Analysis of performance of palmprint matching with enforced sparsity

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In this paper, a new and simple palmprint recognition solution based on sparse representation is suggested. It is shown that when the aim is to recover a palmprint from a limited number of observations as a linear combination of measurements of the same palmprint class, the ensuing representation is intrinsically very sparse. It can be efficiently computed by solving an l_1 norm convex minimisation problem. When combined with well known subspace feature selection techniques such as PCA and LDA as well as with downsampled images, our tests, which have been carried out on 250 classes of the widely used PolyU database, have yielded an EER as low as 0.11% depending on the palmprints selected during the enrolment phase. Coupled with an execution time as short as 8.4 ms, the obtained results outperform similar work in the literature including EigenPals, FisherPals and Gabor based palmprint matching algorithms, which shows the effectiveness of the new solution.

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1. Introduction

For implementing many of the matching techniques that have made fingerprint recognition one of the most relied upon biometrics, palmprint recognition has received a great deal of the research community attention in the last 10 years. As a matter of fact, from very few research papers which appeared in the late 90’s, a survey in [1] has covered more than a hundred papers of palmprint recognition systems. Furthermore, from limited commercial and forensic interests, the topic of palmprint recognition has matured enough to be integrated in both the American Integrated Automated Fingerprint Identification System (IAFIS) and the Australian National Automated Fingerprint Identification System (NAFIS) [2], thus making palmprint a reliable identifier which can augment fingerprint-based systems or even replace such systems for identification and authentication purposes. A palmprint biometric system can establish an identity using the hand palm characteristics and features which include principal lines, wrinkles and ridges as depicted in Fig. 1. As with fingerprints, a palmprint is the photograph of a hand or the impression it leaves on a surface. Since the area of interest, which encompasses the region from the wrist to the root of the fingers, is larger than that of the fingerprint, one can surmise that a palmprint may contain more distinctive information than fingerprints.

The abundance of low level features in palmprints was the most influential factor in the design of palmprint systems. One large class of such systems are devised to utilise lines and points. Line based approaches rely on using spatial techniques such as Canny edge detector, Sobel operator and directional derivatives or on transforms such as the Gabor and log Gabor transforms to extract additional directional information [3,4,6,7]. A few directions should be considered otherwise mainly streaks of the same direction will appear in the processed prints which can reduce the individuality of palmprints and the performance of the matching algorithm [10,29–31]. More low level features can be combined with line-based techniques. This includes geometrical parameters which measure the shape of the hand [3] and the intersection the principal lines with the extended finger skeletal lines [5]. In addition, it has been reported that Harris corners extracted at the intersection of lines and wrinkles can yield good performance in palmprint

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matching [8]. Similar good results can also be achieved using the Scale Invariant Feature Transform (SIFT) which is based on the extraction of Hessian points [2,9]. Another approach in matching palmprints is based on texture extraction. Such a task is usually carried out in the transform domain and uses low order statistics [10,11]. A further common approach in computer vision, which is perhaps closer to the topic discussed in this paper, relies on devising appearance based models and reduced space classifiers such as the widely used linear projections and discriminant techniques. As such, palmprint data are projected into a reduced dimensionality space and the computed coefficients in the new space are regarded as features. Many subspace based techniques have been suggested in the literature, including EigenPalms and FisherPalms which rely on the use of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) [12,13]. In addition, Independent Component Analysis (ICA) and Locality Preserving Projection (LPP) variants have also proved to be useful for palmprint recognition [14,15].

As with the general problem of matching images, the process of matching palmprints using reduced space classifiers is unavoidably rendered more difficult with the presence of noise and generic distortions including illumination variations and misregistration. These random degradations make it more difficult to perform matching and lowers the performance of the matching algorithms. In practice, the extraction of features that best describe an image and differentiate it from similar images of different classes is based on methods which employ the least squares criteria on the $l_2$ norm. The rationale behind such an approach is the statistical argument that least squares estimation is the best over an entire ensemble of prints of the same class across a set of available classes. The range of $l_2$ norm feature extraction techniques include unsupervised techniques such as PCA, supervised LDA and techniques that can either be used in supervised or unsupervised scenario such as LPP [12,13,15]. It has been argued however that a more appropriate norm for many image analysis problems is the $l_1$ norm and its derivatives which are essentially bounded functions, thus suitable when an accurate estimation of the solution is sought [16]. Based on the $l_1$ norm minimisation, techniques for image reconstruction, segmentation, denoising, feature detection, face recognition and computer vision have been suggested in [17–21,26–28].

In this paper, we suggest sparse representations computed via $l_1$ norm minimisation as a new solution to the problem of palmprint matching. The obtained results confirm the usefulness of such representations; evidenced with an Equal Error Rate (EER) of up to 0.11%, thus outperforming similar work in the literature. The suggested solution is also efficient in terms of computation time. As a matter of fact, it takes only 8.4 ms to find a match in a database of 1500 prints divided into 250 classes. The remainder of the paper is organised as follows: sparse representation is introduced in Section 2. In Section 3, it is emphasised that such a solution is only suggested in an empirical setting. The performance of sparse representation, the associated features, the obtained results and the constraints of data size on optimisation are discussed in Section 4. Conclusions are drawn in Section 5.

2. Sparse representation and $l_1$ norm minimisation

Let us consider the case of $n_c$ classes of palm prints; where each class refers to an individual and contains $n_i$ different images collected from the same person. Each image is of size $h \times w$ pixels, where $h$ is the height of the image or the number of its rows and $w$ is its width or the number of its columns. Each image is reshaped to form a single-column vector of $m = h \times w$ rows. All $n = n_c \times n_i$ images are piled to form a matrix in $\mathbb{R}^{m \times n}$ of $m$ rows and $n$ columns. Let $a^{lj} \in \mathbb{R}^m$ be the $j$th print associated with the $l$th class (or person). With a certain error, an image $y$ belonging to the $k$th subject can be approximated using a linear combination of the $n_c$ images of the same class:

$$\hat{y} = \sum_{j=1}^{n_c} a^{kj} x_{ij} \text{ and } x \in \mathbb{R}^n$$

(1)

The fact that the number of prints per class $n_i$ may vary between classes will change very little in our development. In more general terms, the image $y$ can be expressed as a linear combination of all images $a^{lj}$:

$$\hat{y} = \sum_{l=1}^{n_c} \sum_{j=1}^{n_i} a^{lj} x_{ij}$$

(2)

In the above annotation, a vector $x$ can be divided into $n_i$ blocks of $n_c$ entries each referred to as $x_{ij}$ and where $x_{ij}$ is the $j$th entry of the $i$th block of $x$. Since neither the set of vectors $\{a^{lj}\} \ (1 \leq j \leq n_i)$ (of the $k$th class) nor $\{a^{lj}\} \ (1 \leq j \leq n_c$ and $1 \leq i \leq n_c$) is an independent set of $\mathbb{R}^m$, Eqs. (1) and (2) are only approximations of $y$. Nevertheless, one can assume that when $y$ is represented with all the images in the training set, the contribution of the coefficient $x_{ij}$ should be more important than the remainder of the $x_{ij}$ coefficients; ideally:

$$\hat{y} = \sum_{i=1}^{n_c} \sum_{j=1}^{n_i} a^{lj} x_{ij} + \sum_{i=1}^{n_c} \sum_{i \neq k} \sum_{j=1}^{n_i} a^{lj} x_{ij} \quad \text{where } x_{ij} \in \mathbb{R}$$

(3)

Clearly, the setting laid in (3) is an attempt to find a solution $x$ which takes account of the strong correlation between prints belonging to the same class; despite possible co-linearity and inter-independence between prints belonging to different classes. To enforce the constraint $x_{ij} \in \mathbb{R}^m$ for $i \neq k$, one has to seek the sparsest solution of (3):

$$\min_{x} \|x\|_0 \text{ subject to } y = Ax$$

(4)

The $l_0$ norm, though not truly a norm in the usual sense, is the extension of the $p$-quasi norm to $p = 0$ and is defined as:

$$\|x\|_0 = \lim_{p \to 0} \left( \|x\|^p + \|x_1\|^p + \cdots + \|x_m\|^p \right)^{1/p}$$

(5)

The $l_0$ norm simply measures the sparseness of the sought solution. It computes the size of the support of the signal which is the number of its nonzero entries. However, such a computation of a sparse representation via an $l_0$ norm minimisation is a nonconvex combinatorial search problem and NP-hard [22–24]. Nevertheless, recent developments have led to the development of very efficient methods for extracting a finite signal $x$ from a limited number of observations, when such a signal is believed to sparse. Such a problem can be reformulated under certain conditions on the $A$ as an optimisation problem termed $l_1$ norm minimisation with equality constraint:

$$\min_{x} \|x\|_1 \text{ subject to } Ax = y$$

(6)

where the $l_1$ norm is defined as:

$$\|x\|_1 = \sum_{i} |x_i|$$

(7)

3. Sparse palmprint representation

The sparse solution in such a context is recovered by solving a convex optimisation problem. Obviously such a result is very appealing since $(P_1)$ leads to a linear programming problem which is more efficient than greedy algorithms and thresholding [24,28].
The existence of a sparse representation which can be computed using \((P_2)\) in (6), its existence, uniqueness and equivalence with \((P_0)\) in (4) has been the subject of recent research in the field of compressed sensing. It should be pointed out that applying the minimisation technique \((P_1)\) of (6) is presented here in an empirical setting. The palmprints data may not obey some the assumptions made in [22–25].

Working on over complete signal representations, Donoho et al. [22] have shown that in the case of the concatenation of two orthogonal bases, the solution of the \(l_1\) problem is unique and is equal to the solution of \(l_0\) if it contains at most \((1 + M^{-1})/2\) nonzeros, where \(M\) scalar is the maximum inner product \((u,v)\) of any two vectors \(u\) and \(v\) of the two concatenated bases which is smaller than 1. Beyond \(P_0–P_1\) equivalence in [22], more surprising empirical results have shown that a unique solution can be recovered with at most \(m/5\) nonzero entries in a moderately sparse matrix. In [25] Candes et al. have considered the problem of recovering a signal from its incomplete frequency samples. The sampling in question no longer obeys the required Nyquist rate. Provided that the solution is sparse enough, the exact solution can be recovered via \(l_1\) optimisation. Furthermore, by randomly selecting \(m\) rows from an \(n \times n\) Fourier matrix, it was shown empirically that the equivalence \(P_0–P_1\) holds for as many as \(m/4\) nonzeros. However, the Gaussianness of the matrix \(A\) and its independent and identically distributed random columns conditions cannot be ensured within the context of palmprint matching. Nevertheless, despite such a nonconformance with the work of [22–25], one can still be tempted by some widely accepted relaxations in the field of computer vision such as the widely and successful use of LDA for face recognition on nonnormally distributed images, and by the large body of research work on sparse representation with empirical results supporting the fact that the reported findings may only be the tip of the iceberg [27,28].

4. Experiments, results and analysis

The experiments in this paper were carried out using Matlab 7.6 on a Dell desktop with an Intel Core 2 CPU working at 2.13 GHz and 1 GB of RAM. All palmprint images are obtained from the PolyU database of the Hong Kong Polytechnic University which is a public and widely used database of palmprints. Using curvature maxima points between the fingers, a \(128 \times 128\) pixel square Region Of Interest (ROI) is extracted from the original \(284 \times 384\)–pixel images as detailed in [10]. To analyse the performance of using sparse representations in matching palmprints, 250 palmprint classes have been selected; where each class contains 20 palmprints belonging to a single individual. The prints were collected in two sessions at the rate of 10 prints per person per session. In the second session however, some illumination distortions have been purposely incorporated in the collected prints. Taking account of this fact, the enrolment phase during which the matrix \(A\) is built has been conducted in two ways. In the first one, which will be annotated \(Exp\) \(I\) in the remainder of the paper, 6 prints from the first session per person were used for enrolment while in the second experiment, \(Exp\) \(2\), 3 prints are from the first session and the remaining 3 prints are from the second session. In both experiments, 14 query prints per person were used to test the performance of the proposed solution. Obviously in contrast with \(Exp\) \(2\), in \(Exp\) \(I\) we additionally test against illumination variations introduced in the second session of palmprints collection [10]. It should be pointed out that no attempt has been made to normalise the images in order to alleviate the illumination distortions or to use any illumination co-invariant representation. However, the images are re-arranged to 1-D vectors which are then normalised to the unit length and arranged as columns of the matrix \(A\) in (6).

Since the approach based on \((P_1)\) is, in essence, an attempt to recover a sparse signal and that following (3) such a representation should inherently involve only the set of observations of the same class, matching a palmprint to a class takes account of the error of reconstructing a palmprint using only the coefficients associated with such a class in the computed vector \(x\) in \((P_1)\) which in turn leads to the approximation of the query print using the observation of such a class in the matrix \(A\) in \((P_1)\). The obtained results are analysed using the common metrics of False Acceptance Rate (FAR), False Rejection Rate (FRR) and EER. When discussing the performance, the Receiver Operating Characteristic (ROC) which depicts the system FAR versus its FRR is also used. In addition, in our experiments we have also adopted the recovery of sparse representation approach based on minimise the \(l_1\) subject to quadratic constraint:

\[
(P_2) \min ||x||_1 \text{ subject to } |Ax - y|_2 \leq \varepsilon
\]

where \(\varepsilon\) in \((P_2)\) is small and allows for an error in the recovery of \(y\). It recovers an unknown sparse object with an error at most proportional to the noise level.

4.1. Performance of the \(l_1\) norm minimisation techniques on downsampled images

One crucial point so far has been omitted in the previous discussion: the size of the images does not allow for an efficient computation of \((P_1)\) and \((P_2)\). A reduction of the number of rows of matrix \(A\) which captures most of the information contained in the images is of paramount importance. In the presented analysis, the size of the images is reduced via downsampling with a square sampling matrix from the original size of \(128 \times 128\) to sizes \(8 \times 8, 11 \times 11, 16 \times 16\) and \(22 \times 22\). In such a downsampling process, the Nyquist criterion is not taken into account. Furthermore, a second approach to downsampling is to randomly select pixels from the original prints in order to reduce the size of the images. In such a scenario, the number of features is simply the number of selected pixels. Fig. 2 depicts an example of downsampling with a square matrix and with a random selection of pixels to a \(16 \times 16\) image. In the remainder of the paper, the annotations \(DS\) \(_{size}\) and \(RS\) \(_{size}\) will refer to a downsampled image with a square downsampling matrix and a randomly downsampled image respectively.
As can be seen from this figure most of the informative content of the print is lost, including the low level features associated with palmprints in the spatial domain, such as lines and wrinkles. Nevertheless, such a severe downsampling has had little effect on the performance. This is clearly shown in Table 1 in the case of regular downsampling and the minimisation technique of \( P_1 \). Such results are corroborated with the outcome of \( P_2 \). In fact, it is shown in Tables 1 and 2 that both minimisation techniques have yielded similar results although \( P_1 \) in Exp 1 is slightly better whereas in Exp 2, \( P_2 \) is slightly superior. In the remainder of the paper, only the best results of the two techniques are reported. The performance of the minimisation techniques in the presence of severe downsampling is also supported by the finding of Table 3. It is shown that even with random sampling, an EER of up to 1.19% can be achieved; although it is to a certain extent inferior compared to the 0.91% EER achieved in the case of square downsampling, both attained with a representation of 256 pixels per image.

### 4.2. Performance of the \( l_1 \) norm minimisation techniques with LDA and PCA

Though the presented results in Tables 1, 2, and 3 are good, they can be improved even further by using reduced dimensionality representations, such as PCA and LDA. The annotation method\_number of features is used in the remainder of the paper, where method refers to either PCA or LDA as the method used for features generation. The number of adopted projection directions is simply the number of features in the new space in such an annotation. As shown in Tables 4 and 5, \( l_1 \) norm minimisation with PCA and LDA achieves an EER of 0.14% and 0.11% respectively in the case of Exp 2 where in the 6 enrolled prints per class, 3 belong to the first session of prints collections and the remaining 3 were collected in the later session. The obtained results for Exp 1 are slightly lower attaining an EER of only 1.66% and 0.48% for PCA and LDA, respectively. This shows that the minimisation technique is affected by the images selected to form matrix \( A \) in \( P_1 \) and \( P_2 \) during the enrolment phase. Nevertheless, such results even in the more difficult scenario of Exp 1 where we also test against purposely introduced illumination distortions are better by a large margin than the performance of EigenPalsms and LDA-based palmprint matching. As shown in [13], EigenPalsms can achieve a recognition rate of up to 99.15% with 4 prints selected for training and another 4 prints for matching. However, there is no explicit discussion of the EER performance of the system and to which sessions the training and test prints belong. In [12], 10 prints from 300 classes were selected to build an LDA-based matching system. The performance obtained in [12] indicates an EER of 1% on 128 \( \times \) 128-pixel palmprints and an EER of 0.95% and 0.82% on 64 \( \times \) 64-pixel and 32 \( \times \) 32-pixel palmprints, respectively. In the authors’ reproduction of EigenPalsms [13] and FisherPalsms [12], under the same settings of Exp 1 and Exp 2, the best achieved performance produces an EER of just 1.17%. As shown in Tables 6 and 7, there is a clear difference in terms of performance of these two techniques between the setting of Exp 1 and that of Exp 2. The effect of training on the performance which, due to the palmprints selected during the enrolment stage is attenuated in the case of the proposed techniques. Thus, not only the \( l_1 \) norm minimisation techniques outperform PCA and LDA in the context of palmprints matching, they are less vulnerable to the illumination distortions which affect the collected prints of the PolyU database.

One very interesting point that comes out from Tables 1, 2, 3, 4 and 5 is that the performance of the \( l_1 \) norm minimisation techniques vary with the number of selected features per print using LDA, PCA and downsampling. Using both square and random downsampling, the best results were obtained on 11 \( \times \) 11-pixel and 16 \( \times \) 16-pixel (or 256-pixel) prints, improving on those obtained at higher downsampling rates (8 \( \times \) 8-pixel prints) and then dropping on 22 \( \times \) 2-pixel prints. Such a peak in performance can also be observed with LDA and PCA features where the best results were obtained with 32, 64 and 128 features, which are also better than those obtained using downsampling. This shows the amount of information lost with downsampling, either square or random, compared with extracting the best PCA and LDA projections. However, the \( l_1 \) norm technique seeks only to recover a signal. The impact the way of feature selection has on the results can be seen in the performance of EigenPalsms and FisherPalsms in Tables 6 and 7 where a local peak in performance is attained with 64 and 128 PCA and LDA features. This almost coincides with the results of Tables 4 and 5. Furthermore, it shows that using 64 LDA features achieves a very good sparse approximation and at the same time uses the best projections that separate between the palmprint classes.
The performance of LDA_64 in terms of FAR, FRR, genuine and impostor distributions is depicted in Figs. 3 and 4. As shown in these figures, there is a clear cusp between genuine and impostor palmprints distributions at a distance very close to 1. Since all prints are normalised to unity length, this is a strong indication that in the case of impostors, the representations included a large number coefficients close to zero, making the difference between the reconstructed image and the query print close to unity. In terms of EER, the ROC of LDA_64, EigenPalms and FisherPalms is depicted in Fig. 5. Under the setting of Exp 2, LDA_64 can achieve a FRR of 0.4 % for a FAR of 0.0003%.

Furthermore, Table 8 compares the obtained results against the work in [10,30,31]. Based on Gabor transform [10,31] and the Radon transform [30] for extracting directional information, the palmprints in the transform domain are converted into binary codes and a matching score is computed using Hamming dis-
of matrix $A$ is analysed. In the presented experiments, $n$ is constant and is set to 1500 while $m$ varies and can be set to 16, 32, 64, 128 or 256. However, even with a limited number of classes, the number of columns of $A$, $n$, can be increased using dummy data. The analysis takes account of the cumulative distribution of the magnitude of the entries of $x$ as shown in Figs. 6 and 7 for genuine and impostor users respectively. The distributions show the number of coefficients with an absolute value smaller than a threshold and with a step of $10^{-6}$. As the entries of $x$ can be divided into blocks as shown in Eqs. (1), (2) and (3), a genuine representation includes the 6 coefficients used to compute the approximation of a palmprint shown in Eq. (1). These entries are used to compute the genuine cumulative distributions of Fig. 6. The remaining 1494 coefficients are used to build the impostor cumulative distributions of Fig. 7.

One indication from Fig. 7 that suggests that the palmprint data, including the palmprints used in the enrolment phase to generate the matrix $A$ and the prints used for test, may obey Eq. (3) is that the impostor distribution includes 95% entries in an order of magnitude of $10^{-6}$ when 16 LDA features are used. When using more features, the number of near-zero entries seems to be decreasing when the number of selected LDA features increases. However, all distributions in Fig. 7 converge in approximately the same manner. These findings clearly show that (P$_1$) and (P$_2$) minimisation techniques lead to a representation in accordance with Eq. (3) for palmprint data. Since most entries of $x$ are very small though not null, it is very interesting to set a threshold below which entries of $x$ are set to zero. From the genuine distributions of Fig. 6, such a threshold can be selected to be 0.1. It can be noticed from this figure that all genuine distribution curves, after being flat, converge in approximately the same manner at 0.1. Taking account of such a threshold, it can be pointed out that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively.

In the case of genuine users, almost 40% of the entries of $x$ are set to zero. From the genuine distributions of Fig. 6, such a threshold can be selected to be 0.1. It can be noticed from this figure that all genuine distribution curves, after being flat, converge in approximately the same manner at 0.1. Taking account of such a threshold, it can be pointed out that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively. This in turn means that in the 1494 impostor coefficients there is in average 0.5, 0.6, 2.7, 1.2, and 0.5 entries above the selected threshold, respectively.
be emphasised here that there is a significantly higher number of entries of an order of magnitude larger than 0.1. As a matter of fact, in the genuine distributions of Fig. 6, between 30% and 40% of all entries are greater than 0.1, depending on the number of selected features. In average, there is 1.8, 2, 2.2, 2.3 and 2.4 above threshold entries in the genuine user entries of x when 16, 32, 64, 128 and 256 features are selected, respectively. As such, inclusive of the impostor coefficients, the 1500 entries of the computed sparse representation encompass in average 2.3, 2.6, 4.9, 3.5 and 2.9 entries above the selected threshold when m is set to 16, 32, 64, 128, and 256 respectively. This is a very interesting point and further clear evidence that the minimisation techniques may obey Eqs. (9) and (10) and that the sought sparse representation has been computed in the context of our experimental setting.

5. Conclusions

In this paper, the mathematical framework of the $l_1$ norm optimisation techniques has been empirically addressed and its performance assessed in the context of palmprint matching. In the proposed work, a sparse representation of palmprints is sought. It takes advantage of recent progress made in the field of convex optimisation where, with an overwhelming probability, the problem of finding a sparse representation can be cast as a minimisation of the $l_1$ norm instead of the combinatorial NP hard problem of the $l_0$ norm minimisation. The popular reduced-dimension techniques such as LDA and PCA have been used to reduce the number of features used. It was shown in our experiments that a sparse representation of palmprints can be computed when the size of features varies from 16 to 256. When combined with LDA, the proposed solution can achieve very high performance rate evidenced by an EER of up to 0.11%, thus bettering similar work in the literature. The suggested solution is new in the context of palmprint matching. It is also an efficient and simple one which can be evidenced with a computation time of just 8.4 ms.

References


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