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Iris recognition using class-specific dictionaries[‡]

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ABSTRACT

In this research, the concept of class-specific dictionaries is proposed for iris recognition. Essentially, the query image is represented as a linear combination of training images from each class. The well-conditioned inverse problem is solved using least squares regression and the decision is ruled in favor of the class with the most precise estimation. An enhanced modular approach is further proposed to counter noise due to imperfect segmentation of the iris region. As such iris images are partitioned and individual decisions of all sectors are fused using an efficient fusion algorithm. The proposed algorithm is compared to the state-of-the-art Sparse Representation Classification (SRC) with Bayesian fusion for multiple sectors. The proposed approach has shown to comprehensively outperform the SRC algorithm on standard databases. Complexity analysis of the proposed algorithm shows decisive superiority of the proposed approach.

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1. Introduction

Security is an inevitable issue of the modern world. Accordingly, for highly sensitive facilities, the traditional means of security are becoming inappropriate. Keys and cards for instance, are always prone to theft and duplication. Password protected systems could be one solution. However, due to the increasing number of utilities, users tend to have the same password for all applications, consequently making them vulnerable. In this context, biometrics are the most secure means of protection. Users are not required to memorize or carry any piece of information. Among other available biometrics such as face, speech, fingerprint and body gait, the iris has shown to be the most accurate one [1]. In particular, the texture pattern of a person's iris is found to be unique [2] and can therefore be used as a powerful means of identification.

Daugman is considered to be the pioneer of the field [1]. He proposed, for the first time, the use of the Hamming distance classifier for the Gabor features of the iris images [3]. Since then, a variety of approaches have been employed with interesting results [4–6]. The classical concept of weighted Euclidean distance for instance, has been reported to achieve improved results [7]. In [8] the normalized correlation-based method was successfully employed, the approach is however computationally expensive owing to the direct comparison of images. The concept of the fragile bits in context of an iris code is introduced in [9]. Essentially it is shown that all bits of an iris code, derived for instance by using the Daugman's

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method, are not significant. In fact the middle bands of an iris are more consistent than the inner bands. Consequently masking the bits generated by inconsistent regions of an iris (i.e. the fragile bits) has shown significant improvement over conventional methods.

A number of approaches using variants of Gabor features have been widely reported in the literature. The problem of noncooperative iris recognition is addressed using the segmentation of Gabor features in [10]. The matching of color iris images has been efficiently achieved through the hypercomplex Gabor representation [11]. Scale-invariant Gabor descriptors have been introduced in [12] to tackle the effects of hostile environments. The fusion of multiple local features has been used in combination with optimized Gabor filters in [13]. In [14] a hybrid approach has been employed. Essentially the Haar and the 1D log Gabor wavelet features have been used in combination with the SVM and HMM learning algorithms. The hybrid approach has shown to outperform the individual experts in terms of false accept rate (FAR) and false reject rate (FRR).

Recently Gabor features have been used with the state-of-the-art Sparse Representation Classification (SRC) algorithm showing an excellent performance index [15]. Essentially, a test iris image is represented as a linear combination of all training images constituting an underdetermined system of equations. The ill-conditioned inverse problem is solved using the l_1 -minimization. The resulting sparse vector of coefficients has ideally non-zero entries corresponding to the class of the test image.

In this research, we propose to use the intriguing concept of class-specific dictionaries rather than a single global dictionary [16]. A given probe image is simultaneously represented against all class-specific dictionaries. The resultant system of linear equations is well conditioned and the inverse problem can simply be solved using least squares regression. Finally, the decision is made in favor of the class with the minimum residual reconstruction error. With the understanding that the local analysis is more powerful compared to the holistic approach, the proposed framework is further enhanced in a modular fashion. The notion of partition-specific and class-specific dictionaries is thus introduced. As such, iris images are segmented and the individual decision for each partition is reached using the partition-specific and class-specific dictionaries. These provisional decisions are fused using the Distance-based Evidence Fusion (DEF) algorithm [16]. The DEF algorithm uses a distance metric to judge the "goodness" of a given partition thereby dynamically rejecting the non-iris partitions. It further improves the overall recognition accuracy by efficiently fusing the iris segments. To the best of our knowledge, it is for the first time that the DEF algorithm is used in the context of partition-specific and class-specific dictionaries for robust iris recognition.

The main contributions of the proposed research are: (1) least squares formulation of the iris recognition problem through the novel concept of class-specific dictionaries; (2) the use of the notion of partition-specific and class-specific dictionaries to address the problem of imperfect segmentation; and (3) the proposed DEF algorithm for the efficient fusion of the iris segments.

The rest of the paper is organized as follows: the SRC algorithm is briefly discussed in Section 2, followed by the proposed approach in Sections 3 and 4. The complexity analysis of the proposed approach is presented in Section 5. Experiments are demonstrated in Section 6 and the paper is finally concluded in Section 7.

2. Sparse representation classification for iris recognition

Let *N* represent the number of distinguished classes and *p* the number of training samples per class. A class-specific dictionary \mathbf{A}_i is defined by, $\mathbf{A}_i = \begin{bmatrix} \begin{pmatrix} 1 \\ \mathbf{w}_i \end{pmatrix} \begin{pmatrix} 2 \\ \mathbf{w}_i \end{pmatrix} \begin{pmatrix} p \\ \mathbf{w}_i \end{pmatrix} \in \mathbb{R}^{q \times p}, \quad i = 1, 2, ..., N$ such that $\stackrel{(p)}{\mathbf{w}_i}$ is a *q*-dimensional Gabor feature vector of the *p*th training iris image from the *i*th class. We define a global dictionary matrix **A** by concatenating \mathbf{A}_i ; i = 1, 2, ..., N:

$$\mathbf{A} = [\mathbf{A}_1, \dots, \mathbf{A}_N] \in \mathbb{R}^{q \times n}$$
$$= [\overset{(1)}{\mathbf{w}_1}, \dots, \overset{(p)}{\mathbf{w}_1} \mid \overset{(1)}{\mathbf{w}_2}, \dots, \overset{(p)}{\mathbf{w}_2} \mid \dots \mid \overset{(1)}{\mathbf{w}_N}, \dots, \overset{(p)}{\mathbf{w}_N}]$$

where $p \times N = n$. Consider a test feature vector $\mathbf{y} \in \mathbb{R}^{q \times 1}$ with an unknown class label represented as a collaborative linear combination of all training vectors such that

$$\mathbf{y} = \mathbf{A}\boldsymbol{\alpha} \tag{1}$$

where the vector $\alpha \in \mathbb{R}^{n \times 1}$ is given by:

$$\begin{bmatrix} \alpha_{1}^{(1)}, \dots, \alpha_{l}^{(p)} & | & \alpha_{2}^{(1)}, \dots, \alpha_{2}^{(p)} & | & \dots & | & \alpha_{N}^{(p)}, \dots, \alpha_{N}^{(p)} \end{bmatrix}^{T}$$
(2)

If a given probe **y** belongs to the *i*th class, ideally all the entries of the vector $\boldsymbol{\alpha}$ are zero except $\alpha_i^{(1)}, \ldots, \alpha_i^{(p)}$. It has been shown that given the matrix **A**, the sparse vector $\boldsymbol{\alpha}$ can be recovered [17,18]. In principle the sparsest $\boldsymbol{\alpha}$ can be sought through the solution of the optimization problem:

$$\arg\min_{\alpha} \|\alpha\|_{0}, \text{ subject to } \mathbf{y} = \mathbf{A}\alpha$$
(3)

where $\|\boldsymbol{\alpha}\|_0$ is the l_0 -norm of $\boldsymbol{\alpha}$ and the problem in Eq. (3) above is generally non-convex and NP-hard. Several alternate methods have been proposed in the literature to recover the sparse vector $\boldsymbol{\alpha}$. The Basis Pursuit (BP) algorithm, for instance,

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