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An Efficient Boosting Approach for Score Level Fusion of Face and Palmprint Biometrics in Human Recognition

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Abstract: ***Biometrics based personal identification is regarded as an effective method for automatically recognizing a person's identity with confidence. A multimodal biometric system consolidates the evidence presented by multiple biometric sources and typically better recognition performance compare to systems based on a single biometric modality. This paper proposes a novel multipartite algorithm for score level fusion of multimodal biometric system identification using two biometric features i.e. face and palmprint. Multimodal biometric system is developed through fusion of face and palmprint recognition system. Further, to evaluate the performance of boosting-based fusion methods, experimental tests are carried over PolyU and CASIA databases. A comparative study is done by using different classification techniques on two databases.***

Keywords: Biometrics, Classifiers, Multipartite, Palmprint, Face, Multimodal and Recognition Systems.

1. Introduction

In this recently convoluted universe of terrorism, identity burglary, and uncontrolled consumer fraud, biometrics has been proclaimed as a key innovation for identity administration, and thus security. As at no other time has identity administration been so vital. Government and enterprises of all sizes have turned out to be substantially watchful with respect to security. There is dependably a need to rethink and conceivably enhance security, and biometrics is pulling in developing enthusiasm since the fraud increments and the ordinary authentication systems, for example, PINs, passwords, and identity cards demonstrate insufficient security or authentication to counter the developing dangers [1].

Today, security is a standout amongst the most critical test confronted regular's human life. One of the relevant security strategies is human identity using biometrics. As of late, among numerous biometric modalities face has received the most interest. Face acknowledgment is not only a standout amongst the most generally acknowledged modalities; Progress in handling the forces of unpredictable calculations is giving raise to new dimensions in questioning the outcomes. Face acknowledgment pleases no contact with the subject, hence this is effectively acknowledged by people in general and is contrasted with different biometrics, like finger prints or iris location.

1.1. Multimodal Biometrics

Authentication frameworks based upon one and only biometric methodology may not fulfill the prerequisites of requesting applications, in particular: all-inclusiveness, peculiarity, perpetual quality, collectability, execution, adequacy, and circumvention. This lead to present enthusiasm for multimodal biometrics, in which few biometric qualities are all the while utilized [2]. There are various benefits in doing as such, examples: false acknowledgment and false dismissal error rates diminish, the authentication framework turns out to be more vigorous against individual sensor or subsystem disappointments and the quantity of situations where the framework is not ready to settle on a choice is decreased significantly (example awful quality fingerprints because of manual work). The technological environment is additionally suitable in view of the boundless arrangement of multimodal gadgets (PDAs, 3G cellular telephones, Tablet PCs and portable workstations etc.).

The term multimodal biometrics referred to the mix of different biometric qualities; hence mode alludes to biometric methodology. Interestingly, joining different biometric modalities is not the only approach to upgrade a biometric framework, as there are various other data sources that can be consolidated. Taking after late practices during the time spent institutionalization [3], a biometric framework consolidating various kinds of biometric data is referred as a multibiometric framework [2] and these biometric data sources will be referred to as multibiometrics [4]. These numerous biometric data sources have begun from the fusion level and the fusion situation.

2. Literature Survey

Boosting algorithms have been developed to directly address the problem with rare classes. In each iteration of boosting, Rare- Boost [15] scales false-positive examples in proportion to how well they are distinguished from true-positive examples and scales false-positive examples in proportion to how well they are distinguished from true-negative examples. Because AdaCost, unlike RareBoost, does not stratify these measures separately, it is believed that AdaCost may sometimes over-emphasize recall, thus leading to poorer precision. A second algorithm that uses boosting to address the problems with rare classes is SMOTEBoost [14]. This algorithm recognizes that boosting may suffer from the same problems as over-sampling (e.g., overfitting), since boosting will tend to assign weight examples belonging to the rare classes more than those belonging to the common classes—effectively duplicating some of the examples belonging to the rare classes. Instead of changing the distribution of training data by updating the weights associated with each example, SMOTEBoost alters the distribution by adding new minority-class examples using the SMOTE algorithm [13]. Empirical results indicate that this approach allows SMOTEBoost to achieve higher F-values than Adacost [14].

Researches in recent years have show that fusion in biometrics can be done in different levels and the score level fusion is the best in sense of simplicity and amount of information which supposed to be combined. Generally, there are three approaches to score fusion: 1) transformation based score fusion, 2) density based score fusion, 3) classifier based score fusion. Transformation based methods usually are applied after score normalization step. Sum rule, Product rule, Min rule and Max rule belong to this category, amongst them, Sum rule shows the best experimental results [16]. Density based score fusion methods are based on score distribution estimation. Well-known density estimation models like Naive Bayesian [17] and Gaussian Mixture Model (GMM) [18] have been used for fusion. Classifier based score fusion treat scores as features and try to find the best decision boundary like the case of binary classification problem [19, 20]. For instance, in [21] Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) have been used for classifier based score fusion. Multivariate polynomials of hyperbolic functions [22] and its combination with GradientBoost [23] have been applied for score level fusion.

Besides this taxonomy, some algorithms are introduced which try to minimize ranking error and therefore improving Receiver Operating Characteristic (ROC) curve, which is based on maximizing Area under the Curve (AUC) of ROC. In [24], Toh et al. developed least square error based framework to do this and examined their algorithm for score level fusion. Optimizing AUC in kernel based model was presented in [25], and Freund et al. introduced RankBoost [26] for this purpose. Continuing development of RankBoost, Rudin et al. [27] introduced margin based and coordinate descent of RankBoost. Also, they have proved that AdaBoost not only minimize classification error, but also under certain condition, can optimize AUC. Latest discoveries on AdaBoost capability are inspiring to exploit AdaBoost as a credible algorithm for score fusion. To reduce the computational complexity of multi-class learning, Torralba et al. [28] proposed a novel boosting algorithm to exploit the common features that can be shared across different classes. Freund et al. introduced RankBoost in detail and reported the experimental results of applying this algorithm for meta-searching and movie recommendation problems [29].

3. Algorithms for Match Score Level Fusion

Match scores are easily generated and hence this level of fusion is widely used due to its simplicity, less storage requirements and lower computational complexity. Match score level fusion is carried out using [5], [6], [7] two broad categories of methods that is (a) rule based fusion and (b) classification based fusion is as shown in Fig. 1 [11].

Rule based fusion consists of several methods such as sum rule, weighted sum rule, product rule, max rule, min rule, fuzzy rules, t-norms, etc. Classification based fusion consists of methods such as Support Vector Machine (SVM), Bayesian classifier, neural networks, C4.5 decision tree, Linear Discriminant Analysis (LDA), Adaboost, multipartite, etc. Match score level fusion involves integration of matching scores from several unimodal biometric systems. Fusion Algorithms/techniques at match score level for multimodal system involve rule based fusion and classification based fusion techniques. Integration of scores from several unimodal systems is carried out by defining a fixed rule on the scores in rule based fusion technique. This rule based fusion involves methods such as sum rule, Linear Weighted Sum Rule (LWSR), product rule, max rule, min rule, fuzzy rules, majority voting rule, etc. Normalization techniques are used on scores from individual biometric models before applying rule based fusion technique. Normalization scales the score set and transforms them to common domain for compatibility of individual biometric models.

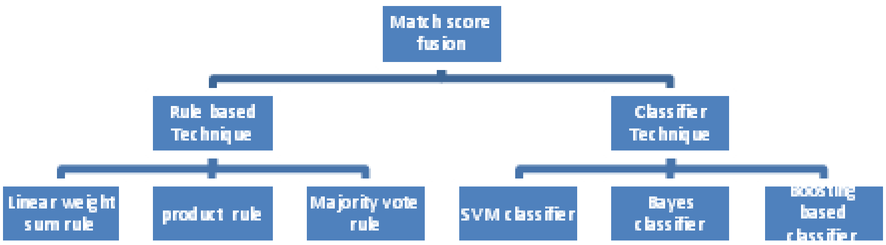


Figure 1: Methods at the Match score level

The main focus is thinking how to precisely rank a set of items by joining a given accumulation of positioning or inclination capacities. This issue of consolidating inclinations emerges in few applications, for example, joining the results of diverse instant searchers, or the *collaborative filtering* issue of positioning biometric attributes taking into account the rankings gave by different characteristics. This paper exhibits a formal structure for this general issue and later portray and break down a productive algorithm called Multipartite Algorithm (MA) for consolidating inclinations taking into account the boosting way to deal with machine learning.

This paper presents a productive learning algorithm called Multipartite Algorithm for joining different rankings or inclinations. This Multipartite Algorithm is same as AdaBoost algorithm and its late successor created by Schapire and Singer [8], [12]. Like other boosting algorithms, Multipartite Algorithm lives up to expectations by consolidating numerous *weak* rankings of the given occurrences. Each of these may be just weakly corresponded with the objective positioning that is endeavoring to conclude and how to consolidate such powerless rankings into a solitary exceptionally precise positioning.

The main idea of the learning algorithm is to produce a linear ordering of the given set of objects by combining a set of given raking features. The learning algorithm needs information about which pairs of objects to be ranked above or below one another is known as feedback. The learning algorithm then endeavors to locate a joined ranking that disorders as few sets as could be expected under the circumstances, with respect to the given feedback.

4. Multipartite Algorithm

A novel *Multipartite Algorithm* (MA) is proposed for score level fusion of multimodal biometrics. This algorithm endeavors to discover a blend of "weak rankers" to make a precise single ranker. In Score Level Fusion, the matching scores of each subsystem are combined to find composite matching score which is then sent to the decision module. One of the standard approaches to score level fusion is to endeavor classifiers for discovering the best decision limit in between imposter and genuine instances.

The boosting algorithm is called as Multipartite Algorithm, and its pseudo-code is shown in Algorithm 1. Like all boosting algorithms, Multipartite Algorithm operates in iterations and is the blend of both AdaBoost and RankBoost.B algorithms. In this algorithm, the weaklearner function is called for each iteration, to generate a *weak ranking*. Multipartite algorithm preserves a distribution D_t over $a_0 \times a_1$ that is passed on to iteration m to the weaklearner. Intuitively, Multipartite Algorithm decides D_t to underline diverse parts of the training data. A high weight is assigned to a couple of instances shows an incredible significance that the weaklearner request that matches effectively.

Algorithm 1: Multipartite Algorithm for Multimodal

1. **Input**: a_1 *and* a_0 *are* disjoint subset of A /* $a_1 \cup a_0 = A$ */

2. Initialize

$$w_1(a) = w \begin{cases} \frac{1}{|a_1|} & \mathit{If}\ (a_1 \varepsilon A) \\ \frac{1}{|a_0|} & \mathit{If}\ (a_0 \varepsilon A) \end{cases}$$

3. for *m := 1,2, . . ., M do loop:*

3.1 WeakClassifier(A)

{

3.2 Given: distribution over $a_1 * a_0$

3.3 set of instance $[t_i]_{i=1}^{N}$

3.4 For each t_i a set of threshold $[\tau_k]_{k=1}^{K}$ such that

$\tau_1 \geq \tau_2 \geq ,\ldots, \geq \tau_k$

3.5 Initialize:

$C^* = 0$

3.6 $r_1 = 1 \quad \mathit{If}(a_i = 1)$

3.7 $r_2 = 0 \quad \mathit{If}(a_i = -1)$

3.8 for *i:=1 up to N* do loop

{

3.9 for k:=1 up to K do loop

{

3.10 Q:=0

3.11 τ =1 /*threshold*/

3.12 $Q = Q + \sum_{a:t_i(a)=1} \beta(a)$ /* Sum of Potentials */

3.13 if $(Q > C^*)$

{

3.14 $i^* = i$

3.15 $\tau^* = \tau_k$

3.16 $r^* = w_i$

3.17 }End if

} End for loop k

} End for loop i

Return (r^*, τ^*, i^*)

} End WeakClassifier function

4. $D_t(a_0, a_1) = w_t(a_0).w_t(a_1)$;

5. Get weak ranking $k_t : A \in R$

6. Select $\Theta_t \in R$

7. Update $w_{t+1}(a) = w_{t+1}(a_0).w_{t+1}(a_1)$ where $(a_1 \varepsilon A)$ and $(a_0 \varepsilon A)$

8. } End of loop m

9. **Output:** Final Ranking function:

$$K(a) = \begin{cases} 1 & \mathit{If}\ (F(a)=1) \\ 0 & \mathit{If}\ (F(a)=0) \end{cases}$$

As it can be inferred from the algorithm 1, despite similarity of AdaBoost and RankBoost.B, there are some differences between them and thus there is a need to improve

weaklearner. Although, the final output of these two cases- AdaBoost and RankBoost.B, is a linear combination of weaklearners, training of weaklearners and computing of θ_t's are accomplished in different ways in this Multipartite Algorithm.
The detail explanation of Multipartite Algorithm is as follows:

- a_1 *and* a_0 *are* disjoint subset of A .
- Initially uniform weights are initialized to $w_1(a)$ for all a_i . So $w_1(a)$ is initialized with $\frac{1}{a_1}$ or $\frac{1}{a_{-1}}$ if $(a_1 \varepsilon A)$ or $(a_{-1} \varepsilon A)$ or with $w_1(a)$ is initialized with $\frac{1}{a_0}$ or $\frac{1}{a_{-1}}$ if $(a_0 \varepsilon A)$ or $(a_{-1} \varepsilon A)$. $|a_0|$ or $|a_1|$ nothing but total number of training sets.
- The feedback algorithm operates in iterations; in each iteration, it calls weakclassifier to find the best weak ranking.
- Weakclassifier is called for each iteration of *m* to maintain distribution D_t over a_0 *and* a_1 .
$D(a_0, a_1) = C = \max\{0; F(a_0; a_1)\}$ Where F is a capacity and for any pair of instances a_0; a_1, F (a_0, a_1) is a real number whose sign shows regardless of whether a_1 ought to be ranked above a_0, and its value shows the significance of its ranking.
- The Feedback Capacity F: $A \times A \rightarrow R$, F(a_0, a_1) > 0 implies that a_1 ought to be ranked above a_0
- Iteratively, ―multipartite" chooses D_t to emphasize different parts of the training data.
- Setting ranking score or feature for finding a weak ranking k that it equal to one of the ranking feature or threshold τ_k .
- Assume that our model is given ‗*n'* ranking feature or score denoted $t_1, t_2, \ldots, t_N$
- C^* Is a pointer variable is used to assign higher scores are assigned to more preferred instances
- Variable r_1 is assigned with 1 if a_i is equal to 1.
- Variable r_2 is assigned with 0 if a_i is equal to -1.
- This algorithm incrementally evaluates on a sorted list of candidate thresholds $[\tau_k]_{k=1}^{K}$ and stores the values i^* and τ^* for which $f(a_1) > f(a_0)$, means that instance a_1 is preferred to a_0 by *f*.
- *for loop* is used to rank all instances of one set over another set
- And same as *for loop*, *if* statement is used to find the best weak ranking condition.
- *Step 4 to 9:* At each iteration of the algorithm first a ranking feature k_t and associated weight w_t are chosen and updated.
- Finally ranking feature k_t can be learned efficiently and each ranking feature is valued.

In this approach the weak learners and their training algorithms are reformulated on the basis of score level fusion. Like boosting based algorithm, Multipartite Algorithm additionally incorporates training weak learner subroutine with slight difference. In Multipartite algorithm, weak learner gives weak ranking rather than weak classification. Likewise, interestingly with the past ranking application that is meta-seeking and film proposal [9], in multimodal biometrics scores are significant, and weak learner dependably has esteem for every instance.

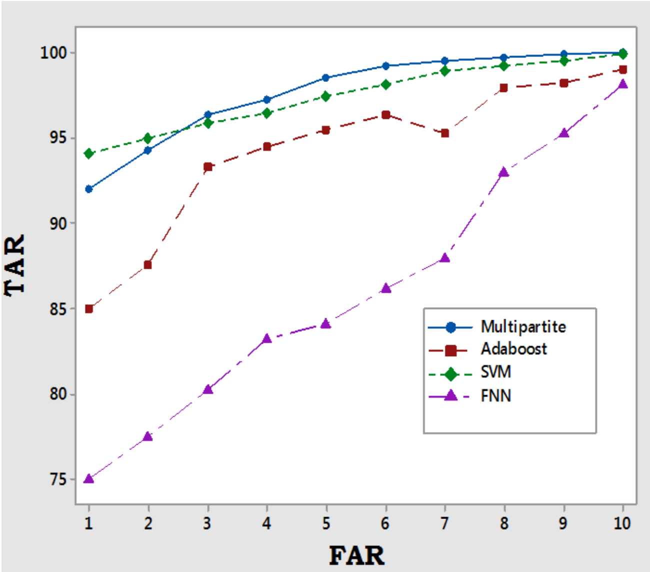
5. Performance of MA with other Classifiers

In order to evaluate performance of boosting-based fusion methods, experimental tests over different databases have been run and different fusion techniques have been used. According to mentioned taxonomy for score level fusion techniques and selected benchmark methods from each category. To compare Multipartite with other classifier based methods, evaluated by AdaBoost. And also considered an implemented version of AdaBoost from Statistical Pattern Recognition Toolbox (STPRTool) [10]. To satisfy AUC optimization condition, weighted instances which is inversely proportional to number of instances in corresponding classes.

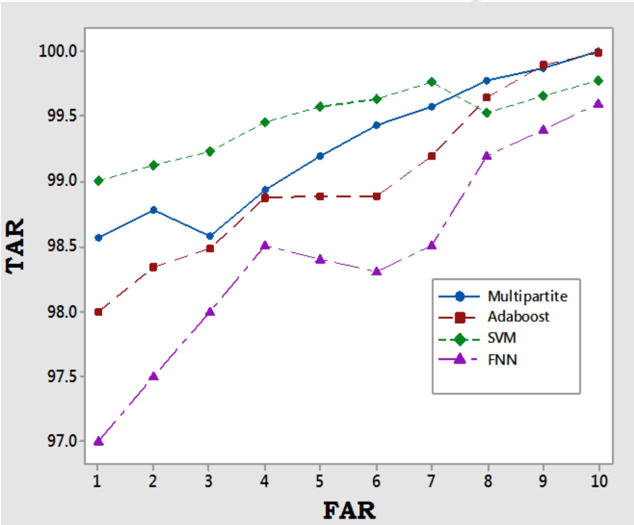
In comparison with Fusion Neural Networks (FNN) and Software Virtual Machines (SVM) in larger area of FAR range ROC of boosting approach are above that of FNN and SVM. Furthermore, it can be seen, AdaBoost achieves performance comparable to that of Multipartite. Results in Table 1 shows that the boosting methods over PolyU database are lower than the other methods. Also results in Table 1 shows that the SVM method over CASIA database is lower than the other methods.

Table 1: Performance of Multipartite with Other Classifiers

Classification Techniques	*PolyU database (seconds)*	*CASIA database (seconds)*
SVM	0.4862	1.5665
FNN	0.4663	1.6353
Adaboost	0.4225	1.3235
Multipartite	0.4036	1.1528



(a)



(b)

Figure 2: ROC curve of Multipartite, Adaboost, SVM and FNN based fusion over (a) CASIA Database (b) PolyU Database

In Fig.2 (a) ROC curves over CASIA have been depicted. It can be inferred that classifier based methods outperformed FNN and SVM. In the Fig.2 FAR refers to False Acceptance Ratio and TAR refers to Total Acceptance Ratio. In this case, boosting approaches (Multipartite and Adaboost) have higher performance than FNN and SVM. Multipartite Algorithm shows high performance than Adaboost algorithm. In Fig. 2 (b) ROC curves over PolyU have been depicted. It can be inferred that classifier based methods outperformed FNN and SVM. In this case, boosting approaches have higher performance than FNN and SVM.

6. Conclusion

A novel *Multipartite Algorithm* is proposed for score level fusion of multimodal biometrics. This algorithm endeavors to discover a blend of "weak rankers" to make a precise single ranker. In Score Level Fusion, the matching scores of each subsystem are combined to find composite matching score which is then sent to the decision module. One of the standard approaches to score level fusion is to endeavor classifiers for discovering the best decision limit in between imposter and genuine instances.

The shorter classifiers lead to better recognition rates additionally to all the more false identifications at every phase of the development. Consequently, resulting stages are given a tougher assignment. Notwithstanding, because of the short classifiers the aggregate number of weak classifiers assessed speaks the truth 60% less, regardless of the number of bins utilized. ROC curves over CASIA and PolyU Database have been depicted. It can be inferred that classifier based methods outperformed FNN and SVM. In this case, boosting approaches (Multipartite and Adaboost) have higher performance than FNN and SVM.

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