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INTEGRATING IMAGE QUALITY IN 2ν-SVM BIOMETRIC MATCH SCORE FUSION

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This paper proposes an intelligent 2ν-support vector machine based match score fusion algorithm to improve the performance of face and iris recognition by integrating the quality of images. The proposed algorithm applies redundant discrete wavelet transform to evaluate the underlying linear and non-linear features present in the image. A composite quality score is computed to determine the extent of smoothness, sharpness, noise, and other pertinent features present in each subband of the image. The match score and the corresponding quality score of an image are fused using 2ν-support vector machine to improve the verification performance. The proposed algorithm is experimentally validated using the FERET face database and the CASIA iris database. The verification performance and statistical evaluation show that the proposed algorithm outperforms existing fusion algorithms.

Keywords: Biometrics; information fusion; quality score; support vector machines.

1. Introduction

Biometrics is one of the most widely used technologies for recognizing an individual using physiological or behavioral characteristics such as face, iris, fingerprint, signature, and gait. Several algorithms have been proposed to authenticate an individual's identity using these traits.[1] Researchers have shown that the use of multimodal biometrics provides better authentication performance over unimodal biometrics.[2–4] Biometric fusion can be performed at image level, feature level, match score level, decision level, and rank level. However, most of the researchers have proposed algorithms for fusion at match score level. Existing match score fusion algorithms are based on well defined rules such as AND rule,[2] OR rule,[2] SUM rule,[3,4] and more recently by using kernel fusion rule.[5] Further research has been carried out to improve the performance of multimodal biometric systems by incorporating different factors such as quality of input biometric signal/image[5] and user specific weights or thresholds.[6]

In this paper, we focus on quality based multimodal biometric match score fusion. The performance of biometric systems depend on the quality of images. Good quality images improve the recognition performance whereas bad quality images reduce the performance. Incorporating quality in multimodal biometrics can thus provide better generalization and improve the verification performance. Quality of a biometric data refers to the intrinsic physical data content and can be quantitatively expressed as quality score. Quality score provides a quantitative representation of the biometric data quality. National Institute of Standards and Technology defines quality score as the accuracy with which the physical content is represented in a biometric data.[7,8] Limited studies on quality based multimodal fusion have been performed. Aguilar *et al.*[5] proposed quality based fusion algorithm using linear support

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vector machine (SVM). The performance of linear SVM based algorithm is better compared to the statistics based fusion rules but the authors have not addressed the complexity of SVM and lack of robust and uniform quality measure. Further, Jain *et al.*[9] proposed quality based weighted sum rule to fuse the information of multiple fingerprint recognition algorithms. They presented improvement over standard sum rule fusion algorithm but non-linearity in the quality scores and match scores is not addressed.

In this paper, we propose two algorithms: generation of image quality score using Redundant Discrete Wavelet Transform (RDWT) and fusion of quality integrated match scores of two biometric traits using dual ν-SVM (2ν-SVM). Figure 1 shows the block diagram of the proposed quality integrated match score fusion algorithm. The quality assessment algorithm uses the frequency response of biometric images to compute the quality score which depends on both the linear and non-linear features such as smoothness, sharp changes, and noise present in the image. Based on the quality scores and the match scores, the proposed 2ν-SVM fusion algorithm fuses the information from two biometric modalities. The fusion algorithm can be applied to fuse match scores of any biometrics. However, the proposed quality assessment algorithm can be applied only to image based biometric modalities. In this research, we use face and iris biometrics to evaluate the performance of the proposed algorithms. The experimental results performed on standard face and iris databases and the statistical evaluation show that the proposed quality integrated multimodal fusion algorithm performs better than existing statistical and learning based match score fusion algorithms.

2. RDWT Based Image Quality Assessment Algorithm

In general, Discrete Wavelet Transform (DWT)[10] is used for image based operations such as image fusion, denoising, and quality measure because DWT preserves frequency information and allows good localization both in time and spatial domain. However, one of the major limitations of DWT is that the transformation is not shift invariant. This causes a major change in the wavelet coefficients of the image/signal even for minor shifts in

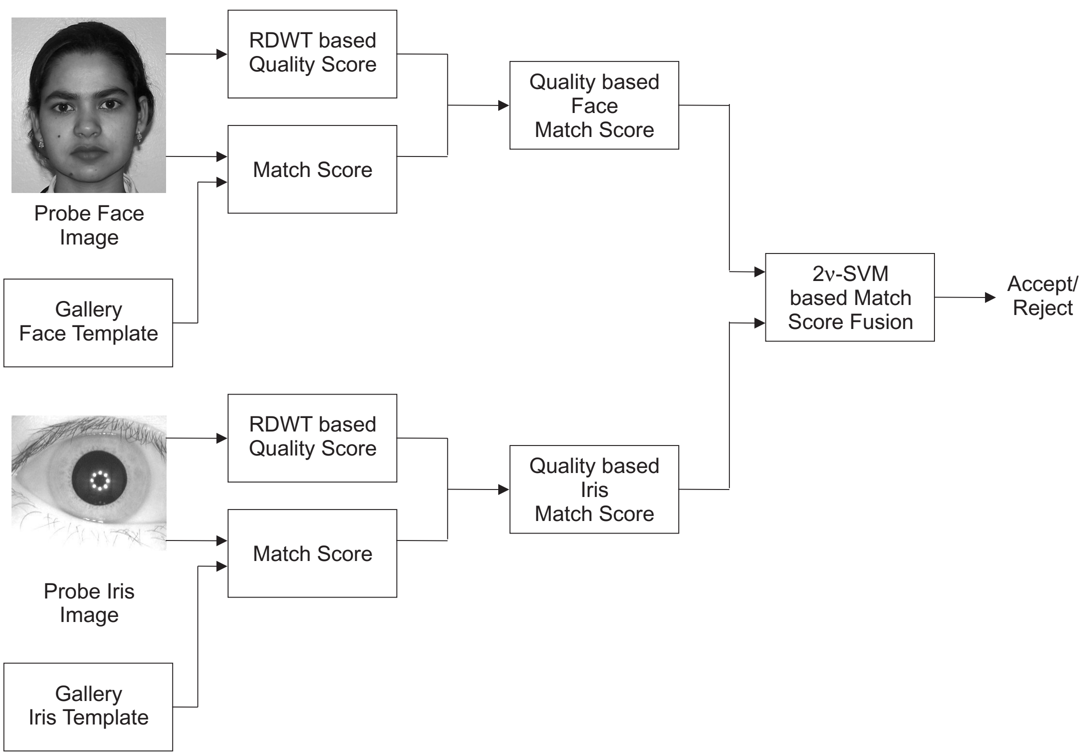

Fig. 1. Block diagram of the proposed quality integrated 2ν-SVM match score fusion algorithm.

the input image/signal which leads to inaccurate data processing. Researchers have proposed several approximation techniques to overcome the shift variance of DWT, one of them is known as redundant DWT.[10] The shift variance characteristic of DWT is due to the down-sampling operation. RDWT removes downsampling such that the spatial sampling rate is fixed across scale and hence is shift invariant.[11] Along with shift invariance, the transform captures not only some notion of the frequency content of the input by examining it at different scales, but also captures the temporal content. Another important aspect of RDWT used in the proposed algorithm is per-subband noise relationship.[11] Fowler[11] has shown that the distortion in the original image from noise in a single RDWT subband depends only on the decomposition scale at which the subband resides and is independent of the other subbands. Also, in an image, high frequency content exists along edges and low frequency content exists where little or no edges occur. Since RDWT provides frequency content at different subband levels, we can extract information pertaining to different types of edges. Coefficients in the subbands are large for edges, and zero, or close to zero for non-edge regions. To determine the quality of the image, we need to find the edge information in the image along with blurriness, smoothness, and noise present in the image. The proposed algorithm computes a composite score, referred to as the quality score, which represents the quality of the biometric image.

Let I denote a face or an iris image of size $n \times n$. I is decomposed to three levels RDWT[10] using Daubechies-9/7 (Db9/7) mother wavelet.[12] Db9/7 is used because for most of the wavelet based image processing operations such as coding and compression, it provides better performance compared to other mother wavelets.[12] The image is decomposed to three levels because quality assessment requires several details of image such as edges, frequency and temporal content, and per-subband noise relationship at different resolution levels, which can be efficiently obtained at three levels of RDWT decomposition. Equation 1 represents the 3-level decomposition of image I,

$$[I_{Aj}, I_{Hj}, I_{Vj}, I_{Dj}] = RDWT(I) \tag{1}$$

where $j = 1, 2, 3$ represents the level of decomposition and A, H, V, and D represent the approximation, horizontal, vertical, and diagonal bands respectively. Approximation and detailed bands of each decomposition level are used to compute the quality factor of the bands. Let Q_A, Q_H, Q_V, and Q_D be the quality factor for the approximation, horizontal, vertical and diagonal bands respectively. The quality factor for each band is computed using Eq. 2.

$$Q_i = \sum_{j=1}^{3} \sum_{k,l=1}^{n} I_{ij}(k,l) \tag{2}$$

where $i = A$, H, V, and D, and (k,l) represent the coordinates of the image. These quality factors are further combined using Eq. 3 to compute the quality score QS of image I,

$$QS = \frac{m_A Q_A + m_H Q_H + m_V Q_V + m_D Q_D}{m_A + m_H + m_V + m_D} \tag{3}$$

where, m_A, m_H, m_V, and m_D are the weight factors computed using Eq. 4.

$$m_i = \sum_{j=1}^{3} \frac{1}{1 + \sum_{k,l=1}^{n} \bigtriangledown I_{ij}(k,l)} \tag{4}$$

where i represents the approximation, horizontal, vertical, and diagonal bands, j represents the level of decomposition, and $\bigtriangledown$ represents the gradient operation. The gradient operation is used because it provides information such as low and high frequency edges, and sharp changes in edges which are important in computing the quality score of the image. Furthermore, the weight factors ensure proper weight assignment to all the bands depending on the information present.

We apply the proposed quality assessment algorithm to face and iris images to generate quality scores QS_F and QS_I respectively. These quality scores are used by the proposed 2ν-SVM fusion algorithm described in the next section.

3. Multimodal Biometric Match Score Fusion

Multimodal biometrics fuses information from two or more biometric modalities at different levels of fusion to enhance the performance of a biometric system. However, among all the levels, match score and decision fusion are widely used because these levels of fusion require only match scores or decisions and are independent of the classifier used. In the following sub-sections, we first provide a brief overview of 2ν-SVM and then describe the proposed 2ν-SVM match score fusion algorithm.

3.1. *Overview of 2ν-SVM*

In biometrics, Support Vector Machine[15] has been used for different learning based operations such as face recognition[16] and multimodal fusion.[5] SVM starts from the goal of separating the data with a hyperplane and extends this to non-linear decision boundaries. SVM is thus a classifier that performs classification by constructing hyperplanes in a multidimensional space and separating the data points into different classes. To construct an optimal hyperplane, SVM uses an iterative training algorithm which maximizes the margin between two classes. However, some researchers have shown that margin maximization does not always lead to minimum classification error.[17,18] Sometimes the training data points are not clearly separable and they are characterized as fuzzy separable data. In biometrics, poor quality images and images containing noise due to sensor often lead to incorrect classification and hence can be considered as fuzzy data. To address the challenges, we use dual ν-SVM (2ν-SVM) originally proposed by Chew *et al.*[19] 2ν-SVM is an attractive alternative to SVM and offers much more natural setting for parameter selection which is a critical issue in practical applications.

Let $\{\mathbf{x}_i, y_i\}$ be a set of N data vectors with $\mathbf{x}_i \in \Re^d$, $y_i \in (+1, -1)$, and $i = 1, \ldots, N$. $\mathbf{x}_i$ is the ith data vector that belongs to a binary class y_i. According to Chew *et al.*,[19] the objective of training 2ν-SVM is to find the hyperplane that separates two classes with the widest margins, i.e.,

$$\mathbf{w}\varphi(\mathbf{x}) + b = 0 \tag{5}$$

subject to,

$$y_i\left(\mathbf{w}\,\varphi(\mathbf{x}_i) + b\right) \geq (\rho - \psi_i), \qquad \rho,\ \psi_i \geq 0 \tag{6}$$

to minimize,

$$\frac{1}{2}\|\mathbf{w}\|^2 - \sum_i C_i(\nu\rho - \psi_i) \tag{7}$$

where ρ is the position of the margin and ν is the error parameter. $\varphi(\mathbf{x})$ is the mapping function used to map the data space to the feature space and provide generalization for the decision function that may not be a linear function of the training data. $C_i(\nu\rho - \psi_i)$ is the cost of errors, w is the normal vector, b is the bias, and ψ_i is the slack variable for classification errors. Slack variables are introduced to handle classes which cannot be separated by a hyperplane. ν is the error parameter that can be calculated using ν_+ and ν_- which are the error parameters for training the positive and negative classes respectively.

$$\nu = \frac{2\nu_+\nu_-}{\nu_+ + \nu_-}, \quad 0 < \nu_+ < 1 \text{ and } 0 < \nu_- < 1 \tag{8}$$

Error penalty C_i is calculated as,

$$C_i = \begin{cases} C_+, & \text{if } y_i = +1 \\ C_-, & \text{if } y_i = -1 \end{cases} \tag{9}$$

where,

$$C_+ = \left[n_+\left(1 + \frac{\nu_+}{\nu_-}\right)\right]^{-1} \tag{10}$$

$$C_- = \left[n_-\left(1 + \frac{\nu_-}{\nu_+}\right)\right]^{-1} \tag{11}$$

and n_+ and n_- are the number of training points for the positive and negative classes respectively. Further, 2ν-SVM training can be formulated as,[19]

$$max_{(\alpha_i)}\left\{-\frac{1}{2}\sum_{i,j}\alpha_i\,\alpha_j\,y_i\,y_j\,K(x_i, x_j)\right\} \tag{12}$$

where,

$$\begin{gathered} 0 \leq \alpha_i \leq C_i \\ \sum_i \alpha_i y_i = 0 \\ \sum_i \alpha_i \geq \nu \end{gathered} \tag{13}$$

$i, j \in 1, \ldots, N$, α_i, α_j are the Lagrange multipliers and the kernel function is

$$K(\mathbf{x}_i, \mathbf{x}_j) = \varphi(\mathbf{x}_i)\varphi(\mathbf{x}_j). \tag{14}$$

Here we use kernel function $K(\mathbf{x}_i, \mathbf{x}_j)$ as the RBF kernel.[15] To train 2ν-SVM, we use the iterative decomposition training based optimization algorithm.[19] This optimization algorithm can be seen as pairwise decomposition method which breaks the problem to a two variable decision problem and solves the subproblem analytically. Chew *et al.*[19] have shown that the optimized 2ν-SVM has a complexity of $O(N)$ which is significantly faster than $O(N^2)$ of the classical SVM. Applying the optimization algorithm thus leads to reduction in the computational complexity.

3.2. *Fusion of match score and quality score using 2ν-SVM*

In this section, we describe the proposed 2ν-SVM based fusion algorithm which combines the match score and quality score for improved recognition performance. Gallery and probe face and iris images are matched using 2D log polar Gabor transform based algorithm proposed by Singh *et al.*[13] and 1D log polar Gabor based algorithm proposed by Vatsa *et al.*[14] respectively. The match scores generated from these algorithms are incorporated with the quality scores of corresponding face and iris images and then fused using the proposed 2ν-SVM fusion algorithm. We can however use the same fundamental concept to fuse two or more feature sets of any other multimodal biometrics.

Let QS_F be the quality score of a face image and MS_F be the corresponding match score. Similarly, let QS_I be the quality score of an iris image and MS_I be the corresponding match score. The product of the quality score with the corresponding match score represents the quality based match score metric, QMS

$$QMS_F = QS_F \cdot MS_F \tag{15}$$

$$QMS_I = QS_I \cdot MS_I. \tag{16}$$

Quality based match scores and their labels are used to train the 2ν-SVM for multimodal fusion. Let the labeled training data be represented as $Z_F = (QMS_F, y)$ and $Z_I = (QMS_I, y)$. For each data, the class label $y \in (+1, -1)$, where $+1$ represents the genuine class and -1 represents the impostor class. Two 2ν-SVMs are trained using these labeled training data; one for face and another for iris biometrics. During the training of 2ν-SVM, error parameters ν_+ and ν_- are computed as follows:

$$\nu_+ = \frac{n_+}{n_+ + n_-} \tag{17}$$

$$\nu_- = \frac{n_-}{n_+ + n_-}. \tag{18}$$

Here n_+ and n_- are the number of genuine and impostor training data respectively. Training data is mapped in a higher dimension feature space such that $Z \to \varphi(Z)$ where $\varphi(\cdot)$ is the mapping function. The optimal hyperplane which separates the data into two different classes in the higher dimensional feature space can be obtained as the solution of Eq. 12.

In the testing phase, quality based fused score $f(QMS_{FI})$ of a multimodal test pattern $[QMS_F, QMS_I]$ is defined as,

$$f(QMS_{FI}) = f_F(QMS_F) + f_I(QMS_I) \tag{19}$$

where,

$$f_F(QMS_F) = w_F\varphi(QMS_F) + b_F \tag{20}$$

$$f_I(QMS_I) = w_I\varphi(QMS_I) + b_I. \tag{21}$$

Here, w_F, w_I, b_F, and b_I are the parameters of the hyperplane. The solution of Eq. 19 is the signed distance of QMS_{FI} from the separating hyperplane given by the two 2ν-SVMs. Finally, to verify the identity, decision of *accept* or *reject* is made on the test pattern QMS_{FI} as follows,

$$Decision(QMS_{FI}) = \begin{cases} Accept, & if\ output\ of\ SVM > 0 \\ Reject, & otherwise \end{cases}. \tag{22}$$

4. Database and Algorithms used for Validation of Proposed Fusion Algorithm

In this section, we briefly describe the face and iris databases and the recognition algorithms used in the experiments.

Database: To validate the performance of the proposed fusion algorithm, experiments are performed on the images obtained from the FERET face database[20] and CASIA iris database Ver 3.0.[21] We have chosen seven face images and seven iris images of 300 classes or individuals from each database. Our database thus contains 4200 face and iris images. Face images have pose variation from 0° to 20° with and without occlusion whereas iris images have variations in occlusion, pose, and noise. Iris database has blurriness, noise, occlusion, and deformation present in the images. The complete database is divided into three parts: training database, gallery database, and probe database. The training face database comprises of three frontal face images with minimum expression variation and three iris images. The training database is also used as the gallery database and the remaining four images per class are used as the probe images for performance evaluation.

Face Recognition Algorithm:[13] First, the face is detected using the triangle based face detection algorithm.[22] The detected face image is transformed into polar coordinates and textural features are extracted using the 2D log polar Gabor transform.[13] These features are matched using the Hamming distance based matching algorithm to generate the match scores, MS_F which are used by the proposed SVM fusion algorithm. In biometrics, match score is a measure of similarity or distance between two biometric templates.

Iris Recognition Algorithm:[14] Iris is first detected from the input eye image and converted into polar coordinates. The detected iris image contains noise due to the presence of eyelids and eyelashes. Masking is performed on the polar image to remove the noise. 1D log polar Gabor wavelet is then used to extract unique textural features from the iris image which are matched using Hamming distance and match scores MS_I are generated.

Fusion Algorithms used for Comparison: To compare the performance of the proposed fusion algorithm, we used three existing fusion algorithms: Sum rule,[3] Q-weighted sum rule,[9] and quality based C-SVM fusion.[5] Sum rule and quality weighted sum rule are fusion algorithms based on statistical rules whereas quality based C-SVM fusion algorithm is a learning based fusion algorithm.

5. Experimental Results

Experimental results are divided into three parts. The first experiment evaluates the performance of three different Support Vector Machines with different linear and non-linear kernels. The second experiment is performed to compare the performance of existing quality based match score fusion algorithms to the proposed quality based fusion algorithm. Finally, in the third experiment, we statistically compare the performance of existing and the proposed quality based fusion algorithms using the McNemar test.[23,24]

5.1. *Validation of 2ν-SVM and RBF kernel for proposed match score fusion algorithm*

In this experiment, we evaluate the performance of the proposed fusion algorithm with three variants of Support Vector Machine namely, SVM[15], ν-SVM[17], and 2ν-SVM[19]. For each of the three SVMs, we also evaluate the verification performance of the fusion algorithms with three kernels, linear, polynomial, and Radial Basis Function (RBF). This experiment is performed to justify the choice of 2ν-SVM and RBF kernel in the proposed multimodal match score fusion algorithm. The three kernels used in this experiment can be expressed as:

Linear kernel:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j \tag{23}$$

Polynomial kernel:

$$K(\mathbf{x}_i, \mathbf{x}_j) = (\gamma \mathbf{x}_i^T \mathbf{x}_j + r)^d, \quad \gamma, r > 0 \tag{24}$$

RBF kernel:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma ||\mathbf{x}_i - \mathbf{x}_j||^2), \quad \gamma > 0. \tag{25}$$

The SVMs and kernels are trained using training face and iris databases, and the probe face and iris databases are used to evaluate the verification performance. The performance is evaluated in terms of verification accuracy at 0.01% False Accept Rate (FAR). The optimal parameters for the SVMs and the kernels are obtained empirically by computing the verification accuracy for different combination of parameters. Table 1 shows the results obtained for optimal parameters.

For 2ν-SVM based fusion, optimal parameters corresponding to the polynomial kernel are $r = 1$, $\gamma = 1$, and $d = 2$ and for RBF kernel $\gamma = 4$. The results show that for all three SVMs, non-linear kernels provide higher verification performance compared to the linear kernel. This is because biometric match scores are non-linearly distributed and hence non-linear kernels provide better classification. Table 1 further shows that with optimal parameters, 2ν-SVM with RBF kernel provides the best verification performance of 98.91%.

5.2. *Comparison with existing match score fusion algorithms*

The experiment described in the previous subsection compares the performance of different SVMs

Table 1. Verification accuracy of different SVMs and kernels at 0.01% FAR.

Support vector machines	Verification accuracy (%)		
	Linear	Polynomial	RBF
SVM	97.34	97.62	97.85
ν-SVM	97.39	97.70	98.01
2ν-SVM	97.66	98.04	**98.91**

with linear and non-linear kernels and validates the use of 2ν-SVM in the proposed match score fusion algorithm. In this experiment, we compare the performance of the proposed quality based fusion algorithm and existing multimodal fusion algorithms. For comparison, we have chosen three algorithms, Sum rule,[3] Q-weighted sum rule,[9] and quality based C-SVM fusion.[5] We also evaluated the performance of individual face and iris recognition algorithms to compute the improvement obtained by using quality based fusion algorithms. The results are presented in terms of verification accuracy at 0.01% false accept rate and receiver operating characteristic (ROC) curves.

Figure 2 demonstrates the performance of the proposed fusion algorithm and compares with face recognition, iris recognition, and other existing fusion algorithms. The ROC plot shows that the performance of the proposed algorithm is better than other algorithms. Table 2 shows that the face recognition algorithm[13] provides verification accuracy of 95.57% and iris recognition algorithm[14] provides the accuracy of 96.88%. Table 2 also shows that the Sum rule,[3] Q-weighted sum rule,[9] and quality based C-SVM fusion[5] provide an accuracy of 97.18%, 97.39%, and 97.63% respectively, whereas the proposed fusion algorithm yields an accuracy of 98.91%. Analysis of the proposed algorithm and experimental results are summarized below:

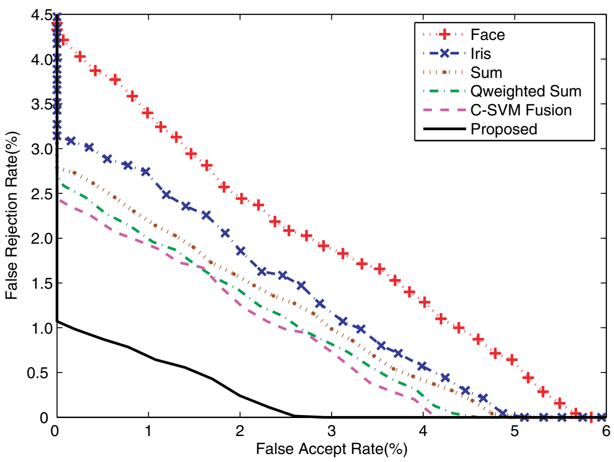

Fig. 2. ROC plot to compare the performance of the proposed match score fusion algorithm with unimodal recognition algorithms and existing match score fusion algorithms.

Table 2. Performance of the proposed and existing quality based fusion algorithms (at 0.01% FAR).

Algorithm	Fusion approach	Verification accuracy (%)
Face[13]	—	95.57
Iris[14]	—	96.88
Sum rule[3]	Sum rule without quality	97.18
Q-weighted sum rule[9]	Quality based Sum rule	97.39
C-SVM fusion[5]	Quality based C-SVM fusion	97.63
Proposed fusion	Quality based 2ν-SVM	98.91

- The proposed RDWT based quality assessment algorithm computes the quality score using edge and other frequency and temporal information along with per-subband noise relationship.[11] This provides a composite score representing different factors such as noise, blurriness, and smoothness.
- The proposed 2ν-SVM fusion algorithm has better generalization capability and low time complexity. It is therefore suitable for real time biometric systems. Results show that the proposed fusion algorithm improves the recognition performance by at least 2.03%.
- Results also show that the proposed quality based fusion algorithm is robust and performs better than existing quality based fusion algorithms by at least 1.28%. The proposed algorithm thus reduces the error by at least 54% compared to existing fusion algorithms.

5.3. *Statistical evaluation of multimodal biometric fusion algorithms*

The verification accuracies and ROC curves presented in the previous section show that the proposed quality based SVM fusion algorithm performs better than the existing fusion algorithms. However, these results do not justify whether the proposed algorithm is statistically different from other fusion algorithms. Several statistical tests and methods have been proposed to evaluate statistical difference between two classifiers.[23,24] In this section, we compare the verification performance obtained from the proposed

Table 3. Statistical comparison of existing fusion algorithms with the proposed quality based SVM fusion algorithm using the McNemar test.

Algorithm		D_2 correct	D_2 wrong	χ^2	Statistical result
Sum rule[3]	D_1 correct	180546	2	5.786	Statistically
	D_1 wrong	12	40		different
Q-weighted sum rule[9]	D_1 correct	180551	0	5.143	Statistically
	D_1 wrong	7	42		different
C-SVM fusion[5]	D_1 correct	180552	0	4.167	Statistically
	D_1 wrong	6	42		different

and existing fusion algorithms using the McNemar test.[23,24]

For two given classifiers, McNemar test determines whether the null hypothesis holds or not. The null hypotheses, H_0, states that if it holds then there is no difference between the accuracies of the two classifiers under consideration.[23] Let D_1 be the existing fusion algorithm in consideration and D_2 be the proposed quality based fusion algorithm. We first compute the number of cases where

- D_1 is correct and D_2 is also correct — N_{11}.
- D_1 is correct but D_2 is wrong — N_{10}.
- D_1 is wrong but D_2 is correct — N_{01}.
- D_1 is wrong and D_2 is also wrong — N_{00}.

If the null hypothesis holds, then the expected number of cases in which D_1 and D_2 provide conflicting results is $(N_{01}+N_{10})/2$. McNemar test computes the difference between the expected number and the actual number of conflicting cases using the following equation,[23]

$$\chi^2 = \frac{(|N_{01} - N_{10}| - 1)^2}{N_{01} + N_{10}} \tag{26}$$

From,[23,24] if the value of $\chi^2 > 3.841$, then the null hypothesis is rejected and the accuracies obtained by the two classifiers are statistically different with 95% confidence. However, if $\chi^2 \leq 3.841$, then the hypothesis holds and the accuracies are statistically not different.

In the experiments, we analyzed the match scores obtained by different fusion algorithms and computed the values of N_{00}, N_{01}, N_{10}, and N_{11} for three cases of comparison. The results are summarized in Table 3. First we compared the proposed fusion algorithm with the Sum rule.[3] Table 3 shows that using the McNemar test, verification performance of the proposed fusion algorithm is statistically different from the Sum rule based fusion algorithm.[3] Further, statistical comparison with Q-weighted sum rule and C-SVM fusion also shows that the proposed algorithm is statistically different and provides better verification performance.

6. Conclusion

The performance of a biometric system depends on the quality of input data. In this paper, we proposed RDWT based quality assessment algorithm and quality based match score fusion algorithm to address this challenge. The proposed algorithm associates each image with a quality score and fuses it with the corresponding match score. To compute the quality score of an image, the distinguishing information present in an image are quantified by applying RDWT. The approximation band and the detailed vertical, horizontal, and diagonal subbands of an image accentuate specific features that provide a quantifiable measure for assessing quality and generating a composite quality score. The respective quality score and the match scores are fused using 2ν-SVM based learning algorithm. The proposed algorithm is validated using 2100 face and iris images from the FERET face database and CASIA iris database. These images have non-homogeneous characteristics representing variations in quality, pose, occlusion, blurriness, and noise. Experimental results and statistical evaluation show that the verification performance of the proposed quality based fusion algorithm is better than existing fusion algorithms.

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