Sparse Representations and Random Projections for Robust and Cancelable Biometrics

(Invited Paper)

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***Abstract*—In recent years, the theories of Sparse Representation (SR) and Compressed Sensing (CS) have emerged as powerful tools for efficiently processing data in non-traditional ways. An area of promise for these theories is biometric identification. In this paper, we review the role of sparse representation and CS for efficient biometric identification. Algorithms to perform identification from face and iris data are reviewed.**

By applying Random Projections it is possible to purposively hide the biometric data within a template. This procedure can be effectively employed for securing and protecting personal biometric data against theft. Some of the most compelling challenges and issues that confront research in biometrics using sparse representations and CS are also addressed.

***Index Terms*—Cancelable biometrics, Random Projections, Sparse Representations, Iris recognition, Face recognition.**

I. Introduction

Biometrics refers to the physiological or behavioral characteristics of a person. Since many physical characteristics, such as face, and behavioral characteristics, such as voice, are unique to an individual, biometric analysis offers a reliable and natural solution to the problem of identity verification.

However, with the increasing use of biometrics, more and more concerns are being raised about the privacy of biometric data and identity theft. Since biometric characteristics cannot be changed, the loss of privacy is permanent if they are ever compromised. To deal with the privacy and protection of personal data, the notion of Cancelable Biometrics has been introduced. A cancelable biometric scheme intentionally distorts the original biometric pattern through a revocable and non-invertible transformation. The objectives of a cancelable biometric system are as follows [3]:

- Different templates should be used in different applications to prevent cross matching.
- Template computation has to be non-invertible to prevent illegal recovery of biometric data.
- Revocation and reissue should be possible in the event of compromise and
- Recognition performance should not degrade when a cancelable biometric template is used.

In recent years, Sparse Representation (SR) and Compressed Sensing (CS) have received a great interest in computer vision and biometrics. They have been successfully used for robust and secure physiological biometrics recognition such as face and iris [6], [7], [9], [1]. In this paper, we categorize approaches to biometrics based on sparse representations.

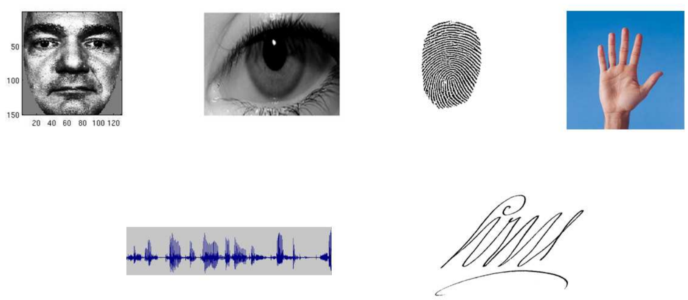

Fig. 1. Examples of different physiological (face, iris, fingerprint, hand geometry) and behavioral (voice, signature) biometrics.

A. Organization of the Paper

This paper is organized as follows. In section II, we briefly discuss some of the methods proposed for biometrics recognition based on SR and CS. Section III presents the sparse representation-based classification algorithm and discuss some of the recognition results on face and iris biometrics. In section IV, we present a way to incorporate security within the SRC algorithm by random projections. We discuss how this method can be extended for other biometrics in section V and some of the challenges and issues confront biometrics recognition using SR and CS are discussed in section VI. Finally, concluding remarks are made in section VII.

II. Biometrics recognition based on SR and CS

In this section, we briefly describe some of the methods proposed for iris and face biometrics based on SR and CS. In [9], Phillips proposed matching pursuit filters for face feature detection and identification. The filters are designed through a simultaneous decomposition of a training set into a 2D wavelet expansion designed to discriminate among faces. It was shown that the resulting algorithm was robust to facial expression and the surrounding environment.

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Compressed sensing has shown it is possible to efficiently compress signals using a sparse representation [10],[11]. In turn, this has lead to a resurgence of interest in the principles of sparse representation for recognition. Recently, Wright *et al.* [1] introduced an algorithm, called Sparse Repersentation-based Classification (SRC), based on SR and CS. This work was later extended to handle pose and illumination variations in [12], [13] and for iris recognition in [6]. Nagesh and Li [14] presented an expression invariant face recognition based on ideas from the distributed compressed sensing and joint sparsity models. Also, Li *et al.* [15] presented a face recognition method based on sparse representation for recognizing 3D face meshes under expressions using low-level geometric features.

Following [1] and [6], in what follows, we briefly describe the SRC method for the physiological biometrics recognition. In particular, we show how one can incorporate cancelability [7] within this framework.

III. Sparse Representation Based Classification (SRC)

The idea proposed in [1] in using SR and CS techniques for classification is to create a dictionary matrix of the training samples as column vectors. The test sample is also represented as a column vector. Different dimensionality reduction methods are used to reduce the dimension of both the test vector and the vectors in the dictionary. One such approach for dimensionality reduction is random projections [7]. Random projections, using a generated sensing matrix, are taken of both the dictionary matrix and the test sample. It is then simply a matter of solving an ℓ_1 minimization problem in order to obtain the sparse solution. Once the sparse solution is obtained, it can provide information as to which training sample the test vector most closely relates to.

Let each image be represented as a vector in $\mathbb{R}^n$, A be the dictionary (i.e. training set) and y be the test image. The SRC algorithm is as follows:

1) Create a matrix of training samples $A = [A_1, ..., A_k]$ for k classes, where A_i are the set of images of each class.
2) Reduce the dimension of the training images and a test image by any dimensionality reduction method. Denote the resulting dictionary and the test vector as $\tilde{A}$ and $\tilde{y}$, respectively.
3) Normalize the columns of $\tilde{A}$ and $\tilde{y}$.
4) Solve the following ℓ_1 minimization problem

$$\hat{\alpha} = \arg\min_{\alpha'} \| \alpha' \|_1 \quad \text{subject to} \quad \tilde{y} = \tilde{A}\alpha', \qquad (1)$$

5) Calculate the residuals

$$r_i(\tilde{y}) = \|\tilde{y} - \tilde{A}\delta_i(\hat{\alpha})\|_2,$$

for $i = 1, ..., k$ where δ_i a characteristic function that selects the coefficients associated with the i^{th} class.
6) Identify(y)=$\arg\min_i r_i(\tilde{y})$.

The assumption made in this method is that given sufficient training samples of the k^{th} class, $\tilde{A}_k$, any new test image y that belongs to the same class will approximately lie in the linear span of the training samples from the class k. This implies that most of the coefficients not associated with class k in $\hat{\alpha}$ will be close to zero. Hence, α' is a sparse vector. This algorithm can also be extended to deal with occlusions and random noise. Furthermore, a method of rejecting invalid test samples can also be introduced within this framework [1]. In particular, to decide whether a given test sample is a valid sample or not, the notion of Sparsity Concentration Index (SCI) has been proposed in [1]. See [1] and [6] for more details.

To illustrate the effectiveness of the SRC algorithm for face and iris biometrics, we highlight some of the results presented in [1] and [6]. The recognition rates achieved by the SRC method for face recognition with different features and dimensions are summarized in Table I on the extended Yale B Dataset [22]. As it can be seen from Table I the SRC method achieves the best recognition rate of 98.09% with randomfaces of dimension 504.

TABLE I
Recognition Rates (in %) of SRC Algorithm [1] on the Extended Yale B Database.

Dimension	30	56	120	504
Eigen	86.5	91.63	93.95	96.77
Laplacian	87.49	91.72	93.95	96.52
Random	82.60	91.47	95.53	98.09
Downsample	74.57	86.16	92.13	97.10
Fisher	86.91	-	-	-

Partial face features have been very popular in recovering the identity of human face [28], [1]. The recognition results on partial facial features such as an eye, nose, and mouth are summarized in Table II on the same dataset. The SRC algorithm achieves the best recognition performance of $93.7\%, 87.3\%, 98.3\%$ on eye, nose and mouth features, respectively and it outperforms the other competitive methods such as Nearest Neighbor (NN), Nearest Subspace (NS) and Support Vector Machines (SVM). These results show that SRC can provide good recognition performance even in the case when partial face features are provided.

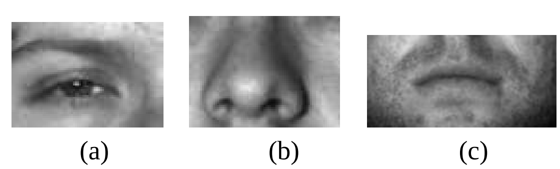

Fig. 2. Examples of partial facial features. (a) Eye (b) Nose (c) Mouth.

TABLE II
Recognition results with partial facial features [1].

	Right Eye	Nose	Mouth
Dimension	5,040	4,270	12,936
SRC	93.7%	87.3%	98.3%
NN	68.8%	49.2%	72.7%
NS	78.6%	83.7%	94.4%
SVM	85.8%	70.8%	95.3%

One of the main difficulties in iris biometric is that iris images acquired from a partially cooperating subject often suffer from blur, occlusion due to eyelids, and specular reflections. As a result, the performance of existing iris recognition systems degrade significantly on these images. Hence, it is essential to select good images before they are input to the recognition algorithm. To this end, one such algorithm based on SR for iris biometric was proposed in [6] that can select and recognize iris images in a single step. The block diagram of the method based on SR for iris recognition is shown in Figure 3.

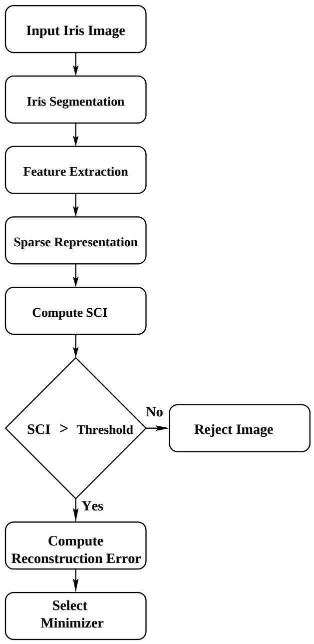

Fig. 3. Block diagram of the method proposed in [6] for the selection and recognition of iris images.

In Figure 4, we display the iris images having the least SCI value for the blur, occlusion and segmentation error experiments performed on the real iris images in the University of Notre Dame ND dataset [23]. As it can be observed, the low SCI images suffer from high amounts of distortion. The recognition performance of the SR based method for iris biometric [6] is summarized in Table III. As it can be seen from the table SRC provides the best recognition performance over that of NN and Libor Masek's iris identification source code [24].

TABLE III
RECOGNITION RATE ON ND DATASET [6].

Image Quality	NN	Masek's Implementation	SRC
Good	98.33	97.5	99.17
Blured	95.42	96.01	96.28
Occluded	85.03	89.54	90.30
Seg. Error	78.57	82.09	91.36

IV. CANCELABILITY THROUGH RANDOM PROJECTIONS

The idea of using Random Projections (RP) for cancelability in biometrics has been introduced before [16], [18], [7]. In [16] and [18], RPs of discriminative features were used for

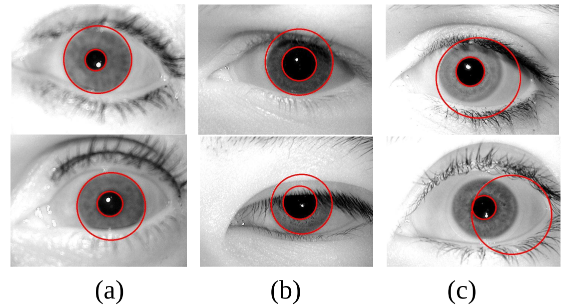

Fig. 4. Iris images with low SCI values in the ND dataset. Note that the images in (a), (b) and (c) suffer from high amounts of blur, occlusion and segmentation errors, respectively .

cancelability in face biometrics. RPs on different regions of iris were applied for cancelability in [7]. In what follows, we show how RPs can be incorporated into the sparse representation framework for cancelability.

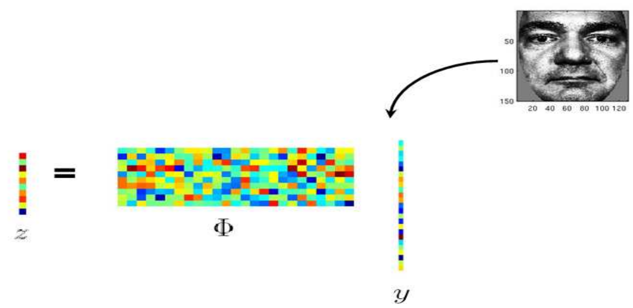

Fig. 5. Random Projections for cancelable biometrics.

Let Φ be an $m \times n$ random matrix with $m \leq n$ such that each entry $\phi_{i,j}$ of Φ is an independent realization a random variable on a probability measure space. Consider the following observations

$$z \doteq \Phi y = \Phi A \alpha = \tilde{A}\alpha. \tag{2}$$

z can be thought of as a transformed version of the biometric y. One has to recover the coefficients α in order to apply the sparse recognition method explained in the previous section. As m is smaller than n, the system of equations (2) is underdetermined and the unique solution of α is impossible. However, due to the sparsity of α and under certain conditions on $\tilde{A}$, one can recover α by solving the following ℓ_1 minimization problem

$$\hat{\alpha} = \arg\min_{\alpha'} \parallel \alpha' \parallel_1 \quad \text{s. t.} \quad z = \tilde{A}\alpha'. \tag{3}$$

One sufficient condition for (1) to stably approximate the sparsest solution of (2), is known as the Restricted Isometry Property (RIP)[10], [21], [20]. A matrix ΦA is said to satisfy the RIP of order K with constants $\delta_K \in (0,1)$ if

$$(1-\delta_K) \parallel v \parallel_2^2 \leq \parallel \Phi A v \parallel_2^2 \leq (1+\delta_K) \parallel v \parallel_2^2 \tag{4}$$

for any v such that $\| \ v \ \|_0 \leq \ K$. When RIP holds, ΦA approximately preserves the Euclidean length of K-sparse vectors. When A is a deterministic dictionary and Φ is a random matrix, we have the following theorem on the RIP of ΦA.

Theorem 1. *([19]) Let $A \in \mathbb{R}^{n\times m}$ be a deterministic dictionary with restricted isometry constant $\delta_K(A)$. Let $\Phi \in \mathbb{R}^{m\times n}$ be a random matrix satisfying*

$$P\left(|\|\Phi v\|^2 - \|v\|^2| \geq \varsigma \|v\|^2\right) \leq 2e^{-c\frac{n}{2}\varsigma^2}, \quad \varsigma \in (0, \frac{1}{3}) \quad (5)$$

for all $v \in \mathbb{R}^n$ and some constant $c > 0$ and assume

$$m \geq C\delta^{-2}\left(K \log(m/K) + \log(2e(1 + 12/\delta)) + t\right) \quad (6)$$

for some $\delta \in (0, 1)$ and $t > 0$. Then, with probability at least $1 - e^{-t}$, the matrix ΦA has restricted isometry constant

$$\delta_K(\Phi A) \leq \delta_K(A) + \delta(1 + \delta_K(A)). \quad (7)$$

The constant satisfies $C \leq 9/c$.

The following are some of the matrices that satisfy (5) and hence can be used as random projections for cancelability.

- $m \times n$ random matrices Φ whose entries $\phi_{i,j}$ are independent realizations of Gaussian random variables $\phi_{i,j} \sim \mathcal{N}\left(0, \frac{1}{m}\right)$.
- Independent realizations of ± 1 Bernoulli random variables

$$\phi_{i,j} \doteq \begin{cases} +1/\sqrt{m}, & \text{with probability } \frac{1}{2} \\ -1/\sqrt{m}, & \text{with probability } \frac{1}{2}. \end{cases}$$

- Independent realizations of related distributions such as

$$\phi_{i,j} \doteq \begin{cases} +\sqrt{3/m}, & \text{with probability } \frac{1}{6} \\ 0, & \text{with probability } \frac{2}{3} \\ -\sqrt{3/m}, & \text{with probability } \frac{1}{6}. \end{cases}$$

- Multiplication of any $m \times n$ random matrix Φ with a deterministic orthogonal $n \times n$ matrix D, i.e. ΦD.

Note that RPs meet the various constraints required for cancelability. By using different RP matrices, we can issue different templates for different applications. If a transformed pattern is compromised, we can reissue a new pattern by applying a new random projection to the iris vector. The RIP properties together with the sparsity of α ensure that the recognition performance is preserved. In the application database, only the transformed dictionary ΦA is stored. If a hacker illegally obtains the transformed dictionary ΦA and the transformed iris patterns of the user, z, he or she will have access to the person's identity. However, it is extremely difficult to obtain the matrix A from ΦA, and without A one cannot obtain the original iris patterns y. Hence, the resulting cancelable scheme is non-invertible as it is not possible to obtain the original iris patterns from the transformed patterns. Furthermore, since this method is based on pseudo-random number generation, we only consider the state space corresponding to the value taken by the seed of the random number generator. Hence, instead of storing the entire matrix, one only needs to store the seed used to generate the RP matrix.

A. Sector-based RPs for cancelable iris biometrics

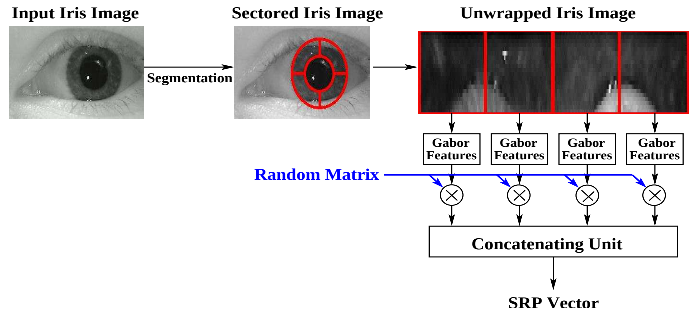

Fig. 6. Block Diagram of Sectored Random Projections [7].

Empirically we have found that applying the random projections directly on the iris images leads to a degradation in performance due to the following reasons. In real iris images, despite good segmentation algorithms, there will still be some outliers due to specular reflections, eye lashes and eyelids. Also, different parts of the iris have different quality [29]. By taking a linear transformation of the entire vector, we combine the good iris regions as well as the outliers and thereby corrupting the data. To avoid this, one can divide the iris into different sectors then apply random projections on each sector separately and concatenate them to form the cancelable template (see Fig. 6) [7]. Hence, outliers can corrupt only the corresponding sector and not the entire iris vector. Since outliers due to eyelids and eye lashes are present only at the top and bottom of the iris images, only a small number of sectors get corrupted in practice. This mitigates the problem of reduction in useful information, mentioned in [17]. Different iris sectors can be viewed as partial features similar to those considered in the previous section for face biometrics. Once RPs have been applied, they can be viewed as transformed versions of the original iris and SRC algorithm can be used for identification. A block diagram of the random projections based cancelable system is shown in Fig. 7.

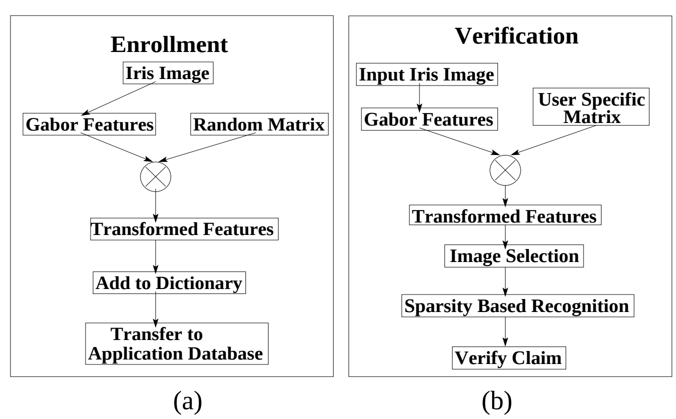

Fig. 7. Block Diagram of the Random Projections based cancelable system.

V. Extension to other biometrics

Even though SR-based recognition algorithms have been proposed for physiological biometrics such as face and iris, they can also be extended for other physiological and behavioral biometrics such as fingerprints, palmprints and speech. For instance, in [8], ideas from the CS theory are used for noise robust speaker recognition. Unlike previous computation frameworks which work on a frame-by-frame basis, the method presented in [8] focuses on exploiting information from a large time-context. Using a sliding window approach, denoised speech representations are constructed using a sparse representation of the reliable features in an overcomplete dictionary of clean, fixed-length speech exemplars. The effectiveness of this algorithm is demonstrated with several experiments.

Even though the majority of fingerprint verification and identification systems are based on the matching of minutiae-based representations, a number of algorithms exist which are based on iconic matching [25]. In this case the gallery of training fingerprint samples can be stacked with the A matrix to form the biometric dictionary. In order to cope for changes in orientation and position of the finger, several images of the finger from the same subject should be included in each column of A. Due to the simple structure of a fingerprint image, a large compression can be performed on the columns of A allowing for a compact representation of the dataset. Alternatively, an hybrid representation can be employed where the test fingerprint image is aligned and de-rotated according to the position and orientation of the fingerprints in the gallery.

VI. Challenges

A number of challenges and issues confront biometrics recognition using SR and CS. Below we list a few.

A. SR-based recognition from video

[6] attempts to propose a method for iris recognition from video based on SR. Is it possible to extend this method for other biometrics recognition from video? In this case the columns of A are composed of "dynamic features" extracted from the video samples of each subject in the dataset [26]. A video-based reduction of redundancy may be easily applied to reduce the dimensionality of the dictionary matrix A.

B. Dictionary-based biometrics recognition

The SRC method discussed in this paper builds the dictionary that consists of the training samples. However, it has been observed that learning dictionaries from the training data provides much better representations and hence can improve the performance of reconstructive approach to discrimination. One such approach for face biometric based on dictionary learning methods was proposed in [9]. Can dictionary learning methods provide better solutions to different physiological or behavioral cancelable biometrics?

C. Number of training samples

The methods presented in [1] and [6] harnessing sparsity are very effective yet they suffer from some limitations. For instance, for good recognition performance, the training image set is required to be extensive enough to span the conditions that might occur in the test set. For example in face biometric, to be able to handle illumination variations in the test image, more and more training images are needed in the gallery. But in most realistic scenarios, the gallery contains only a single or a few images of each subject and it is not practical to assume availability of multiple images of the same person under different illumination conditions. Another limitation of this approach is that the large size of the matrix, due to the inclusion of the large number of gallery images, can tremendously increase the computational as well as the storage complexity which can make the real-time processing very difficult. Can sparsity motivated dictionary learning methods offer solution to this problem?

D. Multi-modal biometrics based on SR and CS

The topic of multi-modal biometrics has gained strong interest in recent years [27]. In this approach, multiple biometrics data (either coming from the same sensing device or from different sources) are fused together and processed with a single matching algorithm or with several concurrent algorithms. The scores produced by different algorithms can be also fused to produce a single matching score for identification. Can SR and CS based methods offer better solutions for multi-modal biometric fusion?

VII. Conclusion

In this paper, we reviewed some of the approaches to biometrics recognition based on the recently introduced theories of sparse representation and compressed sensing. Furthermore, we discussed a way to incorporate cancelability into the SR-based method for biometrics recognition using random projections. Even though, the main emphasis was given to face and iris biometrics, these methods can offer compelling solutions to other biometrics such as gait, speech, palmprint and fingerprint, as well as for multibiometric fusion.

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