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Dimensionality Reduction Method Apply for Multi-view Multimodal Person Identification

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Abstract: In biometric systems, reducing the data dimensionality without compromising intrinsic information is essential in pre-processing high-dimensional data. Many states of the art use techniques to minimize the dimensionality of such data and avoid the so-called curse of dimensionality. When operating on limited datasets, supervised methods suffer from over fitting. Reducing the semi-supervised dimensionality in the next comparison or classification module can affect the recognition efficiency. This article introduces a novel multi-view multimodal semi-supervised dimensionality reduction methodology that applies Multi-view Multidimensional scaling dimensionality reduction based on Gabor 2D-Log extraction features and Fuzzy Multiclass SVM classification (FMSVM), respectively. In addition, it examines its application to multi-view multimodal biometric processing, especially multi-view faces, and fingerprints. An experimental study was conducted, and the results emphasize that this methodology surpasses baseline supervised and semi-supervised methods.
Keywords: Dimensionality reduction, person identification, multi-view multimodal learning, MV-MDS, FMSVM

1. Introduction

Biometric systems correspond to the recognition and authentication process, which requires translating anatomical, morphological, or behavioral features into digital impressions. They aim to certify a person's uniqueness, by measuring an immutable or unquantifiable physical characteristic. Behavioral biometrics is mainly based on muscle and motion control, including signature, keystroke, gait, and voice. In contrast, physiological biometrics is generally based on fingerprints, face, palm print, DNA, and iris [1]. These features are treated as pattern recognition problems.

In applying a biometric system, there are two modes: authentication and identification. The biometric sample is captured and processed throughout the enrollment stage during the authentication mode. It is then compared to the matching template embedded in the dataset (often called one-to-many matching). The result is accepted if the user is authentic or rejected if the user is an impostor. For the identification mode, the biometric sample is collected and analyzed, then compared to all the templates in the dataset (also known as one-to-one matching). Identifying the template to which the individual belongs was determined in [2].

Biometric systems typically include two modules of processes, characteristic extraction and verification. In the characteristic extraction module, the numerical features represent the samples. In the verification module, to determine whether there is a match, the characteristics extracted from the test samples are compared against enrollment samples' characteristics. [2]. The biometric data are represented mainly by high-dimensional characteristic vectors such as 2D Log Gabor for face [3] or fingerprint recognition. It becomes more complicated dealing with multi-view biometric data [4] because it considerably increases computation and storage costs.

Biometric systems often use multiple biometric modalities for person recognition, referred to as multimodal biometrics, to increase the recognition performance of conventional unimodal biometric schemes [5]. In some situations, multimodal biometrics may be utilized from a certain prespective, whether by merging distinct variants of the same modality (e.g., different faces of the same person) or, by mixing heterogeneous biometric modalities (e.g., iris + fingerprint + face) [6]. Fusion modalities remain a complex topic and are usually treated separately from dimension reduction. Several dimensional reduction algorithms have been introduced to address the problem of massive dimensionalities [7], including Principal Component Analysis (PCA) [7], Linear Discriminant Analysis (LDA) [7], and Multidimensional scaling [8]. Nevertheless, these approaches provide only one source of data.

Multi-view learning refers to the data fusion of multiple sets of characteristics. Multi-view data is considered to

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be several different and homogenous representations of features from the same element [4]. Therefore, multi-view dimensionality reduction (MvDR) is very functional for studying high-dimensional multi-view data. MvDR aims to reduce the input space's complexity and extract specific subspaces while sustaining implicit learning. Over the past decade, this area has been the subject of a considerable number of studies [9], [10], [11], which can be classified as supervised [12], unsupervised [9], or semi-supervised [11] MvDR.

Supervised methods for multi-view dimensionality reduction [12] could be trained on current large-scale datasets due to data acquisition's high cost and complexity. Due to various unsupervised functions, including clustering and retrieval, in which labeled data is incomplete, supervised approaches for feature extraction will not be available. Despite some significant differences between them, semi-supervised MVDR techniques, such as those presented in [13], [14], [15], [16], [17], avoid over-fitting by imposing proximity constraints on the unlabeled data pool. The many existing unsupervised MVDR methods are mostly based on Canonical Correlation Analysis (CCA) and its derivatives [4].

Another category of UMVDR algorithms is based on the latent subspace Markov network [18]. This network satisfies a statement of insufficient conditional independence that considers a collection of intrinsic variables, 16 multi-view predictions, and linearly autonomous response variables. The authors in [19] suggested joint low-level hyperplanes for multi-view data processing that seek a related low-level linear projection to reduce the amount of multi-view computation. The research work in [20] introduced a Bayesian multi-view dimensional reduction approach. Data points are mapped to a single subspace from different views without constraining the related data samples of these views. Therefore, regularization of thresholding functions across different views is necessary [21].

Classification is among the most major issues in the area of pattern recognition. KNN [10], decision tree [10], SVM [10] and SRC [22], are widely used classifiers. NN is a modest and standard classifier method without training. The SVM classifier is designed to construct a binary classifier subspace, optimising the disparity among classes. Several variations of SVM have been developed. For example, core vector machine (CVM) [23], ν-SVC [24], structural minimax probability machine (SMPM) [25], support vector ordinal regression (SVOR) [26].

Some studies have recently examined the relationship between dimensionality reduction and classification and suggested that dimensionality reduction and classifier architecture are reliable [21], [27], [28].

This work aims to reduce the witch effect's spatial dimensions on the matching time and accuracy of the biometric system. This purpose can be accomplished by recursive sampling learning of Multi-view Multi-Dimensional Scaling through Fuzzy Multiclass-SVM classification. Mv-MDS remains an expansion of the traditional MDS intended to handle multi-view sets of data. The Mv-MDS algorithm calculates joint Eigen-vectors from the entire homogeneous range matrix to obtain a single space of low dimensions, which combines essential data from all subspaces, thus avoiding the inclusion of unnecessary data. Due to the considerable increase in data size, the need for dimensionality reduction techniques such as multi-view multidimensional scaling has become even more relevant.

The proposed method, called Multi-View Multimodal Dimensionality Reduction for Person Identification, is referred to as the 2MDRPI approach. This approach was evaluated based on multiple biometrics: identification and verification of persons' faces and fingerprints, where both models used high dimensional features. This new method shows the reduction in feature size that impacts the matching time and the identification rate that reaches 99.31%, and the recognition rate that reaches 99.67%.

The remaining contents are organized in the following manner. Firstly, Section 2 is devoted to a short analysis of the relevant methods. The description of the proposed methodology are devoted to Section 3. Experimental evaluation and the results that illustrate the efficacy of the proposed schema are provided in section 4. Lastly, in Section 5, conclusions are drawn.

2. Related work

A. Multi-view learning

Multi-view learning involves datasets with multiple views, which optimizes the quality of learning by analyzing the interactions between numerous views. Thus, multi-view learning approaches can be categorized into three classes [4]. Co-training algorithms represent the first category [29]. Co-training is among the first multi-view learning systems that train to maximize alternately. Multiple kernel learning (MKL) remains the second category [30]. For better generalization than a singular kernel, MKL algorithms train a set of different kernels. MKL [31] is naturally relevant in multi-view learning, since the kernels correlate with different views.

The third group involves sub-space learning that attempts at seeking a mutual sub-space of multiple views. CCA [32] remains the most famous sub-space learning method for multi-view schemes that linearly projected two views onto a contained sub-space to improve the correlation. In addition, several other Multiview Sub-space schemes were suggested [4], [27], [28], [29]. For instance, SVM-2 K, another term for the two-view learning approach, is being introduced by Farquhar et al. [33]. It can be considered a collaborative optimization in which the KCCA works in conjunction with two SVMs. Multi-view fisheries analysis (MFDA) was proposed by Diethe et al. [34] to examine various predictions in a monitored system by generalizing the study of Fisher inequalities. The PC-MSL pairing constraints aim to impose a well-defined low-dimensional subspace and can easily combine multiple features.

B. *Multidimentional scaling*

Multidimensional scaling is a standard technique to reduce dimensionality. It is used in several aspects of machine learning, including search, as an underlying tool [35] classification and data visualisation [36], computer vision and information retrieval [37].

Given a high-dimensional input space $X \subseteq \mathbb{R}^n \times \mathbb{R}^p$, The primary aim of Multidimensional scaling is to achieve a low-dimensional representation of the n points in $\mathcal{X}, \mathcal{Y} \subseteq \mathbb{R}^n \times \mathbb{R}^k$ with $k < p$, such that any point $x_i \in X$ is represented in a novel point $y_i \in Y$ whereas the maximum distance between the points is retained. The length match between X and Y points is referred to as stress and is characterised as :

$$Stress\left(x_1, \ldots, x_n\right) = \sqrt{\frac{\sum_{i,j=1}^{n}\left(\widehat{D}_{i,j} - D_{i,j}\right)^2}{\sum_{i,j}^{n}\widehat{D}_{i,j}^2}} \tag{1}$$

Where $D_{i,j}$ represents the Euclidean distance among points x_i and x_j, $\widehat{D}_{i,j}$ denotes the Euclidean distance between points y_i and y_j. The problem of dimensional reduction can be interpreted as an optimization challenge, with the cost of the solution being the stress function described in Eq. (1). Determining the matrix $\mathcal{B} = \mathcal{X}\mathcal{X}^T$, as described in Algorithm 1, will solve the problem within such a particular cost function.

Algorithm 1: Multidimentional scaling

Input: dataset $X = \{x_1, x_2 \ldots, x_n\}, with x_i \in \mathbb{R}^p$,
required dimension size in the output space: K
Output: data interpretation in a reduced dimension
$Y = \mathrm{y}_1, y_2, \ldots, y_n, with y_i \in \mathbb{R}^k$
Function `MDS(X, K)`**:**
  Calculate the matrix of squared distances: $\mathrm{S}^{(2)} \leftarrow$
  $\left[D^2\left(x_i, x_j\right)\right], \forall i, j =$
  $1, 2, \ldots, n, where D is the Euclidean distance function$
  Determine the matrix of centering: C
  $\leftarrow Id - \frac{1}{n}\digamma, where Id$
  is the matrix of identity and O is a n
  $\times n matrix of ones$
  Double-center the matrix of squared distances:
    $\mathrm{B} \leftarrow -\frac{1}{2}CS^{(2)}C$
  Determine the K highest eigenvalues and
  corresponding
  eigenvectors of B $\mathrm{v}_1, v_2, \ldots, v_k$
  $\underline{\mathrm{y}} \leftarrow \{v_1, v_2, \ldots, v_k\}^T, with y \in \mathbb{R}^n \times \mathbb{R}^k$
end function

C. *The Stepwise Common Principal Components*

The common principal component (CPC) framework [38]is an analytical technique for simultaneously diagonalizing an ensemble of positive-definite symmetric matrices. The term ”combined diagonalization” refers to the process of diagonalizing the input matrices, assuming a common components Q, that implies an orthogonal matrix O with the same diagonal form as shown in formula (2).

$$Q : M'_a = O^T M_a O, a = 1, \ldots, A \tag{2}$$

Where M_a is the symmetrical positive-defined matrix of the input matrix a ; M'_a is the diagonalized structure created by the linear transformation defined in the O matrix.

The eigenvalues are unique for each input matrix, yet the resultant eigenvectors (columns of O) are the same for each input matrix.Otherwise stated, the input matrices are mapped towards the similar sub-space determined by the eigenvectors, for every input matrix being assigned the relative weight of each sub-space axis by a corresponding eigenvalue. The stepwise common principal component algorithm (also known as S-CPC) [39] is increasingly being used to approximate a solution to this problem. Essential eigenvalues are computed first, followed by the common components (common eigenvectors). When it computes the number of common principal components, it stops.

3. PROPOSED METHODOLOGY

This section describes the specific methods used in this research to perform person identification and recognition. The proposed methodology is based on multimodal and multi-view biometrics, including multi-view faces and multi-view fingerprints. Figure 1 illustrates the suggested method's general structure.

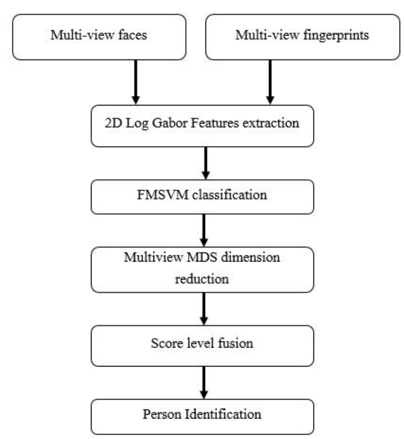


Figure 1. General model of the multi-view multimodal dimension reduction

A. *Feature extraction step*

This step is essential for any multi-biometric recognition framework. The data stored in the database is collected from the image to obtain the biometric features that will then be used in various machine learning algorithms. Most of the current techniques are widely applied in computer vision issues, namely Local Binary Pattern operator and Gabor Filters, with several variants. The 2D Log-Gabor filter was employed in this analysis. Edge detection, image enhancement, feature extraction, and pattern recognition are just some frameworks applied by 2D Log-Gabor filters.

A 2D Log-Gabor filter is applied to generate two-dimensional feature patterns. The filter has acquired a proper frequency and is therefore aligned with the Gaussian distance of the polar coordinate angle. Eq. (3) defines the 2D Log-Gabor filter:

$$G(f,\theta) = \exp\left(\frac{-\left(\log\left(\frac{f}{fo}\right)\right)^2}{2\left(\log\left(\frac{\sigma_f}{fo}\right)\right)^2}\right)\exp\left(\frac{-(\theta-\theta_0)^2}{2\sigma_\theta^2}\right) \quad (3)$$

With:

- f_e : The frequency at the center filter
- σ_f : The frequency parameter wide
- θ_Q :The filter orientation angle
- $\sigma_\ominus$: The orientation parameter wide;

The filter is applied to the image by convolving the filter with the image.The multi-resolution 2D Log-Gabor filter $G(f_S, \Theta_O)$ is a 2D Log-Gabor filter employed in multiple scales (S) and orientation (O) [3]. In this study, the filter was applied to multi-view face and fingerprint images.

B. Classification step

We can note the original multiclass SVM among the best-known semi-supervised classification methods. However, we studied and improved the fuzzy multiclass SVM (FMSVM) for the proposed multi-view multimodal biometric system. Several schemes have been developed to enhance the fuzzy binary SVM for multiclass classification, mainly involving the one-against-one and one-against-all methods [40]. For multiclass SVM classification, the one-against-one method creates n(n-1)/2 classifiers, each of which is trained on data from two classes For the training data, i^{th} class is insolated from the j^{th} class. The input vector v is determined as follows:

$$f_i(v) = \sum_{i\neq j, j=1}^{p} sign\left(f_{ij}(v)\right) \quad (4)$$

where:

$$sign(v) = f(v) = \begin{cases} 1, v > 0 \\ 0, v \leq 0 \end{cases} \quad (5)$$

and classify v into the class

$$i = 1, \ldots, pargmax\ f_i(v) \quad (6)$$

If (6) is fulfilled for plurality i 's, v cannot be classified. In the shaded area (figure 2), $f_i(v) = 1 (i = 1,2,3)$. Therefore, the shaded area cannot be classified. A fuzzy SVM has been put forth [41]to solve unclassifiable regions, in which one-dimensional membership function $m_{ij}(v)$ on the directions orthogonal to the optimal separating $f_{ij}(v) = 0$ is defined as follows:

$$m_{ij}(v) = \begin{cases} 1, & f_{ij}(v) > 1 \\ f_{ij}(v) & otherwise \end{cases} \quad (7)$$

Using $m_{ij}(v)(i \neq j, j = 1, \ldots, p)$, the i^{th} class membership function is specified in Eq. (8):

$$m_{ij}(v) = \min_{j=1,\ldots,n} m_{ij}(v) = \min\left(1, \min_{i\neq j, j=1,\ldots,n} f_{ij}(v)\right) \quad (8)$$

The membership function has the form of a truncated polyhedral pyramid. As $m_i(v) = 1$ is only valid for one class, Eq.(8) is reduced to:

$$m_i(v) = \min_{i\neq j, j=1,\ldots,p} f_{ij}(v) \quad (9)$$

An unknown data x has been reassigned to the following class.

$$argmax\ m_i(x)_{i=1,\ldots,p} \quad (10)$$

Therefore, Figure 3 resolves the unclassified area in Figure 2:

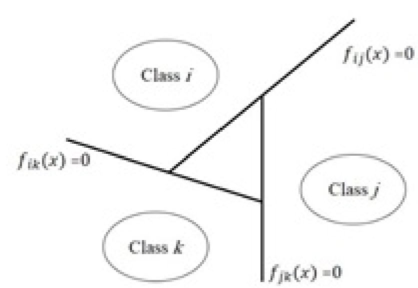


Figure 2. Unclassified region by the two-class formulation

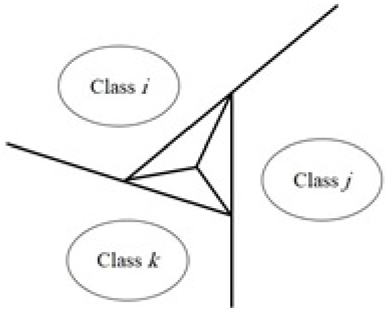


Figure 3. Extended generalization region

C. Multi-view MDS

The Multi-View Multidimensional Scaling (MV-MDS) approach discussed extends the classic MDS for multi-view learning. Rather than a singular source space X, n input samples are extracted through distinct input spaces, resulting in a series of data matrices $x_1, x_2, \ldots, x_m$ as aggregate input to the method. Nevertheless, a single Y projection space as output is anticipated by MV-MDS. MV-MDS attempts to define each space. The distances among points are related to the distances between points in all m input spaces as possible.However, this is not necessarily achievable, considering the distances in one Xi input space may contradict the distances in other Xj input space. Nevertheless, the MV-MDS attempts to provide a projection space independent of each specific input space [42]. It is essential to notice that the input spaces may have distinct dimensions.

Assuming m input spaces' existence, the stress of MV-MDS, as generalised from the concept of stress in Eq.(1), remains the stress of low-dimensional space Y, including all sources, high-dimensional spaces. $x_1, x_2, \ldots, x_m$, The following equation defines it:

$$Stress_{MV}\left(x_1^{(p)}, x_2^{(p)}, \ldots, x_n^{(p)}\right) = \frac{1}{m}\sum_{p=1}^{m}\sqrt{\frac{\sum_{ij}\left(\hat{D}_{i,j} - D_{i,j}^{(p)}\right)^2}{\sum_{ij}\hat{D}_{i,j}^2}} \tag{11}$$

$\forall i, j = 1, 2, \ldots n \cdot \forall P = 1, 2 \ldots, m$

With:

- $x_i^{(p)}$ is the vector with the coordinates of point i in input space $p, x_{ij}^{(p)}$ represents the Euclidean distance between points $x_i^{(p)}$ and $x_j^{(p)}$.
- $\widehat{D}_{ij}$ is the Euclidean distance between points yi and yj.

Given m input matrices $\mathcal{X}_1, \mathcal{X}_2; \ldots \mathcal{X}_m$, the problem of dimensionality reduction defined by Eq. 11 now requires seeking the Matrix of eigenvectors $B^{(p)} = X^{(p)}X^{(p)t}; p = 1, 2, \ldots, m$. The highest eigenvalues and related eigenvectors of m must be computed until the optimal projection space Y is v -dimensional.Addressing this issue will result in a series of m eigenvectors for each input matrix, invaliding the entire process. Nevertheless, if the S-CPC Model is extended to $B^{(p)} = X^{(p)}X^{(p)t}; p = 1, 2, \ldots, m.$, then it is conceivable to compute the v largest common eigenvalues and their eigenvectors.

The S-CPC estimates an eigenvalue for each input matrix. Yet, the eigenvectors are specific and shared by each source matrix; the S-CPC ensures that the eigenvectors are ordered by the maximum total of the relevant eigenvalues, thus meeting the MDS criterion of computing the highest eigenvalues. The projection space that occurred was associated with their eigenvectors. Algorithm 2 describes the MV-MDS algorithm.

Algorithm 2: Multiview Multidimentionnal scaling [42]

Input: v datasets $\chi^{(1)}, x^{(2)}, \ldots, x^{(v)}$, with $x^{(k)} \subseteq \mathbb{R}^p \times \mathbb{R}^{n_k}$ required dimension size in the output space : m

Output: data interpretation in a reduced dimension $\mathcal{Y} \subseteq \mathbb{R}^p \times \mathbb{R}^m$.

Function `MDS(`$\left(x^{(1)}, x^{(2)}, \ldots, x^{(v)}, m\right)$`):`

 Calculate the centering matrix: $J \leftarrow I - \frac{1}{p}\mathbb{O}$, *where* I *is the matrix of identity and* $\mathbb{O}$ *is a* $p \times p$ *matrix of ones*

 for $k \leftarrow 1$ ***to*** v **do**

  Compute the squared distance matrix: $D^{(k)(2)} \leftarrow \left[d^2\left(x_i^{(k)}, x_j^{(k)}\right)\right]$ *with* $i, j = 1, 2, \ldots, p$, *where d is the Euclidean distance function*

  Apply double centering to the squared distance matrix: $B^{(k)} \leftarrow$

$$-\frac{1}{2}JD^{(k)(2)}J$$

 end for

 Compute the m largest common eigenvalues of $\left\{B^{(1)}, B^{(2)}, \ldots, (v)\right\}$ *and their associated eigenvectors* $e_1, e_2, \ldots, e_m$ *using S-CPC.*

$$y \leftarrow \{e_1, e_2, \ldots, e_m\}^T, withy \in \mathbb{R}^n \times \mathbb{R}^m$$

end function

D. Fusion Step

The integration of multiple biometric modalities, or so-called multimodal systems [7], improves recognition efficiency. The multi-view face and fingerprint modalities were combined in this work to create the multi-view multimodal biometric framework using score-level fusion. The combination at the score level provides a perfect balance between data availability and ease of execution. The decision level indicates the insertion of a similarity matrix for all combined scores. If the application has a high score, the system must approve it (high number interest point pair).

4. EXPERIMENTAL RESULTS

A. Databases

The experiments were conducted using different databases combining the multi-view contactless fingerprint database [43] and the Cas-peal-R1 face database [44], as there are currently no multimodal, multi-view biometric databases. Table I summarizes the information from these databases, while Figure 4 shows a selection of sample images.

TABLE I. DESCRIPTION OF THE MULTI-VIEW FACE AND FINGERPRINT DATABASES

Database	Samples	Classes	Sample per class
Multi-view Contactless Fingerprint	109.000	1000	109
Peal face database	21.000	1000	21

a) *The Multi-view Contactless Fingerprint Database* [43] contains contactless fingerprint samples obtained from 1500 fingertips using a commercial multi-view (three-view) fingerprint system. Each finger received two fingerprint samples, with each specimen including three multi-view contactless fingerprints, one top-view, and two side-view. Only 1000 fingers were used, as some fingerprint samples are missing from the database.

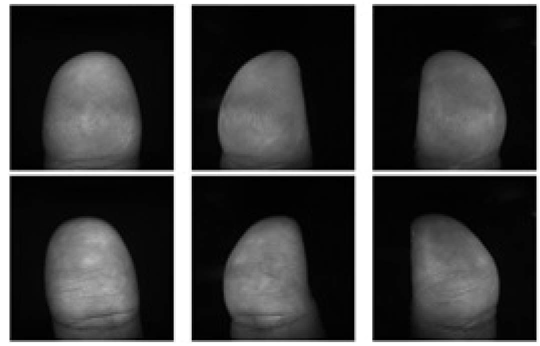
b) *The Cas-Peal-R1 face database* [44] includes 30,900 images of 1,400 individuals (595 men and 445 women). For each image, 21 distinct poses are included with no other variation. The rest of the images in the collection are all frontal pose images featuring various expressions, accessories, and lighting. A subset of 1000 samples with only different poses was used in this experiment.

B. Experimental protocol

A "Repeated Random Test-Train Splits" approach was applied in this research. Each time, the data were randomly divided into training, testing, and evaluating samples, and then the process was repeated several times. The frequently employed evaluation metrics are recognition rates and Cumulative Match Characteristics (CMC) curves for the identification task. For the authentication scheme, the evaluation of the experiment is presented in verification rates and Receiving Operating Characteristic (ROC) curves. The effectiveness of the proposed 2MDRPI was compared with various dimensional reduction methods, namely PCA [7], MDS [8], CCA [4], and SDR-SRC [45] for single-view methods; UCCA [46] SR2MCC [27] for multi-view methods.

C. Results and analysis

Several evaluations were performed to assess the identification scenario. The single fingerprint and face modalities and the score-level fusion scheme were compared. Tables II-IV indicate the average identification rate performance.



(a)Contactless 2D fingerprint database [43]

(b) Cas-Peal-R1 face database [44]

Figure 4. Sample images of the fingerprint and face databases

TABLE II. IDENTIFICATION RATE PERFORMANCE ON THE MULTI-VEW CONTACTLESS FINGERPRINT DATABASE

Method \ Train	2	3	4	5	6
PCA	42.32%	52.44%	61.65%	68.47%	76.37%
MDS	40.64%	52.60%	63.40%	71.85%	77.35%
CCA	42.22%	57.71%	68.63%	72.63%	79.23%
SDR-SRC	42.99%	66.70%	76.30%	82.86%	85.24%
UCCA	50.41%	67.17%	77.09%	83.95%	87.21%
SR2MCC	54.67%	67.97%	81.02%	86.68%	89.21%
2MDRPI	57.38%	69.48%	79.40%	87.39%	95.22%

TABLE III. IDENTIFICATION RATE PERFORMANCE ON THE MULTI-VIEW CAS-PEAL-R1 FACE DATABASE

Method \ Train	2	3	4	5	6
PCA	34.97%	42.71%	61.05%	69.65%	75.20%
MDS	42.01%	53.00%	62.28%	70.47%	76.99%
CCA	48.19%	58.47%	69.29%	72.02%	77.90%
SDR-SRC	44.03%	58.58%	69.63%	78.77%	81.85%
UCCA	59.46%	70.33%	77.26%	82.56%	85.80%
SR2MCC	58.19%	69.48%	79.26%	83.62%	87.90%
2MDRPI	63.86%	75.76%	82.23%	88.58%	94.70%

TABLE IV. IDENTIFICATION RATE PERFORMANCE ON THE FUSED MULTI-VIEW MODALITY

Method \ Train	2	3	4	5	6
PCA	53.10%	63.67%	71.10%	76.97%	80.76%
MDS	54.19%	64.93%	73.00%	78.38%	81.95%
CCA	52.87%	69.17%	74.04%	79.87%	82.26%
SDR-SRC	59.13%	68.47%	79.29%	83.17%	85.47%
UCCA	65.99%	75.27%	80.64%	84.32%	89.80%
SR2MCC	68.27%	82.68%	85.51%	88.01%	91.09%
2MDRPI	86.14%	92.18%	95.39%	96.08%	99.31%

The results indicate that the multi-view frameworks (UCCA, SR2MCC, and 2MDPI) perform better than the single-view frameworks (PCA, MDS, CCA, and SDR-SRC) in both the single and fusion modalities. The effectiveness of the fusion score level with the best single-view accuracy was evaluated for each procedure. A multi-view method appears to have a lower relative advantage than a single-view method because of the information fusion scheme built into it. Nevertheless, since information fusion was already embedded into multi-view dimensional reduction, this result was expected. Furthermore, UCCA, SR2SRC, and 2MDRPI exceed PCA's, MDS's, and CCA's score-level fusion performance regarding single-view accuracy in determining the strength of multi-view dimensionality reduction in evaluating multiple information sources. Although UCCA far outperforms linear CCA, it requires fine-tuning of multi-view parameters. In the end, the proposed 2MDRPI approach outperforms the nearest running SR2SRC approach by a wide margin. The retrieval accuracy is higher with the weaker single view (face) than with the SR2SRC fusion system. The score-level fusion scheme produces near-perfect retrieval efficiency in the 2MDRPI subspaces (Precision = Recall > 99%). A CMC curve was selected to test the effectiveness of the developed method. The CMC curve highlights the cumulative identification rate against the distribution spectrum. It often reveals the degree of proximity required to obtain a correct match. Figure 5 shows that the proposed approach performs better in multi-view methods than single-view methods in the identification scenario.

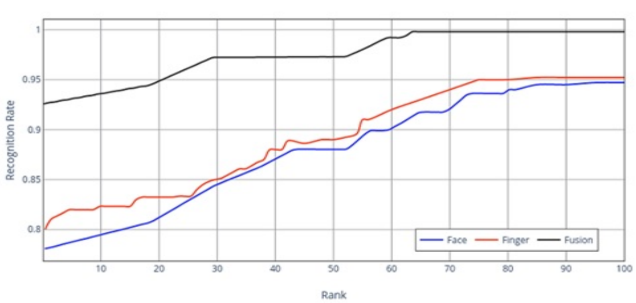


Figure 5. CMC curves of unimodal and multimodal biometric systems

As for the recognition scenario, the same steps were applied. Tables V-VII summarize the recognition rate performance for single and fusion modalities. Thus, the proposed 2MDRPI outperforms all methods in both single modality or fused modalities.

TABLE V. RECOGNITION RATE PERFORMANCE ON THE MULTI-VIEW CONTACTLESS FINGERPRINT DATABASE

Method \ Train	2	3	4	5	6
PCA	43.69%	53.46%	63.20%	70.09%	78.42%
MDS	42.12%	53.72%	65.00%	73.69%	80.01%
CCA	44.03%	58.85%	69.74%	74.77%	82.30%
SDR-SRC	44.86%	67.78%	77.71%	83.65%	86.46%
UCCA	51.53%	68.85%	79.12%	85.27%	90.08%
SR2MCC	56.36%	64.69%	82.10%	88.17%	92.10%
2MDRPI	60.13%	71.35%	83.72%	90.37%	96.77%

TABLE VI. RECOGNITION RATE PERFORMANCE ON THE MULTI-VIEW CAS-PEAL-R1 FACE DATABASE

Method \ Train	2	3	4	5	6
PCA	44.15%	46.19%	62.48%	71.23%	76.84%
MDS	48.37%	56.10%	64.34%	73.67%	78.83%
CCA	52.14%	60.65%	71.13%	75.96%	79.38%
SDR-SRC	54.69%	61.28%	72.51%	80.88%	84.73%
UCCA	61.60%	72.98%	79.95%	82.56%	97.80%
SR2MCC	68.54%	75.07%	82.91%	84.62%	89.90%
2MDRPI	72.52%	80.99%	85.63%	96.85%	95.80%

TABLE VII. RECOGNITION RATE PERFORMANCE ON THE FUSED MULTI-VIEW MODALITY

Method \ Train	2	3	4	5	6
PCA	68.45%	69.27%	74.24%	79.79%	83.90%
MDS	68.96%	72.36%	77.36%	80.00%	84.78%
CCA	70.69%	79.26%	80.02%	82.65%	86.09%
SDR-SRC	75.27%	79.32%	83.67%	86.75%	90.13%
UCCA	80.13%	84.64%	89.97%	92.67%	95.70%
SR2MCC	85.99%	87.04%	90.13%	93.28%	96.23%
2MDRPI	90.06%	94.87%	96.32%	97.81%	99.67%

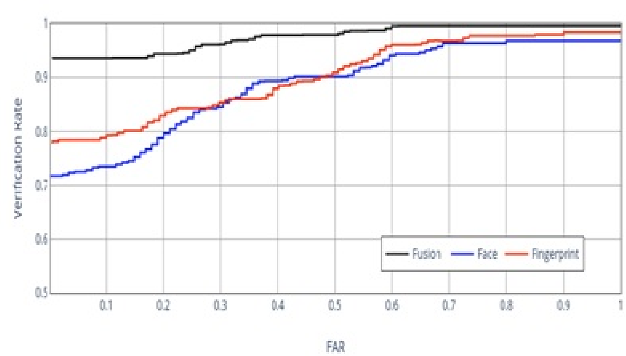
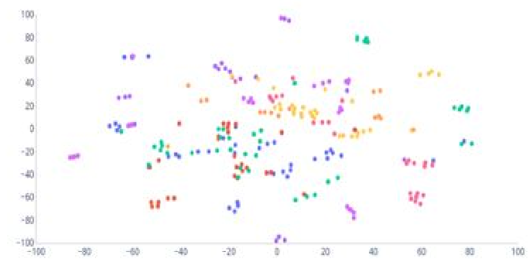


Figure 6. Unimodal and multimodal biometric system ROC curves

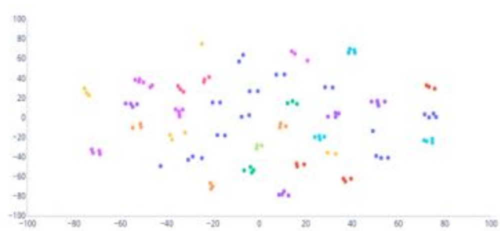
(a) Contactless 2D fingerprint data visualization in MDS subspace.

(b) Cas-Peal-R1 face data visualization in MDS subspace.

(c) Contactless 2D fingerprint data visualization in CCA subspace.



(d) Cas-Peal-R1 face data visualization in CCA subspace.



(e) Contactless 2D fingerprint data visualization in 2MDRPI subspace.

(f) Cas-Peal-R1 face data visualization in 2MDRPI subspace.

Figure 7. t-SNE data visualizations for MDS, CCA, and 2MDRPI subspaces.

It is important to note that a strategy that combines high verification rates (VR) and low false acceptance rates (FAR) should perform well. Figure 6 shows that the suggested strategy outperforms single-view strategies in multi-view approaches in the recognition case.

D. Visualization rate

Data samples in low-dimensional spaces were used in all the approaches compared above. The embedded data scheme must be visualized, and the interaction between the embedded model and the retrieved results must be analyzed. In addition, the embedded subspaces are highly dimensional and difficult to visualize. The T-distributed Stochastic Neighbor Embedding (t-SNE) method [47] is a powerful method to visualize high-dimensional data by combining 2-D and 3-D spaces while maintaining proportional intervals between data representations. Figure 6 shows the MDS, CCA, and 2MDRPI embedding scattering plots after applying t-SNE. In all situations, samples from different classes were represented by different colors. Therefore, the retrieval efficiency is low in this scenario due to the noisy distribution of samples in the MDS subspace (Figure 7a and Figure 7b). Some classes form compact clusters (Figure 7c) in the CCA subspace, while others are mixed (Figure 7d). As shown in Figure 7d, even though the CCA subspace significantly reduces the mixing of different classes, the intra-class scattering is still considerable. This finding was also reported in [27] . CCA improves the centroid scattering of each underlying class (inter-class scattering) but cannot decrease the intra-class scattering. In the end, in the suggested 2MDRPI subspaces (Figure 7e and Figure 7f), the samples of the same class are well-positioned in compact classes with significantly more separation between classes, which shows the best performance. The proposed 2MDRPI method is also well suited for multi-view data classification and retrieval of multi-view data.

5. Conclusion

This paper addressed the challenge of Multimodal Multi-view dimensionality reduction for person identification and recognition. The proposed method intends to generate a subspace projection of each view using Fuzzy Multiclass SVM and the Multi-view Multidimensional scaling algorithm, which improves the traditional multidimensional scaling algorithm to reduce the dimension without losing intrinsic information data from multiple. By computing the corresponding eigenvectors of the normalised distance matrices of each view in the source, a single high-dimensional illustration of the multi-view was obtained, accomplished using the MVMDS method.

The results of experiments on unimodal fingerprint and face modalities and multimodal modalities confirm the higher efficiency of the proposed method in identification and verification scenarios compared to other approaches. More advanced multi-classifiers will be considered in future work. The latest MVDR and classification systems will be introduced to increase the performance of multi-view dimensionality reduction methods and combine or incorporate semi-supervised and/or unsupervised learning tasks.

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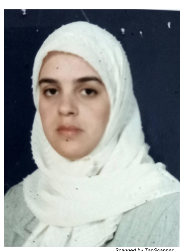

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