Biometric Match Score Fusion using RVM: A Case Study in Multi-unit Iris Recognition

Hunny Mehrotra
NIT Rourkela, India
hunny@nitrkl.ac.in

Mayank Vatsa
IIIT Delhi, India
mayank@iiitd.ac.in

Richa Singh
IIIT Delhi, India
rsingh@iiitd.ac.in

Banshidhar Majhi
NIT Rourkela, India
bmajhi@nitrkl.ac.in

Abstract

This paper presents a novel fusion approach to combine scores from different biometric classifiers using Relevance Vector Machine. RVM uses a combination of kernel functions on training data for classification and compared to SVM, it requires significantly reduced number of relevance vectors. The proposed RVM based fusion algorithm is evaluated using a case study on multi-unit iris recognition. Experimental results on the CASIA-Iris-V4 Thousand database show that RVM provides better accuracy compared to single unit iris recognition and existing fusion algorithms. With respect to SVM fusion, it is observed that, the accuracy of RVM and SVM are comparable, however, the time for RVM fusion is significantly reduced.

1. Introduction

Multimodal biometric fusion utilizes more than one source of evidence for authentication. The fusion can be performed at sensor level, feature level, match score level, and decision level. Further, the fusion algorithm can be multi-classifier, multi-instance, multi-unit, and multi-modal. In a multi-unit system, multiple units of the same modality are used to perform authentication. For instance, information from left and right iris or fingerprint images can be combined to improve the performance. This can be particularly useful when data from one unit is noisy or unavailable. Moreover, the fusion can also be very useful to reduce spoof attack risks.

Several fusion approaches have been proposed in literature. Brunelli and Falavigna used visual and audio cues to combine different classifiers [2]. Kittler et al. developed a theoretical framework for combining the classifiers which includes product rule, sum rule, max rule, min rule, median rule and majority voting [11]. In [8], logistic transform is used to combine three different fingerprint matching algorithms. Gutschoven and Verlinde applied Support Vector Machines (SVM) for multimodal biometric fusion [7]. The scores from d modalities are input to SVM and a binary decision regarding acceptance or rejection is taken. In [13], three well known classifiers for face recognition i.e., PCA, ICA and LDA are combined using sum rule and RBF based fusion strategy. Ross and Jain [1] presented information fusion in biometrics by combining information at score level. In [16], genuine and impostor scores are modeled as finite Gaussian Mixture Models (GMM). The product of likelihood ratio (PLR) fusion is performed on the densities computed from the genuine and impostor scores. The likelihood ratio based approach is capable of handling arbitrary scale and distributions of match scores and is experimentally shown to outperform score fusion approaches based on classification and sum rule. Vatsa et al. designed a sequential fusion algorithm that combines probabilistic learning, belief learning, and classification paradigms [20].

PLR requires large training data to compute densities from the scores. SVM, on the contrary, works with adequate number of training data but the number of support vectors required are significantly high and hence fusion is expensive. To overcome these issues, this paper proposes a fusion approach that uses Relevance Vector Machine (RVM) [17] for fusing match scores and classifying them as genuine and impostor. RVM is a sparse linearly parameterized model like SVM. It has been shown in literature that the generalization performance of RVM is comparable to that of SVM with significantly fewer relevant vectors [17, 22]. This may speed up the fusion process with typically no compromise in accuracy. To evaluate the performance of the proposed fusion scheme, a case study on multi-unit iris recognition is performed. Among various biometrics, iris is considered to be a reliable traits due to accuracy, reliability and speed [4, 5]. Iris recognition using a single instance may suffer from various challenges such as noisy sensor data, mis-localization, occlusion due to eyelids, effect of disease (e.g. cataract) cataract, and spoof attacks. Figure 1 shows instances where the use of only one iris may cause incorrect classification whereas the use of both the iris images may provide correct and improved classification performance.

The rest of the paper is organized as follows: A brief

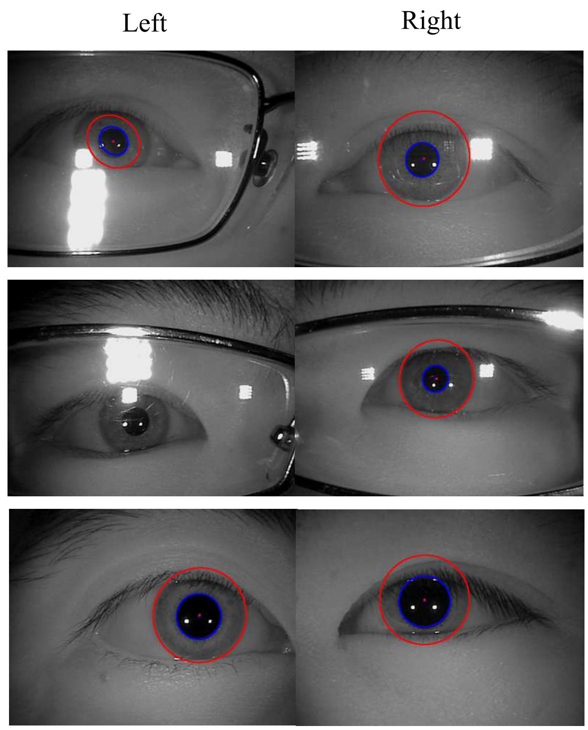

Figure 1. Sample instances where authentication using single iris may fail, however using both the irises can solve the problem. In the first row, the iris boundary of left unit is incorrectly detected due to the presence of reflection. The left image in the second row could not be segmented but the right image is segmented properly. Similar observation can be made in the third row with the effect of dilation and occlusion in the right iris image.

description of Bayesian probabilistic framework for RVM is given in Section 2. Section 3 explains the proposed fusion framework at match score level. The case study on multi-unit iris verification and experimental results are analyzed in Section 4.

2. Overview of Relevance Vector Machine

SVM [15] is a widely used classification technique that avoids over-fitting and leads to good generalization by finding the separating hyperplane that maximizes the margin width. The subset of training data points used to represent the hyperplane are denoted as support vectors. However, SVM suffers from the following limitations [17].

1. The number of support vectors required for classification is relatively large.
2. In classical SVM, there is a need to tune the regularization parameter (C) during the training phase.
3. The kernel function must satisfy the Mercer condition.

RVM is a Bayesian probabilistic model for learning general models given by

$$y(x, w) = w^T \Phi(x) \tag{1}$$

where $w = (w_1, w_2, \ldots, w_N)^T$ is the matrix of weights, $\Phi(x) = (\phi_1(x), \phi_2(x), \ldots, \phi_N(x))^T$ is a set of basis functions and output of RVM (y) is a linear combination of weighted basis functions. RVM is comparable to SVM and, as mentioned by Tipping, it does not suffer from the above mentioned limitations [17]. It is a fully probabilistic learning approach and considers those values of weights which are not peaked around zero. The vectors in correspondence to non-zero weights are termed as *relevance* vectors. RVM is considered to be a better classifier as it performs equivalent to SVM with relatively fewer parameters.

For a given input-target pair $\{x_n, t_n\}_{n=1}^N$, the posterior probability of RVM is a two class Bernoulli distribution, represented by y_n. The linear model is generalized using the logistic sigmoid function $\sigma(y) = 1/(1 + e^{-y})$ to $y(x)$ and the likelihood is defined as

$$P(t|w) = \prod_{n=1}^{N} \sigma\{y(x_n, w)\}^{t_n} [1 - \sigma\{y(x_n, w)\}]^{1-t_n}. \tag{2}$$

The objective is to find the weight matrix w that maximizes the probability $P(t|w)$. This is done using Laplace's approximation procedure [14]. At each iteration, RVM finds the most probable weights w_{MP} over the given hyper-parameters α. The process stops on meeting the convergence criteria and generates

$$\Sigma = (\Phi^T B \Phi + A)^{-1} \tag{3}$$

$$w_{MP} = \Sigma \Phi^T B t \tag{4}$$

where Σ is the covariance matrix of the posterior probability over weights centered at w_{MP}, $A = diag(\alpha_1, \alpha_2, \ldots, \alpha_N)$ and $B = diag(\beta_1, \beta_2, \ldots, \beta_N)$ with $\beta_n = \sigma\{y(x_n)\}[1 - \sigma\{y(x_n)\}]$. The hyper-parameters which result from the above algorithm are used to find a new estimate of target values for new input $x^{'}$ and is defined as

$$y = w_{MP}^T \phi(x^{'}). \tag{5}$$

3. Proposed Fusion Framework

The RVM approach discussed above is used to perform fusion of scores obtained from multiple biometric sources. The training set consists of $\{x_{n1}, x_{n2}, \ldots, x_{nd}, t_n\}_{n=1}^N$ for N scores from d different sources with the corresponding class labels in t_n. The objective is to apply a function to x that provides a clear separation of genuine and impostor scores and transform $\Re^d \rightarrow \Re$. A design matrix ($\Phi(x)$) is generated and fed as an input to the classifier. The RVM approach discussed above is used to add or subtract relevance

Algorithm 1: RVM-Train

Input: x: Input matrix of N scores with dimension d,
t: equivalent target values

Output: R: model of relevance vectors, w_{MP}: most probable weight matrix

Generate $\Phi = [\phi_1(x), \phi_2(x), \ldots, \phi_N(x)]$
Initialize δ_τ `// Threshold for convergence`
`// Initialization of hyper-parameters`
$\alpha \leftarrow (\frac{1}{N})^2$
$\beta \leftarrow 0$
repeat
  $A = diag(\alpha), B = diag(\beta)$
  $\Sigma = (A + B\Phi^T\Phi)^{-1}$
  $w_{mp} = B\Sigma\Phi^T t$
  $C = \beta I + \Phi A^{-1}\Phi^T$
  $\max |L(\alpha) = -\frac{1}{2}[N \log 2\pi + \log |C| + t^T C^{-1} t]|$
  $C_{-i} = C - \alpha_i^{-1}\phi_i\phi_i^T$
  $s_i = \phi(x_i)^T C_{-i}^{-1}\phi(x_i)$
  $q_i = \phi(x_i)^T C_{-i}^{-1} t$
  if $q_i^2 > s_i$ **then**
    Add x_i to R **if** $x_i \notin R$
    $\alpha_i = \frac{s_i^2}{q_i^2 - s_i}$
  else
    Remove x_i from R **if** $x_i \in R$
    $\alpha_i = \infty$
  end
  Update β
  $\delta = \sum_{i=1} \alpha_i^{n+1} - \alpha_i^n$
until $\delta < \delta_\tau$

Algorithm 2: RVM-Classify

Input: x': Test data for classification, R: model of relevance vectors, w_{MP}: weight matrix

Output: y: Predicted class value

$r \leftarrow |R|$ `// Number of relevance vectors`
`// Generate design matrix with relevance model`
$\phi(x') \leftarrow [\phi_1(x'), \phi_2(x'), \ldots, \phi_r(x')]$
$y = w_{MP}^T \phi(x')$

vectors by keeping a prior on hyper-parameter α. For the given values of α, most probable weights, w_{MP}, are found. The detailed description of RVM training is given in Algorithm 1. The trained RVM is used to predict the genuine or impostor class for the test multimodal score vector defined by x' using equation (5). The classification algorithm to predict class label (y) of probe scores from d different modalities is given in Algorithm 2. The proposed approach is a variant of classification framework discussed earlier and performs fusion over classification of scores generated from individual classifiers. During training, the model of relevance vectors and weights are determined for individual unimodal scores $\{R^j, w^j_{MP}\}_{j=1}^d$ from d classifiers. The j^{th} vector and weight $\{R^j, w^j_{MP}\}$ is used to find the corresponding output value (y^j) for each classifier. Finally, the fusion of the outputs are done using weighted sum rule given by

$$y_{final} = \frac{1}{d}\sum_{j=1}^{d} y^j, \quad (6)$$

where y^j is a probabilistic value whose weighted sum ranges between 0 and 1.

4. Case Study on Multi-unit Iris

In this paper, the proposed RVM fusion approach is evaluated in context of multi-unit iris recognition. The left and right iris images can be combined to improve the performance without adding any extra hardware cost to existing iris recognition system. In literature, several measures have been proposed for enhancing the performance of an iris recognition system. An image check algorithm has been proposed in [9] which removes the noise from both the units of iris and offers a qualified image to Wavelet for feature extraction. Finally, SVM is used for classification and verification accuracy of 99.1% is obtained. Wu et al. have extracted features using 2D complex Gabor filters and the match scores are generated using Hamming distance approach from individual irises [21]. Several fusion strategies such as min rule, max rule, sum rule, and product rule are studied. The minimum total error (MTR) is obtained and it is observed that MTR of min and product rules drops to 0%. Vatsa et al. [19] used belief function theory to effectively combine match scores obtained for left and right irises and density estimation approach to compute belief assignments. Decision is finally made using likelihood ratio. In [12], a multimodal biometric system is proposed by combining iris and retina features. In order to enhance recognition performance, the scores are generated from independent units of iris and combined using weighted sum rule. The score level fusion of left and right irises generated an accuracy of 96.4%. Similar approach has been proposed by Kang and Park [10], where the good quality images are used to generate match scores from left and right units of iris. The scores are combined using weighted sum rule and an improvement in accuracy has been achieved compared to other existing fusion approaches.

In this paper, similar effort has been made to combine multiple units of iris to improve the recognition perfor-

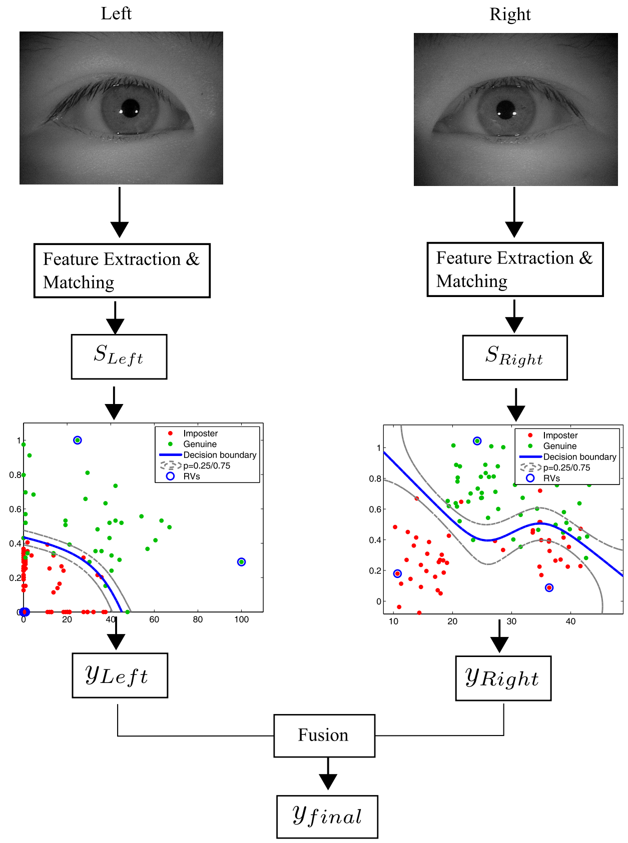

Figure 2. Illustrating the steps involved in the proposed multi-unit iris recognition algorithm.

mance. Iris images are preprocessed and segmentation is performed using the elliptical model [18]. Gabor features are then extracted using the approach presented in [18] and match scores (S^{Left} and S^{Right}) are obtained for left and right units respectively. RVM is used to find the probabilistic values of the scores obtained. The left scores from N iris images are used to train the RVM using Algorithm 1. Similarly training is done using scores from right iris images. This generates two sets of relevance vectors and weights as defined by

$$\{R^d, w^d_{MP}\} = \text{RVM-Train}(S^d, t^d) \tag{7}$$

where $d \in \{Left, Right\}$ denotes the left and right iris images respectively. Each set of relevant vectors and weights are used to approximate the corresponding output value for the multi-unit probe score $x^{'}$.

$$y^d = \text{RVM-Classify}(R^d, w^d_{MP}, x^{'}) \tag{8}$$

These class values are integrated using equation (6) and a decision is made using the fused probabilistic score. The block diagram of the proposed multi-unit iris recognition algorithm is shown in Figure 2.

Table 1. Average verification accuracy (in %) at 0.01% FAR for different fusion algorithms, commercial system, and existing iris recognition algorithm [18].

	VeriEye	**Vatsa et al. [18]**
Left eye	94.79	94.48
Right eye	93.53	92.71
Sum rule [1]	96.41	95.89
PLR fusion [16]	96.75	95.41
SVM fusion [6]	98.87	98.70
Proposed RVM fusion	98.92	98.81

4.1. Experimental Protocol

The experiments are performed on publicly available CASIA-Iris-V4 thousand database [3]. This database contains 20,000 iris images from 1000 subjects; for each subject 10 instances of both left and right eye images are captured using dual-eye iris camera ($1000 \times 2 \times 10 = 20,000$ images). The main sources of variations in this database are eyeglasses, specular reflections, and dilation. Using this database, training is performed on images from 30% of the subjects (i.e. 300 subjects - each with 10 left and 10 right eye images). The remaining images pertaining to 700 subjects (70% population) are used for testing (gallery - probe). This train-test partitioning is performed three times for cross validation. Results are computed in verification mode (1:1 matching) and average accuracies are reported at 0.01% False Accept Rate (FAR). The performance of the proposed algorithm is compared with three fusion algorithms, namely Sum rule [1], Product of Likelihood Ratio fusion [16], and SVM fusion [6]. In addition, we also performed experiments with commercial matcher (Verieye by Neurotechnology).[1] The scores obtained from left and right iris images are then combined using different fusion algorithms.

4.2. Results and Analysis

Figure 3 shows the receiver operating characteristics (ROC) curves of the left and right irises along with fusion algorithms and Table 1 illustrates the average verification accuracies at 0.01% FAR. Key results and observations are summarized below:

- Both iris recognition algorithms/systems (Vatsa et al. [18] and Verieye) yield slightly higher verification accuracy for left eye compared to right eye images.
- Match score fusion of left and right irises improves the performance; on CASIA-Iris-V4 thousand database,

[1] The SDK does not allow to draw ROC but provides the verification accuracy at 0.01% FAR and the match scores pertaining to genuine users (There are some failure to segment, false reject, and false accept cases which has been included for computation of accuracy).

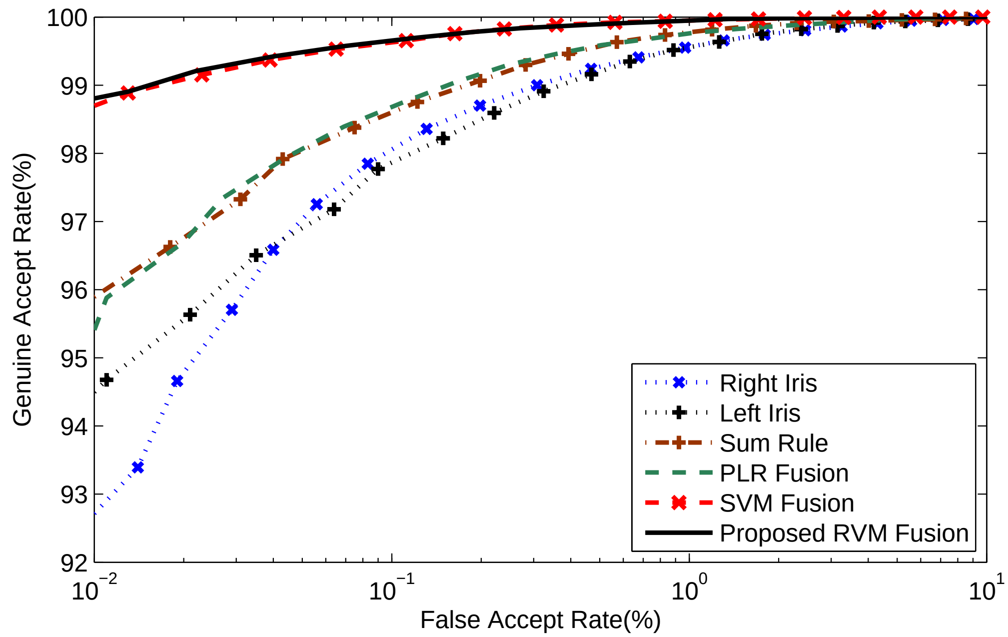

Figure 3. ROC curves comparing the performance of the proposed RVM based match score fusion algorithm with single iris and other match score fusion algorithms.

Sum rule [1] and PLR [16] improve the performance by 1.5% whereas SVM fusion [6] and the proposed RVM fusion improves it by 4%. As discussed earlier, the performance improves when one of the iris is segmented incorrectly or erroneous feature extraction due to specular reflection, occlusion or dilation/constriction.

- Statistically, results obtained from SVM and RVM fusion are not different. However, it is observed that SVM requires around four times more number of support/relevant vectors compared to RVM. Since the proposed RVM fusion algorithm requires less number of relevant vectors, testing time is also faster and requires around four times less computations compared to SVM. Table 2 shows the number of vectors required by SVM and RVM along with their testing time. Further, compared to SVM, RVM requires less parameters to learn. In the experiments, Gaussian kernel (with parameter value 3) yields the best verification accuracy over three cross-validation trials.

- Unlike SVM, RVM by design, provides probabilistic output - which in biometrics is very helpful, especially in soft thresholding. In SVM, different formulation exists for soft thresholding but it requires more training samples and support vectors - which is not the case with RVM.

Figure 4 illustrates the sample instances where images in the first row are correctly classified by SVM but RVM fails to generate desired probability values. The second row demonstrates the cases where RVM performs accurately but SVM fails. These results suggest that RVM may be a good alternative to SVM for match score fusion and should be explored further in different context and fusion levels.

Table 2. Time comparison of SVM and RVM (in milliseconds) along with number of vectors required for classification on an Intel i7 processor with 8 GB RAM under MATLAB environment.

	SVM	**RVM**
Number of vectors	42	9
Average testing time (ms)	0.17	0.04

5. Conclusions

This research presents a Relevance Vector Machine based biometric match score fusion algorithm. RVM can be viewed as an attractive alternative to SVM as it is capable of achieving generalization equivalent to SVM and utilizes significantly fewer parameters. The class probabilities are calculated from individual unimodal scores which can be indeed useful instead of binary decisions. The proposed RVM fusion algorithm is evaluated in context to multi-unit iris recognition. The match scores obtained from left and right iris are combined and performance is compared with other fusion algorithms on CASIA-Iris-V4 thousand

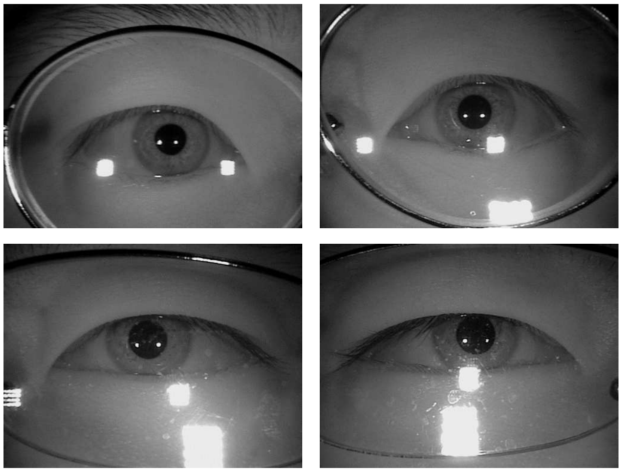

Figure 4. Sample results: in the first row, SVM performs accurately but RVM gives inaccurate results. In the second row RVM generates accurate output whereas SVM fails.

database. The proposed algorithm improves the accuracy by 4% compared to single unit iris recognition. It is our assertion that more research is required to utilize the full potential of RVM in biometrics.

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