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Biometric authentication using curvelet transform

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ABSTRACT

In this paper, we propose a feature extraction method for two-dimensional image authentication algorithm using curvelet transform and principal component analysis (PCA). Since wavelet transform can not adequately describe facial curves features, the proposed approach involves image denoising applying a 2D-Curvelet transform to achieve compact representations of curves singularities. To assess the performance of the presented method, we have employed three classification techniques: Neural networks (NN), K-Nearest Neighbor (KNN) and Support Vector machines (SVM). Extensive experimental results and comparison with the existing methods show the effectiveness of the proposed recognition method in the ORL face database and CASIA iris database.

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1. INTRODUCTION

In the past 20 years, biometric recognition technology has Quickly developed. Biometric authentication is a set of procedures of comparing data to determine resemblance for the characteristics of the individual to the biometric ”template” of that person. Fingerprints, facial features, tone, hand mechanics, handwriting, retina, and iris have formed biometric frameworks. We have seen new techniques such as Principal component analysis (PCA) and Linear discriminant analysis (LDA) and Independent component analysis (ICA) emerge over the past few years [1-3]. Multiresolution multidirectional transforms with the wavelet transform for pattern recognition was compared in [4] and since the conventional wavelet transformation can only describe the singularity of the point in the image that affects the wavelet coefficients, it is difficult for the wavelet to achieve satisfactory curve expression results [5-7].

Recently a number of new multiresolution analysis tools like, ridgelet [8], contourlet [9-12], etc. were developed to solve the above problem. These tools have better directional decomposition capabilities and better ability to represent edges and other singularities along curves than wavelets. Following the introduction of Curvelet transform theories by Emmanuel and Donoho, multi-scale analysis in image processing has been widely applied [13-16]. The developed continuous curvelet transform can represent image objects with edges and other singularities along the curve which were not captured by wavelets. The curvelet transformation [17] is implemented in the proposed method in order to capture facial features at various angles and scales. Face and Iris recognition experiments and have been carried out on ORL and CASIA database. The curvelet transform with classifiers such as neural network (NN) and support vector machine (SVM) and k-nearest neighbors (KNN) has been used to yield better recognition results as compared to existing methods. Rest of the paper is structured as follows: Section 2 describes the curvelet transform, Principal Component Analysis and classification algorithms in more details. Section 3 and 4 gives a discussion and experimental results with conclusion.

2. THE PROPOSED METHOD

In order to develop a practical approach to Biometric authentication, we proposed several methods based on the combined Curvelet and PCA and three classification algorithms (SVM-KNN-NN), the accuracy of these approaches are carried out by simulation and comparative study. In Figure 1, the proposed system starts with applying the Curvelet transform to handle curves using only a small number of coefficients. Hence the Curvelet handles curve discontinuities well. After that, the image is sent to the PCA step, based on the creation of low dimensional representation. Next, we select the eigenvectors with the higher value of eigenvalue. Finally, we have used SVM and KNN then NN for feature classification, based on these methods we can present three recognition approach, the first one is curvelet+PCA+SVM, the second one is based on curvelet +PCA+KNN, and the last one is curvelet+PCA+NN. The different used methods for these approaches are educed in the following subsections.

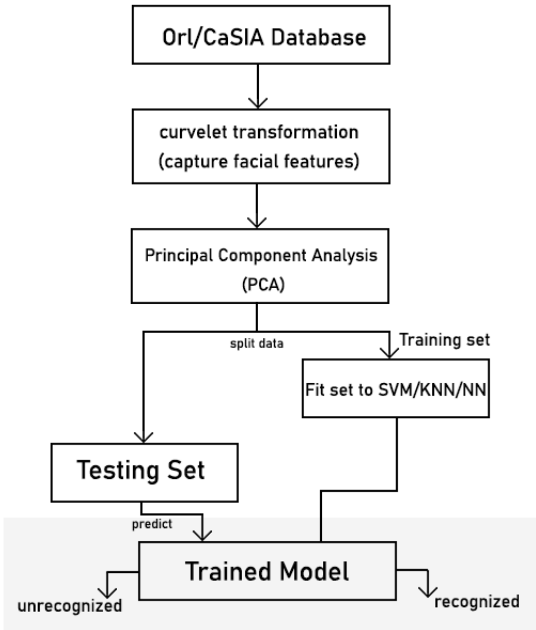

Figure 1. Proposed algorithm

2.1. Curvelet transform

The curvelet transform was first introduced by Candes and Donoho 1999 to overcome the drawbacks and limitations Of widely used multiresolution methods such as the wavelet transform and Ridglet transform. The multiscale transform principle is a property common to curvelet and wavelet transform where each has multiple frames indexed by location and scale parameters. However, the Curvelet transform, unlike the wavelet transform, has a very high degree of directional flexibility, and the frame size is subject to the anisotropic scaling principle. Curvelet transform have two possible implementations, the first well-known Implementations is Called Curvelet G1 and the second one is called Curvelet G2. In this paper we will cover only the first one since it's the one we worked with [18, 19].

2.1.1. First generation curvelets (DCTG1)

The first generation discrete curvelet transform (DCTG1) of a continuum function $f(x)$ makes use of a dyadic sequence of scales, and a bank of filters with the property that the bandpass filter Δ_j is concentrated near the frequencies $[2^{2j}, 2^{2j+2}]$,e.g.

$$\Delta_j(f) = \Psi_{2j} * f, \Psi_{2j}(\boldsymbol{\nu}) = \Psi(2^{-2j}\boldsymbol{\nu}) \tag{1}$$

In wavelet theory, one uses a decomposition into dyadic sub-bands $[2^j, 2^{j+1}]$. In contrast, the sub-bands used in the discrete curvelet transform of continuum functions have the nonstandard form $[2^{2j}, 2^{2j+2}]$.

This is nonstandard feature of the DCTG1 well worth remembering (this is where the approximate parabolic scaling law comes into play). The DCTG1 decomposition is the sequence of the following steps:

- Sub-band Decomposition, (The object f is decomposed into sub-bands).
- Smooth Partitioning, (Each sub-band is smoothly windowed into "squares" of an appropriate scale (of side-length $\sim 2^{2j}$)).
- Ridgelet Analysis, (Each square is analyzed via the DRT).

In this definition, the two dyadic sub-bands $[2^{2j}, 2^{2j+1}]$ and $[2^{2j+1}, 2^{2j+2}]$ are merged before applying the ridgelet transform. As shown in Figure 2.

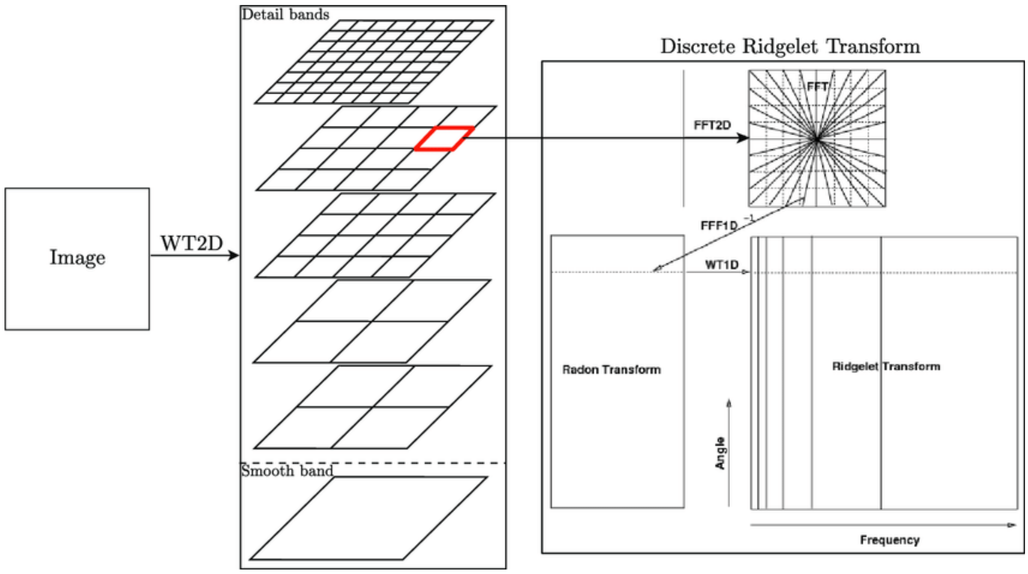

Figure 2. First generation discrete curvelet transform (DCTG1) flowchart. The figure illustrates the decomposition of the original image into sub-bands followed by the spatial partitioning of each sub-band. The ridgelet transform is then applied to each block

2.2. Principals component analysis (PCA)

Principal component analysis is suggested by Turk and Pent land in 1991 [20], which is often used for extracting features of the image. Principal Component Analysis is the most widely used method considering the facial feature extraction in image processing. The basic idea behind the PCA is, the set of images are initially transformed into Eigenfaces i.e. lower data space by using the K-L transform method. This method includes the linear transformation of the higher data space into the lower data space using linear transformation method. This extracted lower-dimensional image preserves most of the data or information from the original higher-dimensional facial image. This mapped lower data space is called as the Eigenface. Then the test Eigenfaces vector from the database is projected on the trainee Eigenfaces vector to get the correct match. For PCA, the two-dimensional image matrix must be first transformed into a one-dimensional vector with high order. While the number of training samples is small, it is challenging to calculate the covariance matrix of the training sample accurately. Furthermore, structure information will be lost during processing. The Eigenfaces vector as considered as the vector for constructing the covariance matrix. Here, the pixel information of each image is used to construct the Eigenvector. This Eigenvector information is used to select the Principal Component having a higher Eigenvalue. Each image location Contributes to each Eigenvector so that we can display the Eigenvector as a sort of face. Computing PCA:

- First,we take a set of images in column matrix or the row matrix form,named β

$$\beta = ({}_1, {}_2, {}_3, \ldots\ldots, {}_M) \tag{2}$$

where, M is the totale of objects present in total database. [-] Find the average of the defined matrixβ

$$\mu = \frac{1}{M}\sum_{n=1}^{M} n \quad (3)$$

Here, n is the total number of images in single object of Database μ is the Mean of the defined matrix β

- Then find the differential distance between the trainee images and the mean calculated

$$\alpha =_j -\mu \quad (4)$$

2.3. Support vector machines (SVM)

A linear model for classification and regression tasks is the SVM or Support Vector Machine. It can handle linear and non-linear problems and function well for many practical issues. SVM's idea is simple: the algorithm generates a line or hyperplane that divides data into groups.

$$\vec{w}.\vec{x} - b = 0 \quad (5)$$

where $\vec{w}$ is the (not necessarily normalized) normal vector to the hyperplane. This is much like Hesse normal form, except that $\vec{w}$ is not necessarily a unit vector. The parameter $\frac{b}{\|\vec{w}\|}$ determines the offset of the hyperplane from the origin along the normal vector $\vec{w}$.

From both sets, we consider the points nearest to the line according to the SVM algorithm. Such points are known as vectors of support. Now we measure the distance between the vectors of the line and the support. The margin is called this gap. Our goal is to optimize the margin. The ideal hyperplane is the hyperplane for which the margin is a peak. SVMs are essentially classifiers for two classes. The traditional way to classify multi-class SVMs is to construct $|C|$ one-versus-rest classifiers (commonly referred to as "one-versus-all" or OVA classification), And the select the class that classifies the maximum margin of the test data. Another technique is to create a set of one-versus-one classifiers and to pick the class selected by the most classifiers. While this involves building $|C|(|C|-1)/2$ classifiers, As the training data set for each classifier is much smaller, the time for training classifiers may actually decrease.

2.4. K-Nearest neighbors (KNN)

As with most advances in technology in the early 1900s, the KNN algorithm was born out of armed forces work.Two offices of the USAF School of Aviation Medicine Fix and Hodges (1951) published a technical report proposing a non-parametric method for pattern identification, which has since become popular as the nearest neighbor algorithm. KNN falls in the **supervised learning** family of algorithms. This means that given a labelled dataset consisting of training observations ***(x,y)*** ,we would like to capture the relationship between **x** $\rightarrow$ **the data** and **y** $\rightarrow$ **the label**. More formally, we want to learn a function $g: X \rightarrow Y$ so that given an unseen observation $x, g(x)$ can confidently predict the corresponding output **y** .

KNN's objective is to label the test set. To label a test point, in its neighbourhood, we search for existing labels. The latter are known as the training set. We choose the k labeled points that lie closest to our test point. Then we assign the label to the majority of these k neighbours [21, 22].

2.5. Artificial neural networks (ANN)

Warren McCullough and Walter Pitts, two scientists at the University of Chicago who moved to MIT in 1952 as founding members of what is often considered (the first department of cognitive science), were the first who suggested neural networks in 1944. The idea is to take a wide range of training examples and then develop a system that can learn from them. Neural networks are different from the way conventional machine-learning algorithms like SVM and KNN are implemented. To see how neural networks are approach solving problems, we start by defining a few notations. Let's begin with a notation which lets us refer to weights in the network in an unambiguous way. We'll use w^l_{jk} to denote the weight for the connection from the k^{th} neuron in the $(l-1)^{\text{th}}$ layer to the j^{th} neuron in the l^{th} layer. We use a similar notation for the network's biases and activations. Explicitly we use b^l_j for the bias of the j^{th} neuron in the l^{th} layer. And we use a^l_j for the activation of the j^{th} neuron in the l^{th} layer. The following diagram examples of notations as shown in Figure 3.

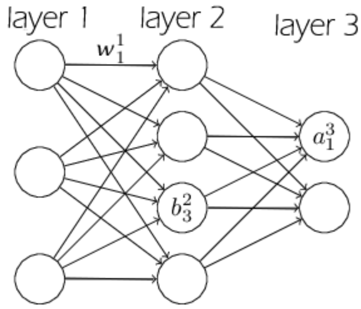

Figure 3. Multilayer perceptron (MLP)

With these notations the activation a_j^l of the j^{th} neuron in the l^{th} layer is related to the activations in the $(l-1)^{\text{th}}$ layer by the equation:

$$a_j^l = \sigma\left(\sum_k w_{jk}^l a_k^{l-1} + b_j^l\right) \tag{6}$$

3. RESULT AND DISCUSSION

3.1. Experiment on ORL database

The ORL Faces Database includes a collection of facial images taken in the AT&T Laboratories in Cambridge, from April 1992 to April 1994. There are 10 different images of every 40 individuals. The images were taken at various times, for some subjects, with different illuminations, facial expressions (open/closed eyes, smiling / no-smiling) and face specifics (glasses / no glasses). All images were taken with the subjects in an upright, frontal posture (with tolerance for some side movement) against a dark homogeneous background as shown in Figure 4. Firstly, the curvelet transform is applied to the ORL images where the vital information are extracted from the original images as shown in Figure 5.

Figure 4. ORL images database

Figure 5. Curvelet applied image

Then, the essential features are extracted from the new images by using the PCA algorithm, the given forth first important eigenvalues are represented, in Figure 6. Finally, the obtained eigenvectors are classified by classification algorithms the accuracy of each algorithm is shown in the following Figure 7. Figure 7 show the experiment results of recognition rate obtained for ORL faces database using PCA+Curvelet for feature extraction step, A three weak classifiers are used and we have achieved average recognition rates of 97.2, 98.75 and 92.5 respectively KNN, NN and SVM.

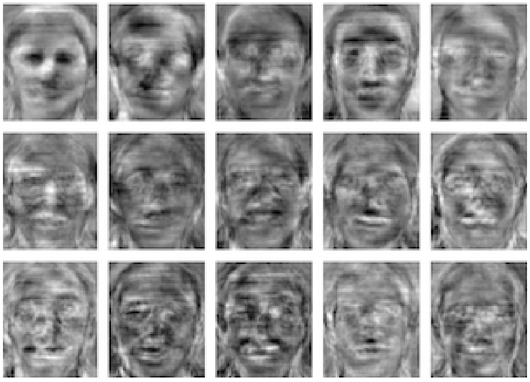

Figure 6. The first important eigenvalues extracted by PCA

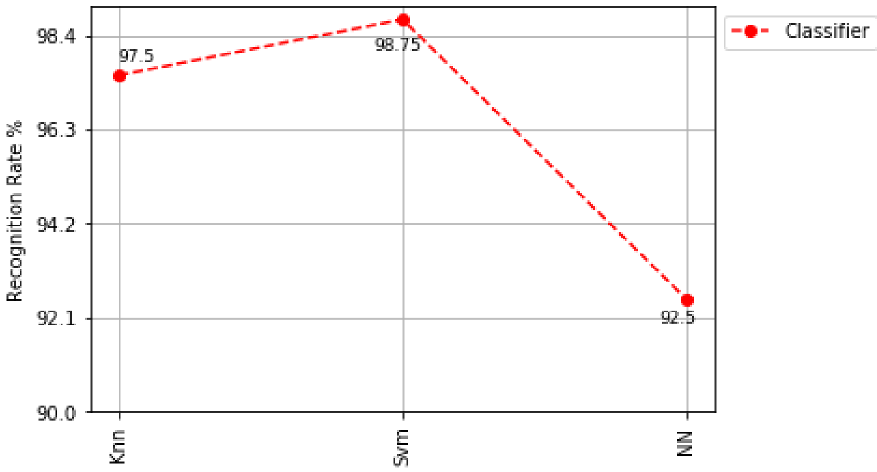

Figure 7. Recognition rate for ORL database with three classification algorithms

3.2. CASIA Iris image database

With a homemade iris camera, iris images of CASIA V1.0 were captured. Eight NIR illuminators of 850 nm are arranged circularly around the sensor to ensure that the iris is illuminated uniformly and correctly. To protect our IPR in the design of the iris camera (especially the NIR lighting system) before patents are issued, Pupil areas of all CASIA V1.0 iris imaging were automatically detected and replaced with a constant circular area, masking the specular NIR illuminators reflections in advance of their publication. Such processing may affect the detection of pupils but does not affect other components of an iris recognition system such as iris extraction, only the pupil and Sclera area, i.e. the ring-shaped iris area [23].

- CASIA Iris Image Database (v1).0) includes 108 eye pictures with 756 iris, and in 2 sessions with three and four samples collected during the first and second session, seven pictures in total are captured for each eye as shown in Figure 8.
- It is recommended that when you want to measure the in-class variance, you compare two samples from the same eye taken from different sessions. For example, the iris images in the first session can be used as the training dataset, and those from the second session can be used for testing.

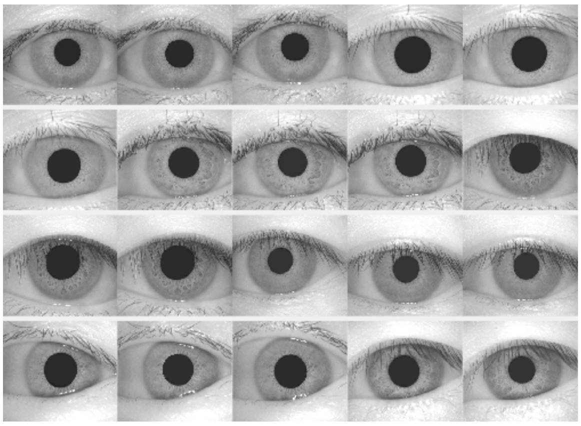

Figure 8. CASIA iris image database V1

Firstly, we apply the curvelet transform to extract curved singularity information from original images then segmentation and normalization of the iris are used on the new images as shown in Figure 9. Next, the essential features are extracted from the new images by using the PCA algorithm, like we did the previous ORL database. Finally, the obtained eigenvectors are classified by classification algorithms. The accuracy of each algorithm is shown in the following Figure 10.

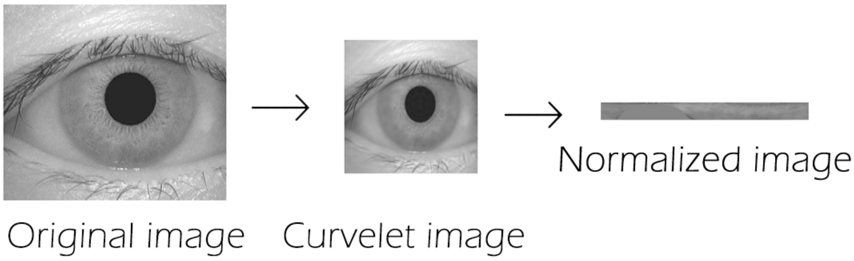

Figure 9. Curvelet iris image with normalization applied

Figure 10 shows the experiment results of recognition rate obtained for CASIA iris images using PCA+Curvelet for feature extraction step. The same three weak classifiers are used, and we have achieved average recognition rates of 92.0%, 93.0% and 97.0% respectively KNN, NN and SVM.

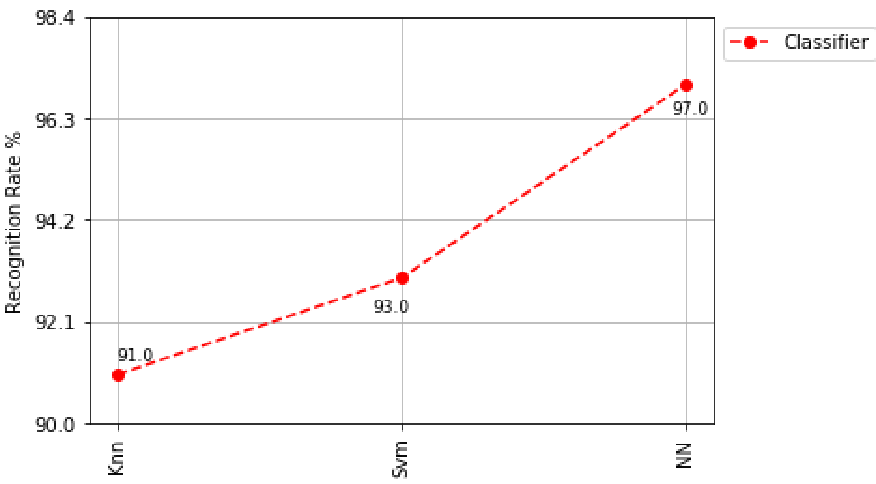

Figure 10. Recognition rate for CASIA database with three classification algorithms

3.3. Comparison of experiment results

In this paper, the recognition system PCA+curvelet have been used with three classification algorithms for comparison. These methods have been checked both ORL and CASIA database, and the testing protocols used in the experiment are almost the same. Table 1, shows a comparison of this two recognition systems. This comparison shows that the best recognition rate on ORL database was presented for PCA+curvelet using SVM with 98.7%, and the best recognition rate on the CASIA database was presented using NN with 97.0 %.

Table 1. Recognition rate for different algorithms

Approaches	Used algorithms	Database	RecognitionRate (%)
[24]	PCA+SVM	ORL	90.24
[25]	DWT+PCA+SVM	ORL	96.00
[26]	PCA+ ANFIS	ORL	96.66
[27]	FD+Manhattan Distance	CASIA	96.00
[27]	PCA+Euclidean Distance	CASIA	92.00
Proposed approach	DCTG1+PCA+SVM		**98.70**
	DCTG1+PCA+KNN	ORL	**97.5**
	DCTG1+PCA+NN		**93.7**
//	DCTG1+PCA+SVM		**93.00**
	DCTG1+PCA+KNN	CASIA	**91.0**
	DCTG1+PCA+NN		**97.0**

4. CONCLUSION

In this paper, an efficient and powerful facial feature extraction approach, such as DCTG1/PCA is proposed. The latter is selected as a fast and strong technique in representing edges and curves, and reducing the dimensionality of the images face/iris. As a case study of use, we presented an automatic 2D face/iris recognition system using (curvelet+pca) feature extraction algorithm.in the classification step, we have used the SVM, KNN, NN. The results were implemented on two well-known image datasets (ORL face database and CASIA iris database). The results show that the access speed feature extraction and the accuracy for the recognition system of the (Curvelet+pca) are more accurate than that of the only PCA.

REFERENCES

[1] S. A. F. A. I. M. Rahman, S. Naim, ”Curvelet texture based face recognition using principal component analysis,” *Proceedings of 13th International Conference on Computer and Information Technology*, pp. 45-50, 2010.
[2] J. W. Q. Y. Y. Mandal, T., ”Curvelet based face recognition via dimension reduction,” *Signal Processing*, pp. 2345-2353, 2009.
[3] e. a. Xu X.-B. Zhang D.-Y. Zhang X.-M.,”An algorithm for multimodal biometric recognition based on feature level and the second-generation curvelet transform,” *Journal of Xi'an Jiaotong University*, pp. 32-36, 2009.
[4] B. A. Majumdar, A., ”A comparative study in wavelets, curvelets and contour-lets as feature sets for pattern recognition,” *Int. Arab J. of Information Technology*, 2009.
[5] F. P. Amira, A., ”An automatic face recognition system based on wavelet transforms,” *IEEE International Symposium on Circuits and Systems*, pp. 6252-6255, 2005.
[6] W. H. Liu, C.-J., ”Independent component analysis of gabor features for face recognition,” *IEEE Transactions on Neural Networks*, pp. 919-928, 2003.
[7] Z. R.-C. Su, H.-T., ”Face recognition based on wavelet transform and multiple classifier,” *Computer Applications*, pp. 25-27, 2002.
[8] V. M. Do, M.N., ”The finite ridgelet transform for image representation,” *IEEE Trans. on Image Processing*, pp. 16-28, 2003.
[9] L. X. W.-S. L. H. Li, A., ”A multiscale and multidirectional image denoising algo-rithm based on contourlet transform,” *Int. Conf. on Intelligent Information Hiding and Multimedia*, pp. 635-638, 2006.
[10] G. P. Belbachir, N., ”The contourlet transform for image compression,” *IEEE Conf. on Physics in Signal and Image Processing*, 2005.
[11] C. A. D.-M. Zhou, J., ”Nonsubsampled contourlet transform: filter design and application in denoising,” *Proc. of Int. Conf. on Image Processing (ICIP)*, pp. 469-472, 2005.

[12] G. B. N.-W. Yang, L., ”Multimodality medical image fusion based on multiscale geometric analysis of contourlet transform,” *Neurocomputing*, pp. 203-211, 2008.
[13] M.-G. W. S. e. a. Jiao, L.-C. Gong, ”Advances in natural computation,” *Machine Learning and Image Understanding*, pp. 224-243, 2008.
[14] A. S. Nikam, S.B., ”Curvelet-based fingerprint anti-spoofing,” *Signal, Image and Video Processing*, pp. 75-87, 2010.
[15] R. Lakshmi, A., ”New curvelet features for image indexing and retrieval,” *Computer Networks and Intelligent Computing*, pp. 492-501, 2011.
[16] S. M.-X. WuX.-X., Zhao J.-Y., ”Face processing in human-computer interaction using curvelet analysis,” *Image and Graphics*, pp. 1309-1317, 2010.
[17] D. L.-D. D. Y.-L. Candes, E.J., ”Fast discrete curvelet transform,” *SIAM Multiscale Modelling and Simulations*, pp. 861-899, 2005.
[18] J. Fadili and J. L. Starck, ”Curvelets and ridgelets,” *Computational Complexity: Theory, Techniques, and Applications*, pp. 754-773, 2012.
[19] L. Y. Emmanuel Candes, Laurent Demanet, David Donoho, ”CurveLab http://www.curvelet.org/.” [Online]. Available: http://www.curvelet.org/
[20] F. Bellakhdhar, K. Loukil, and M. Abid, ”Face recognition approach using Gabor Wavelets, PCA and SVM,” *International Journal of Computer Science Issues*, vol. 10, no. 2, pp. 201-207, 2013.
[21] D. Machanje, J. Orero, and C. Marsala, ”A 2D-approach towards the detection of distress using fuzzy K-nearest neighbor,” *Communications in Computer and Information Science*, vol. 853, pp. 762-773, 2018
[22] Z. Yao and W. L. Ruzzo, ”A regression-based K nearest neighbor algorithm for gene function prediction from heterogenous data,” *2018 BMC Bioinformatics*, vol. 7, 2006.
[23] CASIA - Center for Biometrics and Security [Online]. Available: http://www.cbsr.ia.ac.cn/IrisDatabase.html, ”CASIA V1.0database.”
[24] A. Bouzalmat, J. Kharroubi, and A. Zarghili, ”Comparative study of PCA, ICA, LDA using SVM classifier,” *Journal of Emerging Technologies in Web Intelligence*, 2014.
[25] Z. B. Lahaw, D. Essaidani, and H. Seddik, ”Robust Face Recognition Approaches Using PCA, ICA, LDA Based on DWT, and SVM Algorithms,” *41st International Conference on Telecommunications and Signal Processing*, pp. 1-5, 2018.
[26] R. Sharma and M. S. Patterh, ”Pose Invariant Face Recognition using Neuro-Fuzzy Approach,” *IOSR Journal of Computer Engineering Ver. II*, vol. 17, no. 3, pp. 2278-661, 2016.
[27] M. H. Hamd and S. K. Ahmed, ”Biometric system design for iris recognition using intelligent algorithms,” *Int. Journal of Modern Education and Computer Science*, vol. 10, no. 3, pp. 9-16, 2018.

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