. Results in this paper ensure the substantial improvements for future development and in future application.

5. Conclusions

In here we have applied SVM and RF in face recognition. This study is the continuation [15, 16] for further application in mobile recognition system. First was implemented with PCA in [15]. Moreover, we have examined the machine learning and tree performance of facial recognition, where in the future progress this will be combined with application for mobile phone. Here, we have evaluated SVM poly kernel, puk and RF. We have performed highest recognition rate of RF for face recognition of 97.17%. In this study it can be seen than parameter of value *C* in SVM has shown that it can change the performance of accuracy.

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