Robust Analysis of Multibiometric Fusion Versus Ensemble Learning Schemes: A Case Study Using Face and Palmprint

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Abstract

Identification of person using multiple biometric is very common approach used in existing user validation of systems. Most of multibiometric system depends on fusion schemes, as much of the fusion techniques have shown promising results in literature, due to the fact of combining multiple biometric modalities with suitable fusion schemes. However, similar type of practices are found in ensemble of classifiers, which increases the classification accuracy while combining different types of classifiers. In this paper, we have evaluated comparative study of traditional fusion methods like feature level and score level fusion with the well-known ensemble methods such as bagging and boosting. Precisely, for our frame work experimentations, we have fused face and palmprint modalities and we have employed probability model - Naive Bayes (NB), neural network model - Multi Layer Perceptron (MLP), supervised machine learning algorithm - Support Vector Machine (SVM) classifiers for our experimentation. Nevertheless, machine learning ensemble approaches namely, Boosting and Bagging are statistically well recognized. From experimental results, in biometric fusion the traditional method, score level fusion is highly recommended strategy than ensemble learning techniques.

Keywords: Fusion, Multi Biometrics, Ensemble, Support Vectors, Perceptron, Probability.

1. INTRODUCTION

Biometrics, an integral component in measuring individual's identity features and the statistical analysis that have received significant attention from the beginning of last three decades. It is gaining momentum in many areas. Biometrics authentication system is an automated method for identity verification of a person on the basis of some biological or behavioral characteristic which has become the basis of trust to modern society, it is one of the most challenging issue in access control. The biometric authentication system take Face, Fingerprint, Palmprint , Voice, Signatures, Iris scan, Gait, Ear and DNA which are some of the well-known biometric modalities, the features are extracted for human identification to draw a reliable conclusion on the automated biometric system, but the security of the system can be fooled by criminals with their self-enriching efforts in targeting the new evolving technologies like presenting a fake biometric sample like artificial fingers for finger scanners, replay attack, compromising the database directly etc. Passwords are the de facto standard which can be easily intercepted, transferred to other person, susceptible to eavesdropping.

A more secured way of hardening the security of the system in this scenario is by deploying a mechanism that allows the use of the physiological features of the authorized user. This assertion implies that the use of biometrics is not subjected to authentication ills such as repudiation, impersonation and identity spoofing, since each individual's physiological traits are unique to the individual and are non -transferable. Unimodal biometric system uses a single source of biometric modality like fingerprint, palmprint, face, voice or iris etc., for authentication. Unimodal biometrics is vulnerable to spoofing, prone to interclass similarities, limited discriminability, compromising in accuracy, noisy data. Single biometric may not be able to achieve the desired performance requirement. Some of these limitations can be solved by adopting multimodal biometric system. Multimodal biometric confirmation framework utilize more than one human modalities and consolidates them into a single unit from single or multiple sensors to improve the overall recognition rate of the biometric system. The traditional fusion techniques are, **sensor level fusion**, raw Information obtained directly from the different compatible sensors are fused into a single unit, which gives an effective representation for identification. In **Feature level fusion**, different feature sets extracted from different sensors are first subjected to feature extraction and the feature sets are concatenated to form a single feature vector, this strategy is also used to reduce dimensionality of features. In **score level fusion**, features are extracted from biometric modalities and matched to the corresponding template to compute the match score. In **Decision level fusion** claimed identity is either accepted or rejected after the decisions of different biometric classifiers that are fused to obtain a single decision.

The main motivation of this work is to list out different state-of-art research work using multibiometric and machine learning techniques in the field of biometrics. Numerous classification models have been used for biometric recognition. Linear classifiers are well-known due to their performance in terms of speed and accuracy, including Artificial Neural Network (ANN). However, classifier ensembles are viewed to be more accurate than individual classifiers which clarifies that why the generalization ability of an ensemble is usually much stronger than that of a single learner.

This work emphasizes on comparative study between well know Multibiometric fusion schemes and ensemble techniques of machine learning. In multibiometric fusion, we have considered feature level and score level fusion schemes that determines robust level of fusion. Whereas in machine learning well know Bagging and Boosting schemes are chosen. The performance evaluation is done both under clean and noisy database. Face and palmprint modalities are subjected for our experimentation.

The framework of the paper is as follows: Section 2 presents the related literature work of this paper. Section 3 presents methods briefly used in experimentation. Section 4 discusses analysis of experimental results. Conclusion are drawn in Section 5.

2. RELATED WORK

M. Choras [1] Showed that, palmprint biometric modality is much larger and has more distinctive features such as point features, texture features and line features that makes palmprint biometric a perfect identifier. Palmprint biometric modality is non-intrusive, user-friendly which are very useful in biometric security. Palmprint feature extraction methods are mainly based on geometrical parameters. So, it is possible to build a highly accurate biometrics system by combining all the features of palmprint. The palmprint consists of features like principal lines, wrinkles and ridges. Each person's palm varies in size, shape, texture. T. A. Budi Wirayuda et.al [2] conducted their experiments on 40 individuals by examining the finger width, finger length, palm width, and the ratio between the length of the middle finger, index finger and ring finger and obtained the best accuracy. Preprocessing is very much important in feature extraction and matching, initially the RGB image is converted into binary image. Smoothening and edge detection are followed in the later stages. System performance is measured using vector normalization and without normalization.

S. Y. Kung et.al [3] proposed a face and palm recognition system based on decision based neural networks employing the publicly available (FERET) and in-house (SCR) databases. The System consists of three stages. Decision-based neural network (DBNN) that has been used for all these three modules. First the image is acquired using a CCD camera to detect the facial image, then localization of eyes are determined and the intensity of facial region is normalized and the dimensionality is reduced to lessen the storage place. Lastly, the feature vector is fed into the face recognizer to recognize the person has genuine or imposter, the system has achieved higher recognition rate. Face Recognition biometric system suffers from lighting, facial expressions and misalignment.

Daniel Maturana et.al [4] have proposed two algorithms to deal with these facial drawbacks. Histograms of Local Binary Patterns (LBP) has been used as a discriminative descriptor, then the matching is done with spatial pyramid matching (SPM) and Naive Bayes Nearest Neighbor (NBNN) algorithms. The proposed work contributes flexible spatial matching scheme, the training data is better used with “image-to-class” distance which enhances the system performance with respect to intra-class variations. In Ahonen’s system the facial image is divided into square regions and the histograms are computed individually that are combined to a single vector called “spatially enhanced histogram” which produces relatively a larger dimensional feature vector. The accuracy of the proposed algorithm is compared with the Ahonen’s original LBP-based face recognition system by selecting the combination of multiple LBP histograms at different resolutions. Facial features varies with expressions, illumination and lighting conditions.

Goutam Chakraborty et.al [5] proposed a face identification method using Multi-layer perceptron technique in addressing orientation drawback of face biometric modality. PCA and ICA are employed to extract facial features. The data is trained at different angles using MLP and fairly good interpolation could be achieved. The neural networks are trained with angle variations of facial images with the horizontal plane, fixing the threshold is very much important for decision making that in turn yields good system performance. The facial features depend on the angle of orientation, facial expressions, lighting conditions etc. Hsiuao-Ying Chen et.al [6] proposed a face detection system and facial expression recognition system, they have employed multi-class hybrid-boost learning algorithm in selecting the dominant Gabor (for global appearance) and Haar-like(for local appearance) features in the facial image. Facial region is segmented from the background image and morphological operations are performed to get better image, a multi-class classification algorithm is used to solve the multi-pose face detection problem and to have good facial detection of all kinds of poses. Due to occlusion, the learning algorithm may get confused to some extent.

The AdaBoost algorithm was proposed by Yoav Freund and Robert Shapire in 1995, Adaboost algorithm is a machine learning algorithm that provides good system performance. Boosting is a sequential method of turning a weak learnt algorithm into a great learning algorithm. Weights of the weak learnt classifiers are increased adaptively as shown in the work of Wang et.al [7]. Dimensionality reduction is one of the challenging task in pattern recognition and image processing, Gabor features can be optimally selected from spatial analysis and frequency domain. Support vector machine was developed by Vapnik, which is a strong classifier. Loris Nanni et. Al [8] proposed a unimodal fingerprint biometric fusion based on a single acquisition device and multiple matching algorithms that provides better complimentary results that gives good performance. Fingerprint fusion can be performed at sensor level, rank level etc. Minutiae feature is one of the dominant feature in fingerprint biometric system. Fusion can be classified into three categories Transformation-based, Classifier-based, and Density-based.

Fusion techniques are independent of sensors used. S. Chaudhary et.al [9] proposed a multi-biometric recognition system to reduce fraudulent access that improves system performance when compared to unimodal systems. Palmprint, finger print and face biometric modalities are used in developing a biometric recognition system, the feature vectors are extracted and the matching scores are computed individually, then the score normalization is computed in the fusion module. Lastly the decision module predicts whether the claimed client is genuine or an imposter. Fusion at feature level is complex, because the concatenated feature set may face the dimensionality problem but feature level fusion contains rich set of information and provides better results. Face recognition is very much important in public areas, Przemyslaw Kocjan et.al [10] have used classifiers like KNN, Naive Bayes and Discriminant Analysis and have proposed a face descriptor that uses Toeplitz matrices, which contains lesser eigen values that are invariant to image transformations like rotation, translation and scaling.

3. METHODS

In this section, we describe the different classification and ensemble techniques used in this work. Firstly, we discuss different classification algorithms and ensemble methods in detail.

3.1 Support Vector Machines (SVM)

SVMs classification technique was proposed by Vapnik [11]. SVM is a discriminating classifier defined by separating hyper plane. A large community works on SVM in optimization of feature selection, statistics, hypertext categorization, neural networks, functional analysis, etc. SVM now an active field of all Machine Learning research which provides empirically good performance on high dimensional data classification with small training set. The training dataset of points are of the form $(x_1, y_1),..., (x_n, y_n)$, x_i is the data point to be decided to either of the classes it belongs, which can be viewed as 'x' dimensional vector and (x-1) dimensional hyper planes separate them, finding the maximum margin so that the nearest data point on each side is maximized. A linear classifier has the form $f(x) = W^T x_i + b$ Where 'W' is known as the weight vector which is normal to the plane and 'b' is the bias. $W^T x_i + b=+1$, $W^T x_i + b=-1$ are the + ve and – ve vectors respectively. The margin is given by $\frac{2}{||w||}$. SVM's can be optimized by, Max $\frac{2}{||w||}$ subject to

$$\left\{ W^T x_i + \text{b} \frac{\geq 1 \; if \; y_i = +1}{\leq 1 \; if \; y_i = -1} \right\}$$

The kernel function ϕ is a similarity function used to transform the input data.

3.2 Naive Bayes (NB)

Naive Bayes classifier was introduced by Duda and Hart [12]. The naive Bayes classifier (NBC) is based on the probabilistic Bayes rule and a good classification tool for larger data sets as the training process takes less time. Naive Bayes classifier is a statistical classifier and assumes that the effect of the attribute value of a given class is independent, this assumption is called class conditional independence and uses the maximum likelihood principle for classification of data. In a classification task, set of attribute variables X: $(x_1, x_2... x_n)$ the different classes $(c_1, c_2, c_3, \dots \dots c_m)$, NBC predicts the attribute variable X belongs to class c_a if and only if, P (c_a/x) > P(c_b/x) where a ≠ b P(c_k) is the prior probability in detecting the features from the training dataset.

The conditional probability of the baye's rule is given by $P(c_k|x_1, x_2, x_3, \dots \dots x_n) = \frac{P(c_k)\, P(x_1, x_2, x_3, \dots \dots x_n|c_k)}{\sum P(c_k)\, P(x_1, x_2, x_3, \dots \dots x_n|c_k)}$

The class c_k for which P $(c_k$/X) is maximized, which is called as maximum posteriori hypothesis. The most probable value of c_k can be determined by,

$$c_k \leftarrow argmax_{c_k} P(c_k) \prod_{i=1}^{n} P(x_i|c_k)$$

3.3 Multi-Layer Perceptron (MLP)

A multilayer perceptron (MLP) is a learning algorithm [13] and feed forward artificial neural network model, which can learn nonlinear models in real time. MLP consists of an input layer, one or more hidden layers, and an output layer. The original data is received by input layer and the information is transferred to the intermediate layer along with the weights called the hidden layer. The output is computed from an activation function, weights are arranged until the desired output is achieved and the errors are at minimal rate. It is better practice to prepare the data before training. MLP is harder to train than single layer networks. One hidden layer MLP is a function $f: R^D \rightarrow R^L$, D is the dimensionality of input vector **x** and ***l*** is the size of the output vector $f(x)$. The input layer consists of the neurons ($x_1, x_2, x_3, \ldots\ldots x_m$), the hidden layer transforms the input data with the weighted linear summation is given by,

$w_1x_1 + w_2x_2 + w_3x_{3+} \ldots\ldots . w_mx_m$ Followed by an sigmoid activation function,

$$f(x) = \frac{2}{1+e^{-2x}} - 1$$

3.4 Ensemble Method

Ensemble of classifiers has become very popular in the field of machine learning. Ensemble design combines the predictions from multiple base classifiers, the aggregation from multiple classifiers achieves generalization capability. Ensemble learning is applied in a number of research fields.

The commonly used popular ensemble learning techniques are Bagging and Boosting [14]. Ensemble is learning models that combine the predictions of machine learning algorithms on the dataset that increases accuracy, reduces generalization error that gives robust prediction as compared to prediction done by individual models [17].This is called an ensemble prediction. Ensemble is best suitable for the noisy database and for the missing features, which gives high diversity in predictions and gives better classification rate. The base classifiers for ensemble should be chosen such that the classifiers are diverse in predicting the same data point differently. The classifiers if they are more diverse, then the accuracy of base classifiers are low. The inductive biases of different learning algorithms are highly correlated and it is said that ensemble low-correlated model predictions performs better which reduces the variance of classifiers. Combining the classifiers prediction by voting, a powerful ensemble technique [16], every model votes for each test instance and finally output prediction is the one that receives more than half of the votes. Giving priority to the model is called weighted model. We cannot necessarily employ all the features, it is important to select the attributes by filtering and the classifier is built using the selected attributes, then the prediction is earned.

Boosting: Boosting is a machine-learning method that iteratively converts weak learning algorithm that had provided poor performance to strong learning algorithm, which gives accurate prediction rule hopefully. The Boosting algorithm was introduced in 1995 by Schapire [19]. The particular boosting algorithm in our experiment is AdaBoost, short for “adaptive boosting algorithm” which runs in polynomial time and a well-known technique [15], boosting decreases bias but not the variance. The weak learner is trained with the weighted data after the adaptive parameter is computed. The classifiers that shows the diversities are combined to get a reliable system, so a single classifier is not capable of confronting the errors alone.

Bagging: Bagging is an Ensemble Learning technique proposed by Leo Breiman in 1994 [18]. Bagging is also called as Bootstrap aggregating which avoids over fitting and dataset variability. Bootstrap is the statistical method for calculating the size of the training set data, generating random samples from the original training data which may contain duplicates called bootstrap samples, the samples that are not considered as bootstrap samples are called Out-of-Bag samples. Then the classifiers are trained independently using bootstrap samples and the final classification is done from the target classifiers by voting method to create a single output. Bagging performs better with unstable classifiers those behave diverging with minor changes in the training dataset, Bagging is not suitable for high bias. Bagging decreases the variance and works well with complex models.

3.5 Multibiometrics

In Multibiometric fusion, the information can be fused in four levels namely sensor level, feature level, score level and at decision level. Since sensor and decision level will not play a much role with respective to classification. We chose feature and score level fusion in this work.

Feature level: The feature level involves in the integration of feature sets corresponding to various modalities. Fusion Prior to Matching can take place either at the sensor level or at the feature level. Since the feature set contains richer information about the raw biometric integration at this level, it is expected to provide better recognition results. However, fusion at this level is difficult to achieve in practice because of the concatenating two feature vectors which may result in a feature vector with very large dimensionality that leads to the curse of dimensionality problem. For example, fusion of feature vectors of face and palmprint in order to improve the performance of a multimodal biometric system. In feature level fusion each individual modality process outputs a collection of features. The fusion process fuses these collections of features into a single feature set or vector.

Score Level Fusion: Score level fusion is the most commonly used approach in multibiometric systems. In score level fusion, output by different matchers are combined to generate a new match score which is done at confidence level. Score level fusion is done using the sum rule and min-max normalization are used to find the best match among the probable match list.

4. RESULTS

In order to evaluate and compare ensemble learning and multibiometric fusion, we carried experimentation on Face and Plamprint modalities to find the recognition rate of the biometric system adopting NB, MLP, SVM classification algorithms. We have used the facial biometric modality with different features for our experiments and the performance is measured in terms of accuracy. We have employed the AR face database and Ploy-U palmprint database, which are subjected to NB, MLP and SVM classifiers on clean and noisy databases and the results are tabulated. Databases free from the redundant, irrelevant, wrong data is called as clean database. Corrupted data is called as noisy data. In our experiments we have subjected the facial and palmprint database to undergo salt and pepper noise and accuracy is measured in analyzing the reliability of biometric identification system. Root mean square error (RMSE) is a statistical metric usually employed in model evaluation studies which we have employed in our work.

Table-1 and Table 2, shows the results from different classifiers on clean and noisy AR-face database and Ploy-U palmprint database, Out of the three classifiers subjected for classification, MLP outer performs with the recognition rate of 74.29 % and 63.62 % and F-measure with 0.54 and 0.45 respectively on clean and noisy (salt and pepper noise is induced) face database, also having the lowest RMSE value of 0.27 and 0.30 on clean and noisy face database respectively when compared to the RMSE values of other two classifiers. On further analyzing the palmprint trait when subjected to the classifiers for recognition rate, one can observe that again MLP is outer performing on both clean and noisy databases compared to the other classifiers with the lowest RMSE values. SVM classifier is comparatively better than NB in terms of recognition rate and F-measure results obtained is depicted in detail in the Table-1 and Table-2.

Classifiers	Face corrupted by noise			Palmprint corrupted by noise		
	NB	MLP	SVM	NB	MLP	SVM
Recognition	35.50	63.62	55.44	32.60	58.34	56.77
F-measure	0.30	0.45	0.40	0.28	0.39	0.38
RMSE	0.41	0.30	0.32	0.45	0.38	0.36

TABLE 1: Results from different classifiers on Face and Palmprint database.

Classifiers	Face			Palmprint		
	NB	MLP	SVM	NB	MLP	SVM
Recognition	42.84	74.29	62.96	45.50	78.94	75.34
F-measure	0.34	0.54	0.45	0.65	0.89	0.73
RMSE	0.43	0.27	0.31	0.42	0.24	0.26

TABLE 2: Results from different classifiers which is corrupted by noise Face and Palmprint database.

Classifiers	Feature level			Score level		
	NB	MLP	SVM	NB	MLP	SVM
Recognition	47.32	88.35	90.12	57.85	92.32	95.80
F-measure	0.68	0.76	0.84	0.40	0.80	0.88
RMSE	0.47	0.30	0.28	0.38	0.24	0.16
	Data corrupted by noise					
	NB	MLP	SVM	NB	MLP	SVM
Recognition	36.61	68.50	62.65	39.24	71.56	72.60
F-measure	0.52	0.61	0.59	0.48	0.72	0.74
RMSE	0.48	0.40	0.42	0.51	0.31	0.28

TABLE 3: Results from different classifiers obtained on traditional fusion strategies (feature level and score level) for Face and Palm print modalities on both clean and noisy database.

The face and palmprint modalities are fused using the traditional fusion techniques namely feature level and match score level fusion. At feature level fusion of face and palmprint traits, SVM performs better than the other two classifiers (NB, MLP) with the recognition rate of 90.12%, F-measure of 0.84 and with the lowest RMSE of 0.28 on clean data, Continuing our experimentation at feature level fusion on noisy data MLP is outer performing with the recognition rate of 68.50% than the other two classifiers employed. At score level fusion of face and palmprint traits, SVM performs best with the good recognition rate of 95.80% and 72.60% on clean and noisy data with the lowest error values as shown in the Table-3. MLP is comparatively better than NB.

Classifiers	Boosting			Bagging		
	NB	**MLP**	**SVM**	**NB**	**MLP**	**SVM**
Recognition	49.80	96.87	96.32	46.15	97.11	96.49
F-measure	0.71	0.86	0.88	0.64	0.91	0.90
RMSE	0.36	0.24	0.27	0.43	0.12	0.14
	Data corrupted by noise					
	NB	**MLP**	**SVM**	**NB**	**MLP**	**SVM**
Recognition	38.60	74.50	68.55	40.45	76.40	72.92
F-measure	0.60	0.76	0.69	0.58	0.78	0.74
RMSE	0.50	0.35	0.41	0.48	0.30	0.32

TABLE 4: Results from different classifiers obtained from ensemble methods on fusion of Face and Palm print modalities on both clean and noisy database.

On fusing AR-face database and Poly-U palmprint database, the clean and noisy database is subjected to Boosting (AdaBoost) ensemble method. With the clean database experimentation, we have chosen NB as classifier which produces the accuracy rate of 49.80%, lesser than 50% accuracy level. Since the misclassification rate is more later we applied on data MLP classifier and also SVM classifier is employed for the process, which in turn has increased the recognition rate of MLP and SVM with the accuracy rate of 96.87% and 96.32% respectively. With the noisy (salt and pepper) database experimentation. The NB was classifier, it has produced the accuracy level of 38.60%, and the other classfication is applied such as MLP and SVM classifiers which gives 74.50% and 68.55% accuracy rate.

On fusing AR-face database and Poly-U palm print database, the clean and noisy (salt and pepper induced noise) database is subjected to Bagging ensemble method. In bagging process the training data is randomly picked, the bootstrap samples may be duplicated. With the clean database experimentation, NB classifier has given the accuracy rate of 46.15%. MLP and SVM has produced the accuracy results of 97.11% and 96.49% respectively. On applying bagging ensemble method on noisy data, MLP outer performs with recognition rate of 76.40%.On the results obtained from the classifiers on Boosting (Adaboost) and Bagging method, we can conclude that ensemble methods works excellently for noisy data also.

5. CONCLUSION AND FUTURE WORK

The performance of classifiers depends on specific parameters that could bring improved accuracies. Selection of classifiers depending on the dataset plays an important role in recognition rate. The use of ensemble techniques is one of the option in improvement of performance. Our experiments was focused on obtaining the better results employing the benchmark databases namely, AR face database and Ploy-U palmprint databases , these biometric modalities were subjected under the classifiers NB, MLP and SVM. From the results obtained on unimodal biometric recognition, we can say that MLP classifier outer performs than the other classifiers on both clean and induced noisy data. On unimodal recognition rate, comparing the face and palmprint traits based on the results obtained, we can infer that the palmprint trait is performing better with the good recognition rate compared to the face modality. Further on our experiments of traditional fusion strategies, namely feature level fusion and score level fusion on clean and noisy face and palmprint databases, score level fusion is performing best than the feature level fusion.

On carrying our experiments in exploring the powerful ensemble techniques Boosting (Adaboost) and Bagging on face and palmprint modalities. Boosting technique was performed choosing NB as our base classifier and MLP, SVM classifiers were followed by the base classifier. MLP performs high with the best recognition rate on noisy face and palmprint database.

From our experiments, one can conclude that ensemble methods on fusion of face and palmprint modalities performs better and yields increase in accuracy rate compared to traditional fusion strategies (feature level and match score level fusion). From experimental results, in biometric fusion the traditional method such as score level fusion is highly recommended strategy than ensemble learning. If the features are heterogeneous then it is necessary to normalize the feature set, choosing levels of fusion and fusion rules indicates the performance. Match score level fusion contains sufficient information in achieving confidence level. Our future work will focus on further modeling performance using different composition methods on various biometric modalities.

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