



A Three-stage Filtering Approach for Face Recognition using Image Hashing

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ABSTRACT

Face recognition has become a crucial topic in recent decades, which offers important opportunities for applications in security surveillance, human-computer interaction, and forensics. However, it poses challenges, including uncontrolled environments, large datasets, and insufficiency of training data. In this paper, a face recognition system is proposed to iron out the above problems with a new framework based on a hashing function in a three-stage filtering approach. At the first stage, candidate subjects are chosen using the Locality-Sensitive Hashing (LSH) function. We employ a voting system to select candidates via disregarding a large number of dissimilar identities considering their local features. At the second stage, a robust image hashing based on Discrete Cosine Transform (DCT) coefficients is used to further refine the candidate images in terms of global visual information. Finally, the test image is recognized among selected identities using other visual information, resulting in further accuracy gains. Extensive experiments on FERET, AR, and ORL datasets show that the proposed method outperforms with a significant improvement in accuracy over the state-of-the-art methods.

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1. INTRODUCTION

Within the past decade, face recognition has become one of the most powerful applications of image processing and visual surveillance systems [1]. Although face recognition systems have seen striking improvements, they are remarkably affected by several issues such as uncontrolled pose and illumination conditions, large volume of data, and computational complexity optimization [2,3].

Performance of face recognition systems is significantly affected by its feature extraction step. Several feature extraction methods have been introduced in literature for face recognition, such as handcrafted feature like histogram of oriented gradients (HOG) [4], local binary patterns (LBP) [5], and learned feature like Fisher Vectors Faces [6] and learning-based (LE) descriptor [7]. However, they may not achieve a suitable performance in uncontrolled scenarios and large volume of dataset.

Image hashing is considered as an approach to cope with the limitations of face recognition [8]. Using

hashing functions, one can map high-dimensional data into low-dimensional codes. Because of their low memory usage and low computational cost, many hashing approaches have been proposed in literature to form compact codes for image representation. Modern hashing methods can be divided into two categories: data-dependent and data-independent. In data-dependent hashing methods, hashing functions are learned from data by preserving the data structure. Data-independent hashing methods, such as LSH [9], generate codes by using random projections.

In this work, a new face recognition method is proposed using a multi-stage filtering framework. Our basic intuition is that if we disregard dissimilar identities to the query image using different visual information at different stages, a better result will be achieved. To solve the time complexity of the search strategy, an image hashing function is used in each stage. The performance of the proposed method is evaluated in several face recognition scenarios: face recognition in semi-

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uncontrolled conditions, aging condition, limitation in training data, and large datasets².

Indeed, the proposed method applies a cascaded filtering in three stages for analyzing different visual information in each stage using image hashing. A large number of dissimilar identities in terms of local visual information are disregarded in the first stage using the Locality-Sensitive Hashing (LSH) function. Then, image candidates are further refined by comparing their global features with the corresponding global feature from the query image, using an image hashing applied on Discrete Cosine Transform (DCT) coefficients of the images. Finally, by comparing the LBP features of the refined identities and the query image, the best matching candidate was chosen to recognize the query image from the database. Performance of the proposed face recognition method was evaluated using different datasets. Experimental results in this manuscript showed that the proposed method improves face recognition's performance.

Image hashing is useful for saving a remarkable amount of computational power by reducing features space [8,10]. In addition, the use of LSH in the first stage can also reduce the execution time of the search [9]. Another advantage of our three-stage filtering framework is that it analyses different visual information of face images in each stage. The proposed method, with its low computational cost and high accuracy is suitable for face recognition in a large dataset.

The rest of paper is organized as follows: section 2 briefly reviews related works in face recognition. The proposed method is explained in section 3. Experimental results are illustrated in section 4. Finally conclusions are drawn in section 5.

2. BACKGROUND

One of the most crucial steps in designing a face recognition system is feature extraction. Existing descriptors referring to facial images are generally in two categories: global appearance descriptors and local image descriptors for face recognition [11]. While global features represent the whole appearance features in a vector, the local features consider fiducial points like the nose, eyes, and mouth and inherently possess orientation selectivity and spatial locality. Common local descriptors for face recognition include scale-invariant feature transform (SIFT) [12], LBP [5], and Gabor Wavelets [13]. The Principal Component Analysis (PCA) [14] and the Linear Discriminant Analysis (LDA) [15] are two

common methods to employ global descriptors for face recognition.

Several promising face recognition approaches have been developed in literature using image hashing [16-18]. LSH is a classic hashing algorithm that generates hash code by random projection functions [19]. LSH is helpful when training data is insufficient. In this regard, some researchers have proposed various models using LSH. An efficient hashing method has been introduced by Cassio et al. [20]. They employed LSH along with Partial Least Squares (PLS) to achieve a high recognition rate with a high speed for face recognition. Recently, Dehghani et al. [21] have evaluated different versions of LSH according to different hash families. Also, many hashing based approaches have been proposed in face recognition. For example, a novel method for face recognition called Bayesian Hashing was proposed by Dai et al. [22]. They achieved competitive performance with low memory cost by generating binary codes. In order to obtain hash codes from face images, common techniques can be used such as DCT which is an exceptionally good way to express the visual contents of the image. Tang et al. [23] introduced a robust image hash code by hashing the DCT coefficients into a compact feature vector.

Many face recognition methods have been proposed in recent years to cope with uncontrolled conditions [2,24,46,47]. These methods have achieved a high recognition rate under unconstrained conditions. Recently, some methods have been proposed for robust face recognition where each of them focused on a particular challenge for face recognition. Li et al. [25] proposed a framework called Recurrent Regression Neural Network (RRNN) to address sequential changes of images, including poses, by unifying two classic tasks of cross-pose face recognition. Extended Sparse Representation-based Classification (ESRC) was proposed by Deng et al. [26] to overcome occlusion and non-occlusion challenges leading to a high recognition result. Chakraborti et al. [27] proposed a novel feature selection method for face recognition using binary adaptive weights based on Gravitational Search Algorithm (GSA). They overcome several challenges of face recognition using local gradient patterns, the modified census transform, and LBP. A hybrid approach was introduced by Ouyang et al. [28] based on a combination of the Probabilistic Neural Networks (PNNs) and the Improved Kernel Linear Discriminant Analysis (IKLDA), resulting in encouraging recognition performance in face recognition. In another work, Dora et al. [29] extracted Gabor energy feature vectors from face images by introducing an Evolutionary Single Gabor

² MATLAB codes of the proposed method are available at <https://www.dropbox.com/sh/jkn33y8pjgkzk7b/AAAir4-hxmvZhA1wPOEGV-da?dl=0>.

Kernel (ESGK) based filtering approach. Liao *et al.* [30] applied the Subspace ESRC (SESRC) and the Discriminative Feature Learning (LDF) in order to address some challenges in face recognition.

In many face recognition approaches when the number of identities increases, the recognition rate considerably drops. Since the size of training data affects the performance of face recognition, many researchers focused on tackling this challenge in face recognition by considering a single sample per person for training [31], [32]. Zeng *et al.* [33] introduced a well-trained deep convolutional neural network (DCNN) model for face recognition using combining traditional and deep learning methods. Fisher Linear Discriminant Analysis (FLDA) was developed by Gao *et al.* [34] to estimate the intra-class variance in datasets with a single sample per person. Also, Lu *et al.* [35] introduced a patch-based face recognition method called Discriminative Multi-Manifold Analysis (DMMA). They achieved a high performance on a large dataset via segmenting the training samples to obtain patches and using them to learn discriminative features.

Multiple feature extraction generally leads to high recognition performance. High-dimensional facial features can be extracted using several feature extractors. In this regard, some methods have been proposed to improve face recognition performance by employing multiple feature extractors. Schwartz *et al.* [36] employed a large set of feature descriptors for face identification and achieved a high recognition rate across varying conditions. Also, Liu *et al.* [37] presented a face recognition technique that extracts multiple features and acquired a good recognition rate.

3. THE PROPOSED APPROACH

In this paper, we proposed a new multi-stage filtering framework based on image hashing for face recognition. As mentioned before, the proposed method consists of feature extraction and recognition phases. In this section, initially, the feature extraction phase is explained. Then, the proposed face recognition method is described.

3.1. Feature Extraction Phase

In this phase, we first adjust the brightness and size of images to a normal standard. In order to detect the face area, the Multi-Task Cascaded Convolutional (MTCNN) algorithm is used [38]. This approach can precisely detect faces from a wide range of poses. To detect face and landmark locations, this framework implements a cascaded architecture with carefully designed deep convolutional networks. Then, the captured face is analyzed using different visual information in parallel. Figure 1 shows the feature extraction phase. The SURF and LBP descriptors are used to extract local visual

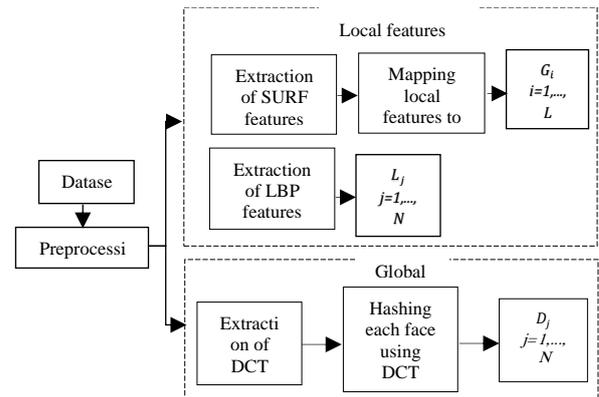


Figure 1. Diagram of the feature extraction phase for the proposed method

information from the image. The DCT is also applied based on hashing functions to extract global feature associated with the image.

The SURF descriptor extracts local features, which is robust to image scaling, translation, rotation, and to some extent is robust to 3D projection and illumination changes [39]. The SURF feature descriptor is a vector and its length is 64 in this research. Using local feature vectors from the gallery set, a set of randomized LSH tables are built. In this case, a query feature vector can be mapped to a set of buckets in which nearest neighbor candidates with the corresponding identity can be found. Therefore, feature vectors from all the images are mapped to L randomized hash tables $G_i, i=1, \dots, L$. In this regard, we employ P-stable LSH [9] which approximates the high-dimensional similarity search without any sub-linear dependence on the size of data. This scheme is a hashing framework that maps close feature vectors to the same buckets with high probability, and keeps dissimilar features to different buckets of the table. P-stable LSH is a development version of LSH. It can be employed in d -dimensional Euclidean space and has a better query response [9]. The following notation belongs to the extended P-stable LSH. We indicate the space R^d with the Euclidean norm l_2 , and data set X , in any metric space with the point $v \in X$. $B(v, r) = \{q \in X | D(v, q) \leq r\}$ is the ball of radius r centered at v .

Definition 1. A LSH family $H = \{h: S \rightarrow U\}$ is called (r, cr, p_1, p_2) -sensitive for a distance measure if for any $v, q \in S$

$$\begin{cases} \text{if } v \in B(q, r) \text{ then } P_r[h(q) = h(v)] \geq p_1 \\ \text{if } v \notin B(q, cr) \text{ then } P_r[h(q) = h(v)] \leq p_2 \end{cases}$$

where $p_1 \geq p_2$ and $c = 1 + \varepsilon$.

The process of making a hash table is the process of applying a hash operation on each vector. Local feature hash tables in P-stable LSH are made using $h_j(v) = \left\lfloor \frac{a \cdot v + b}{r} \right\rfloor$, in which v is a feature point, $j = 1, \dots, n$ and a is a d -dimensional vector with entries selected randomly

and independently from a stable distribution; b is a real number selected uniformly from the range $[0, r]$. First, the high-dimension vector v is projected onto a real line which is cleaved into equal parts of size r . Then, regarding the segment it projects onto, the vector v is assigned as a hash value. The reader can find more information regarding the P-stable LSH in literature [9].

The LBP captures the spatial structure of the local image texture [40]. The basic LBP operator labels the pixels of an image and uses the histogram of the labels as a texture descriptor. The idea behind using this descriptor is that we can see the images as a combination of micro-patterns that are robust to illumination and rotation variations. A global description of the image is achieved by combining these micro-patterns. LBP feature of each face is stored in $l_j, j=1, \dots, N$, which N is the number of images in dataset.

Also, image hashing is applied on DCT coefficients of the images to extract global features. Low-frequency DCT coefficients are more essential than high-frequency coefficients in describing the image because they have larger values and contain the main part of the signal energy [41]. Hence, via the hashing, the less important frequencies are removed and the most important frequencies of the image are kept. For more information about this algorithm, we refer the reader to the work introduced by Tang et al. [23]. Similarly, each hash code is stored in $D_j, j = 1, \dots, N$, which N is the number of images in dataset. Following the feature extraction phase for all cropped faces, the query face images can be recognized through the multi-stage filtering.

3. 2. Recognition Phase In order to recognize a query face, after resizing and cropping, the image is imported to a three-stage filtering framework. The three stages of this framework are as follows.

(1) In the first stage, local features are extracted from a query image, using the SURF descriptor. The similarity of extracted local features, between each feature of the query image and those from the gallery images, is specified using LSH. For each feature from the query image, its reverse normalized distances with the selected features using the LSH are considered as their associated weight to match with the gallery images. The votes to each feature from the query image are computed via summation of its weights to the features associated with the gallery images [42]. Finally, a small percentage of identities with the highest number of votes are considered as similar candidate identities which are sent to the second stage to analyze their other visual information. For example, as it can be seen in Figure 2, we found identities whose local features are most similar to the local features of the query image.

(2) Middle-stage refinement is believed to be extremely beneficial to find identities that are similar to the test image in terms of global visual information. Firstly, this

level converts high-dimensional features of the query face into a much more compact representation using DCT coefficients. Then, it further refines the output result from the first level according to their extracted hash codes. The best matching candidates' gallery for the test image are found by the k-nearest neighbors (KNN).

(3) At the last stage, the query face is analyzed by another visual information. In this case, we apply the LBP algorithm to extract robust features from the images. Finally, the query face is recognized among the remaining subjects from the previous stages by using this information. The overall pipeline of the recognition phase is shown in Figure 3. For a given query image, a considerable number of the gallery images are filtered out in each stage, which saves the computational cost.

4. EXPERIMENTAL RESULTS

In this section, first, we introduce the face image datasets, including FERET, ORL, and AR. Then, the performance

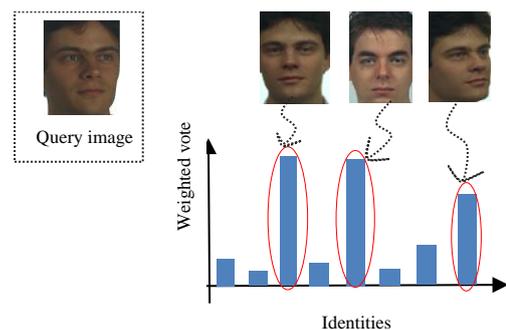


Figure 2. Most similar identities to the query image

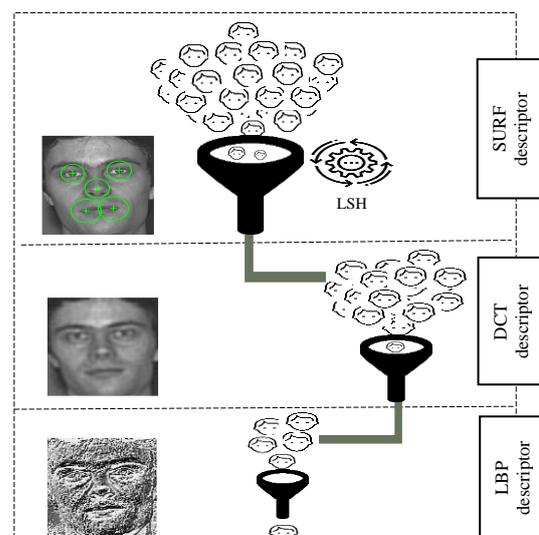


Figure 3. Overview of the recognition phase of the proposed method

of our method is evaluated by conducting several experiments. Finally, the running time of the proposed method is examined to estimate its computational cost in face recognition.

4. 1. Datasets: AR This dataset includes over 4000 faces corresponding to 70 males and 56 females. The pictures were captured in two different sessions which contain various illumination conditions, facial expressions, and occlusions. Sample images from the AR dataset are shown in Figure 4.

ORL: This dataset contains 400 frontal face images from 40 people photographed at different times with differing illuminations, facial expressions, facial details and somewhat pose variation. Samples from the ORL dataset are illustrated in Figure 5.

FERET: The FERET dataset contains 14,126 facial images from 1199 individuals. This dataset consists of different subsets of frontal images, quarter left, quarter right, profile left, profile right, half left, half right, and rotated images. The images were taken at different times and demonstrate variation including expressions, lighting, facial expressions, pose variation, and ages. Figure 6 demonstrates a number of sample images from this dataset.

Combinatorial dataset: To evaluate the proposed method on a large dataset, we collected identity images from several available datasets and provided a combinatorial dataset. For this purpose, images were collected from FERET, MUCT, PICS, FEI, and Face 94 datasets. Faces in the collected dataset are mostly frontal, but they may differ in facial expressions and brightness.



Figure 4. Sample images from the AR dataset



Figure 5. Sample images from the ORL dataset



Figure 6. Sample images of the second subset from FERET dataset

The total number of identities in this collection is 1684 with two samples per person. A number of samples from the data are shown in Figure 7.

4. 2. Parameters Setting The number of hash tables and the hash length of each bucket in the LSH algorithm are equal to 5. Likewise, the width of each bucket is 2. The number of nearest neighbors considered in each entry point is 10. In the DCT-based image hashing method, a 3×3 Gaussian filter is considered. As mentioned earlier, in the first stage of the recognition step, identifiers that are not similar to the filtered out test image. In this regard, the identities whose vote value is more than 65 percent of the highest voting value are considered for the next stage of recognition.

4. 3. Recognition Rate Here, different scenarios are considered and the proposed method is evaluated using the three datasets (i.e. AR, ORL, and FERET), and the results are compared with those from other recently developed face recognition methods.

In order to evaluate the effects of the number of images per person on the recognition rate, we have conducted two different experiments on the AR and ORL datasets. In Experiment 1, we randomly chosen 50 percent of the images from each identity for the feature extraction step, and the remaining were used for testing. But, in Experiment 2, 60 percent of the images from each identity were randomly selected for the feature extraction step and the rest for testing. Table 1 compares results of



Figure 7. Sample images from the combinatorial dataset

different face recognition methods in Experiments 1 and 2. The reason behind considering these two experiments is that we can train our method with a different number of data. In this case, the result can be more trustable. As can be seen, the proposed method achieved the highest recognition rates compared to other existing methods in both of the experiments. In addition, the results showed more robustness of the proposed method compared to other methods in terms of reducing the number of training sample per person in the dataset. The hyphen (-) in the table indicates that no result was reported in the literature for the associated method in that experiment.

Also, our proposed method is evaluated using the two different image subsets of the FERET dataset. The first subset contains 990 identities with 1980 face images which each individual has two samples that are frontal with two different expressions. Using this subset, our method can easily be assessed when only a single sample per person is available. We obtained the highest recognition rate on the first subset of FERET dataset which can be seen in Table 2. In the second subset, the performance of the proposed method is evaluated using 4017 face images from 994 individuals. This subset includes more images with challenges of variation including lighting, facial expressions, pose variation of $\pm 15^\circ$, $\pm 25^\circ$, and ages. Table 3 shows the comparison results on the second subset. Other existing approaches have considered a subset with a less number of identities. In order to compare the performance of our method with them, we achieved the result with their subset too.

Also, our method obtained a 96.62 percent recognition rate in the combined dataset. Figure 8 shows the variation of the recognition rate with a number of identities using the proposed method on this dataset.

4. 4. Running Time Next, we evaluate the running time of our proposed method on the second subset of the FERET dataset. The experimental set-up is on a 64-bit

TABLE 1. Recognition rate of different methods on ORL and AR

Name of method	Experiment 1 (%)		Experiment 2 (%)	
	AR	ORL	AR	ORL
SVM [42]	87.31	78.47	85.68	75.77
SRC [43]	96	-	95	-
LBP [40]	-	88	-	83
LGP+BAW-GSA [27]	-	92.5	-	90.7
IKLDA + PNN [28]	97.46	93.95	95.86	91.44
PLSH [9]	80	94.16	78	92.33
ESGK [29]	-	97.5	-	96
Proposed method	98	100	96.08	100

TABLE 2. Recognition rate of different methods on the first subset of FERET

Method	Number of images in dataset	Number of identities	Accuracy (%)
ESRC [26]	1400	200	51.60
LBP [5]	1400	200	74.90
RRNN [25]	1400	200	77.90
PCA [44]	1400	200	83.16
ESGK [29]	1400	200	84.5
PCA & LDA [45]	1400	200	86.10
SESRC & LDF [30]	1400	200	93.75
Proposed	1400	200	95.04
Proposed	4017	994	93.29

TABLE 3. Recognition rate of different methods on the second subset of FERET

Method	Number of images in dataset	Number of identities	Accuracy (%)
FLDA-SVD [34]	400	200	90.5
DMMA [35]	400	200	93
TDL [33]	400	200	93.9
Proposed	400	200	98
NNMF [32]	1980	990	92.73
Proposed	1980	990	97.29

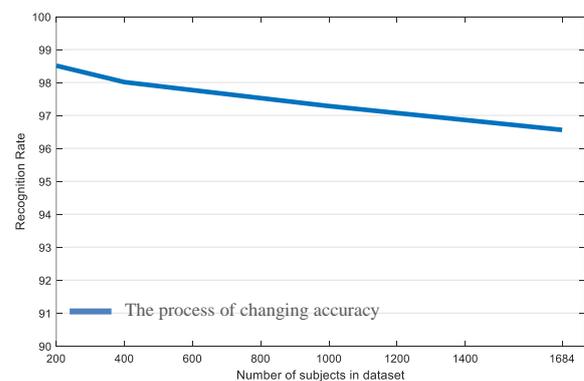


Figure 8. Recognition rate of the proposed method regarding to the number of identities in the combinatorial dataset

Windows operating system using the Intel Core i5 with 4 GByte RAM. All the programs were performed in MATLAB. In some cases, the test image is recognized in the first stage, hence there is no need to analyze them in the other stages. Figure 9 shows the impact of increasing the number of identities on recognition time. As shown

in the figure, when the number of identities increases, the recognition time increases almost linearly.

Figure 10 shows samples of wrong recognition using the proposed method. As can be seen, even humans may consider the faces shown in each row to be similar.

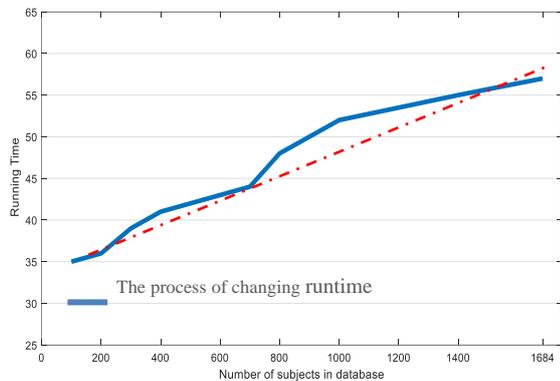


Figure 9. Running time of the proposed method regarding to the number of identities in the combinatorial dataset

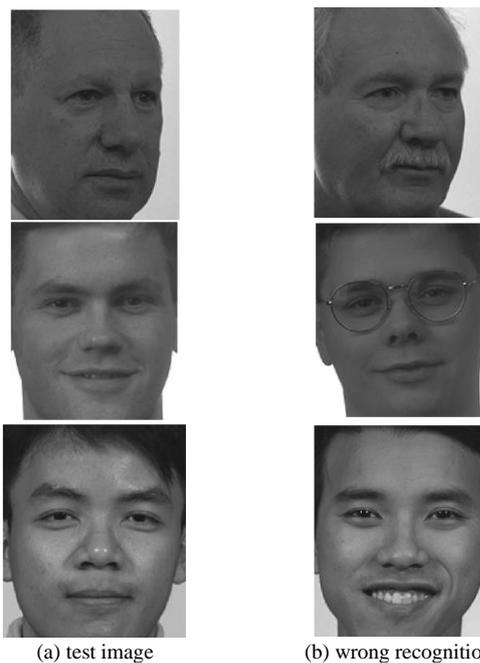


Figure 10. Some samples of wrong recognition in the proposed method. The left hand images were applied to the method and the right hand images were wrongly retrieved

5. CONCLUSION

In this paper, we have proposed a novel three-stage filtering framework for human face recognition. In this approach, different feature extraction methods are used to analyze different visual information in each stage. A

hashing function is used for feature extraction to reduce computational cost and improve accuracy of the proposed face recognition system. The merits of the proposed method are: (i) easy implementation; (ii) better performance than state-of-the-art methods across various face recognition scenarios; (iii) good performance when a single sample per person is available; (iv) scalable to the incremental enrollment of identities in the gallery; (v) significantly reduced the time complexity in face recognition. Several experiments were conducted on different datasets to evaluate the performances of the proposed face recognition in terms of changes in facial expressions, illuminations and pose variation, and perspective variations. The result shows that the proposed method outperforms current state-of-the-art methods.

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Persian Abstract

چکیده

سیستم شناسایی چهره به عنوان یکی از مهم‌ترین زمینه‌های تحقیقاتی، کاربردهای فراوانی در حوزه‌های مختلف از جمله تعامل انسان و کامپیوتر، پزشکی قانونی و نظارت امنیتی دارد. اما این سیستم‌ها با چالش‌هایی از جمله شرایط محیطی کنترل نشده، مجموعه داده‌های بزرگ و ناکافی بودن داده‌های آموزشی مواجه هستند. در این مقاله، با بهره‌گیری از یک چارچوب شناسایی چهره‌ی جدید و به کمک فیلترگذاری سه مرحله‌ای مبتنی بر درهم‌سازی تصویر به مشکلات فائق می‌آییم. در مرحله‌ی اول این روش، تعدادی از هویت‌ها از طریق عملکرد درهم‌سازی حساس به مکان (LSH) انتخاب می‌شوند. به‌طوری‌که با استفاده از یک سیستم رأی‌گیری، تعداد زیادی از افراد غیرمشابه با تصویر آزمون از نظر دیدگاه بصری جزئی‌نگر حذف می‌شوند. در مرحله‌ی دوم، از یک تابع درهم‌سازی تصویر قوی بر اساس ضرایب تبدیل گسسته کسینوس (DCT) برای بررسی بیشتر کاندیدهای مرحله‌ی اول از نظر دیدگاه بصری کلی‌نگر استفاده می‌کنیم. در آخرین مرحله، با استفاده از یک دیدگاه بصری کلی‌نگر دیگر، تصویر آزمون از بین افراد باقی‌مانده شناسایی می‌شود. نتایج آزمایش بر روی مجموعه داده‌های AR, FERET و ORL نشان می‌دهد که روش پیشنهادی عملکرد بهتری نسبت به روش‌های موجود دارد.
