An Efficient Technique for Iris Recognition using Wavelets and Artificial Neural Networks

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Abstract

In this paper, an iris recognition system is presented and developed. The proposed system utilizes an integro-differential operator to segment the input iris image. The isolated irises are normalized to vectors of the same length. Classification features from the normalized vectors are extracted using Wavelet packet decomposition (WPD) combined with a novel amplitude-thresholding approach. The extracted features are then applied to an ANN for classification. The iris images used in this study are obtained from the CASIA database. To show the robustness of the proposed system, its performance is compared to that of vector quantization (VQ), a minimum-distance classifier that uses the Euclidean distance. Simulation results show that the proposed ANN system produces a low recognition error of less than 5% and always outperforms the VQ system.

Keywords: Iris, Wavelet packet decomposition (WPD), Artificialneural network (ANN), Vector quantization (VQ), Biometrics, Feature extraction.

1 Introduction

In many biometric applications such as access control, information protection, and authentication, it is important to determine the identity of a person. Conventional methods of recognizing the identity of a person by using identification cards or passwords are not always reliable since passwords can be forgotten; and identification cards can also be lost, stolen, or forgotten. Consequently, there is tremendous interest in identification (authentication) methods which depend on measures that cannot be lost, forgotten, or stolen. Biometric methods identify people based on physiological characteristics such as face, fingerprint, palm print, hand geometry, DNA, iris, and retina.

Behavioral characteristics such as gait, voice, and handwriting (signature) can also be used by biometric systems. In general, any human behavioral or physiological characteristic could be a biometric given that it satisfies the following requirements: (a) permanence (the characteristic should be invariant with time), (b) uniqueness (no two persons are the same with respect to the characteristic), (c) universality (every person has the characteristic), and (d) collectability (the characteristic can be measured quantitatively) [1, 2].

Among all the human physical characteristics, the iris has been widely regarded as the most accurate biometric. The iris has many outstanding properties including its unique visible characteristics, stability over a person's lifetime, and its secure nature (being an internal organ, it is difficult to replace or remove the iris; thus, decreasing the possibility of deceiving the recognition system). The iris is the colored ring (membrane) of the eye, bounded by the white sclera and the black pupil. It controls the amount of light reaching the interior of the eye (retina). The iris and the pupil are covered by a clear covering called the cornea. The iris consists of pigmented fibro vascular tissue known as stoma. It is the most forward portion of the eye and the only one seen on trivial inspection. The iris has an intricate structure that includes a rich pattern of minute characteristics such as coronas, furrows, freckles, and crypts.

In this study, we propose and develop a biometric system for iris recognition. The system employs an integro-differential operator to locate the iris structure. Distinctive features are then obtained from the segmented iris image using an operation based on Wavelet packet decomposition (WPD) and a thresholding technique that keeps the values and the locations of the high-magnitude approximation coefficients while discarding the rest of the approximation and detail coefficients. Classification of the iris feature vector is then achieved using an Artificial Neural Network (ANN) classifier. To prove the validity and robustness of the proposed method, its performance is compared to that of a vector quantization (VQ) system that uses the

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March 9-11, 2015, Honolulu, Hawaii, USA

Euclidean distance. To test the proposed system, we use the Chinese academy of sciences institute of automation (CASIA) database, a freely available iris database containing images of human irises.

This paper is organized as follows. In section 2, we provide a survey of related work in the area of iris recognition. In section 3, we discuss the materials and methods. We present the results and analysis of the experiments in section 4. The conclusion is provided in section 5.

2 The State of the Art in Iris Recognition

This survey provides a brief coverage of the current state of the art in iris biometrics and its commercial applications. Most of the research publications in this field have made contributions to one of the four main areas in iris biometrics: image acquisition, iris segmentation, feature extraction, and classification. The most important contribution in the early history of iris biometrics was made by Daugman [3, 4] where he described an automatic iris recognition system. Daugman's approach has laid the ground for most of the later research in iris biometrics and has become a standard reference model. In [5] Daugman describes a border-control application of iris recognition that is currently being used in the United Arab Emirates (UAE) to check visitors to the country. The UAE database contains 632,500different iris images. Daugman reports that by using an iris recognition system, about 47,000people have been caught trying to enter the UAE using false travel documents. The UAE police reports that so far all the matches have also been confirmed by other means. Another commercial example of the successful use of iris identification systems is presented by the Cairo-Amman Bank (CAB) in Jordan. In 2008, the CAB in cooperation with leading biometric security manufacturer Iris Guard was the first bank in the world to implement the ocular security scan technology. The CAB now offers this service in more than 80branches and 215 ATM machines [6].

Kekre*et al.* worked on the iris recognition problem using Haar Wavelets for feature extraction and the Euclidean distance for classification [7]. They used the Palacky database and found that Haar lets level-5 outperforms lower-level Haar lets. Sarhan used the CASIA database and developed an iris recognition system in which he used an ANN for classification and the discrete cosine transform (DCT) for feature extraction [8]. Sarhan also tackled the iris feature extraction problem using Wavelets [9]. A comparison of different iris feature extraction methods was developed by Vatsa *et al*. [10]. An experimental comparison of different segmentation methods was developed by Proenca *et al*. [11]. Proenca also developed an iris recognition system using structural pattern analysis methods [12].Phillips *et al.* presented on the ICE web sitean evaluation report of the current state-of-the art in iris biometrics [13]. Ives et al worked on the compression of iris images for applications in portable iris systems (such as in law enforcement applications), to reduce the transmission time of the iris images [14].
Several iris databases are freely available online. The list includes the CASIA database, the iris Challenge Evaluation (ICE) database [15], the IIT Delhi (IITD) iris database [16], and the UBIRIS database, which was developed by the University of Beira Interior in Portugal [17]. The UBIRIS v.1 database contains 1877 images collected from 241 eyes and has a spatial resolution of 800 × 600 pixels. It simulates less constrained imaging conditions. As an alternative to iris database collection, Wei *et al*. presented a framework to synthesize large realistic iris databases [18]. Segmented iris images are available from the Palacky database, a relatively small iris database created at Palacky University [19]. It contains 3 × 128 segmented iris images (3 × 64 left eyes and 3 × 64 right eyes). The images have a RGB format with spatial resolution of 576 ×768 pixels and 24 bits per pixel. Fig. 1 shows three iris images of a left eye.

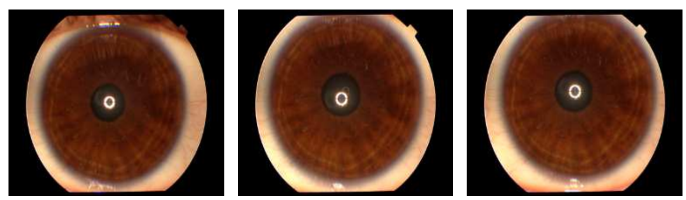

Figure 1: Palacky database: Three iris images of the same eye

3 Material and Methods

3.1 System block diagram

A block diagram of the proposed system is depicted in Fig. 2. The input to the system is an image of the iris. The iris database used in this paper is the CASIA, v.2 database which contains 1200 raw eye images. The images are for 30 persons. For each person, there are 20 iris images for the left eye and another 20 images for the right eye, giving a total of 40 images for each person. Note that the left and right irises for a given person are different from each other. The original size of each image is 480×640 pixels, with 256 grey levels per pixel. We used images from seven classes (right eyes only), with 20 samples per class. Thus our dataset contained 140 images; half of which are used for training and the other half are used for testing.

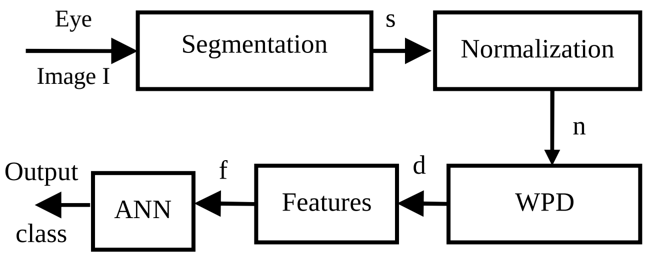

Figure2: Block diagram of the proposed system.

3.2 Iris segmentation

There are various techniques to perform image segmentation. Commonly used iris segmentation methods include the integro-differential, active contour models, and the Hough transform techniques. The classical Hough transform was originally introduced by Paul Hough as an image feature extraction technique for identifying lines in the image [20]. Later, the generalized Hough transform technique was presented by Richard Duda and Peter Hart in 1972 to identify positions of arbitrary shapes, especially circles and ellipses [21]. The Integro-differential operator introduced by Daugman can be used as a circular edge detector algorithm that assumes circular structure of the pupil and limbus. It finds all circles in an image. The sum of pixel values within each circle is compared to the values of adjacent circles. The circle with the maximum difference from its adjacent circlesis recognized as the iris.

Iris discs have different sizes for different input images. However, for proper processing, the input irises must have the same size. Here we propose an operation that unifies the sizes of all the irises in the dataset. Specifically, the input iris disc is normalized by converting it to a vector whose length is the same as the length of the vector corresponding to the smallest iris disc in the dataset. In the next stage of the proposed system, the normalized vector is transformed using the WPD.

3.3 Wavelet packet decomposition

Lossless transforms do not change the information content or energy of the signal. Suitably selected transforms can be used effectively in various signal and image processing applications including compression, restoration, coding, and feature extraction. A new transform, known as the wavelet transform (WT), has proven to be more effective in many DSP applications and has been used widely in recent years. The most commonly used wavelets are the **Daubechies** (db) and the Haar wavelets. The proposed system employs the **Daubechies** db1 wavelet which is considered the first and simplest wavelet.

In wavelet nomenclature, approximations and details are often used where details are the high-frequency, low-scale components, and approximations are the low-frequency, high- scale components of the signal. The discrete Wavelet transform (DWT) is a subset of the wavelet packet decomposition (WPD) transform.

Because of its outstanding energy concentration capability, the DWT has found many practical applications in signal and image compression. The powerful energy compactness property of the WPD is evident in the limited number of high-magnitude coefficients found in the transformed signal.

The strong energy compactness of the WPD makes it very useful in pattern recognition applications [22, 23]. In the proposed system, we exploit the signal compression characteristic of the WPD to form a valid feature vector (f) representing the input iris vector. Since the most important part of a signal is often contained in the lower-frequency components of the signal spectrum (approximation coefficients), we propose a scanning technique that keeps the values and locations of the high-magnitude approximation coefficients while discarding the rest of the approximation coefficients. The details coefficients are not considered here since they represent a small fraction of the signal energy. As illustrated by Fig. 3, the proposed masking technique keeps only the higher-magnitude coefficients (positive and negative) and also preserves their locations. Note that Fig. 3 uses a threshold level of 15.1; thus, the scanning operation keeps only the coefficients whose absolute values are greater than 15.1.

The output of the masking operation performed on the approximation vector d produces the feature vector f. In the last stage of the proposed system, f is presented to an ANN for classification. ANNs are trainable algorithms that can "learn" to solve complex problems from training data that consists of pairs of inputs and targets (desired outputs). ANNs have been successfully used in many applications including prediction, classification, image processing, regression, and adaptive control [24]-[27].

The basic building block of the ANN is the neuron, depicted in Fig. 4. The output of the neuron is a linear combination of its inputs. The neuron's scaled output y is given by $y = f(a)$, where f is a transfer function. A typical ANN consists of interconnected neurons. The weights of the neurons are calculated iteratively so as to optimize a certain criterion such as the Mean-Squared-Error (MSE) between the ANN output and its desired output. Optimum weights in the sense of Least Squared Errors were derived by Widrow and Hoff and the algorithm is known as the Widrow-Hoff rule or as the Least Mean Squares (LMS) algorithm.

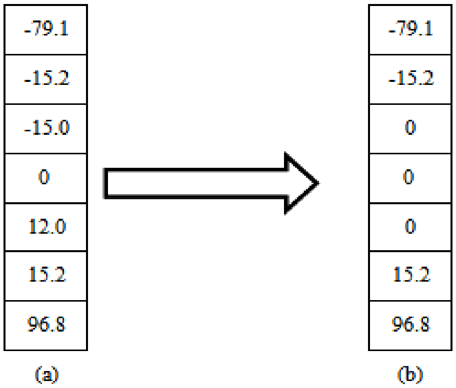

Figure 3: Illustration of the proposed masking operation using a threshold level of 15.1: (a) Input approximation coefficients and (b) output feature vector.

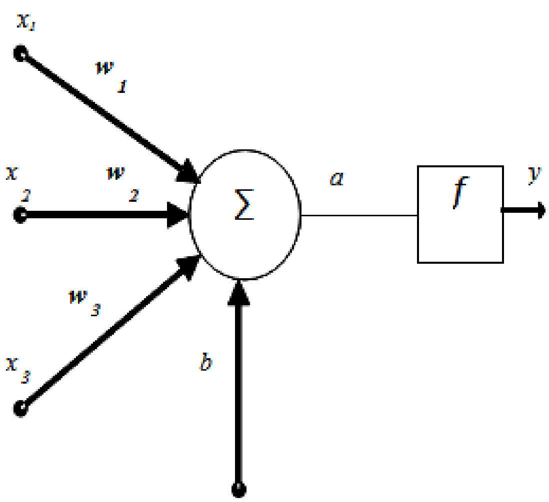

Figure 4: The structure of a single neuron: x_i,w_i, *b*, and *a* are the inputs, weights, bias, and output, respectively.

All the ANNs examined in this study are trained with the same sets of inputs and outputs that are used to train the VQ system, and have the following specifications:

1. The networks receive as input the feature vector representing the input iris sample.
2. The network structure is a two-layer feed-forward neural network. The output layer has seven neurons in order to represent seven classes. For example,
3. $y = [0\ 0\ 1\ 0\ 0\ 0\ 0]^T$, where T denotes the transpose operation, represents the third class.
4. The learning algorithm used here is the back propagation algorithm.
5. The log sigmoid function, which can approximate binary values, is used as the transfer function of the output layer.

To prove the merits of the proposed system, its performance is compared to that of a VQ system that uses the Euclidean distance. For decades, VQ has been used as a popular technique in applications involving signal and image compression. In recent years, VQ has been effectively used as a classifier in pattern recognition applications [28,29].

An *M*-level vector quantizer is a mapping of each input vector to a specific partition defined by an index and an associated vector called a code word or a reproduction vector (class). The collection of M code words is referred to as the code book. The VQ technique uses a minimum-distance rule to classify(encode) a test or input vector (whose class is unknown).Several distortion measures have been proposed in the literature including the Euclidean distance, the Manhattan distance, the Holder norm, the Hausdorff distance, the Hamming Distance, the Mahalanobis distance, the Chebyshev distance, and the Minkowski distance [30].

4 Results and Discussion

In the first stage of the proposed system, the iris ring is isolated from the input eye image. Segmentation is achieved here using the Integro-differential operator. Fig. 5 shows a noisy iris detected by the proposed system. The figure shows circles overlaying the iris inner and outer borders.

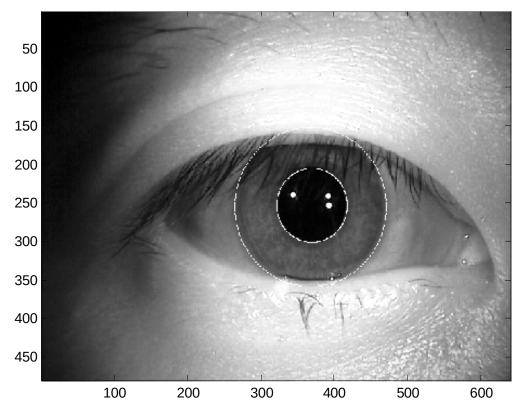

Figure 5: segmentation of a noisy iris image.

In the proposed system, after the iris is detected, it is normalized. Normalization is achieved here in two stages. In the first stage, the image representing the iris region is converted to a vector. For example, let the segmented iris region be defined by the matrix

$$s = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix}.$$

The corresponding iris vector n is then found by first converting the matrix *s* to a vector as follows

$$n= [a_{11}\ a_{12}\ a_{13}\ a_{21}\ a_{22}\ a_{23}].$$

Iris vectors have variable lengths depending on the input eye image. In the second stage of the normalization process, all iris vectors are forced to have the same length. This is achieved by truncating all iris vectors so that their lengths are equal to the length of the smallest iris vector belonging to the dataset under study. The truncation process ensures that the iris vectors can be suitably presented to an ANN after being transformed by the WPD, the next stage in the proposed system. All input vectors to an ANN must have the same dimension. Fig. 6 depicts the lengths of the iris vectors in our dataset. It shows that the maximum and minimum lengths of the iris vectors are 34609and 29510 (coefficients), respectively. Thus, to normalize the dataset, all iris vectors are truncated to have 29510 coefficients.

The normalized vectors are then transformed using a WPD that employs the dB1 wavelet. The transformation yields approximation and detail vectors. In the proposed system, we retain the approximation coefficients and discard the detail coefficients since they carry a small portion of the signal energy. Fig.7 shows the average of the approximation vectors corresponding to iris vectors of four classes. Each class had 20 samples.

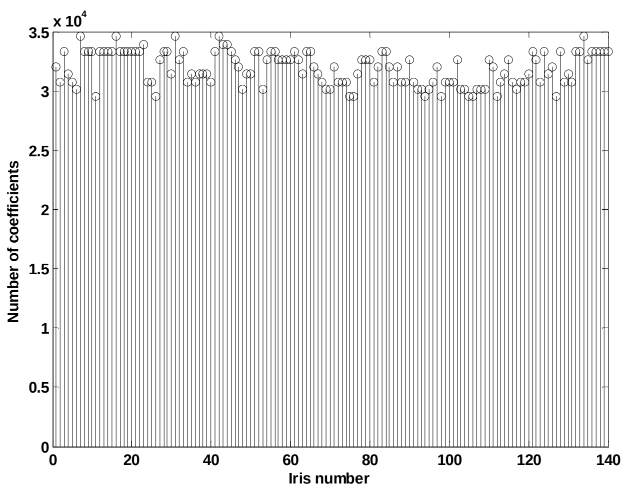

Figure 6: lengths of the iris vectors for 7 classes with 20 irises per class

It can be seen from Fig. 7 that approximation vectors of different classes have different peak values and different peak locations. We exploit this characteristic of the WPD transform to obtain distinctive features. Specifically, the proposed scanning technique is applied to the approximation coefficients to obtain the feature vectors. In the last stage of the proposed system, f is applied to an ANN for classification. In the experiments, we test the performance of the proposed ANN system and the VQ system versus decomposition and threshold levels. Moreover, the proposed system is tested as a function of the number of neurons used. The VQ system used in the experiments employs the Euclidean distance. In the first experiment (Fig. 8), we test the error rate of the proposed ANN system versus wavelet decomposition level and number of neurons used in the first layer. The system employs the dB1 wavelet and he output (second) layer has 7 neurons corresponding to the number of classes. Fig.8 shows that the proposed system exhibits a minimum error rate of 5%when the decomposition level is 8 and the number of neurons is 11.In the second experiment (Fig. 9), we examine the error rates of the proposed ANN and VQ systems versus wavelet decomposition level, using the dB 1wavelet. Here, the approximation vectors are presented to both systems without thresholding and the NN system used 10 neurons in the first layer. Fig. 9 shows that the ANN system outperforms the VQ system and produces a low error rate of 5 %(when the decomposition level is 8) while the lowest error rate for the VQ system is 43.57%(obtained when the decomposition level is10). The highest error rate for both systems occurs when the decomposition level is at its maximum value of 14.In the last experiment (Fig. 10), we test the performance of the VQ system as a function of both threshold level and decomposition level. Fig. 10 shows that that the VQ system has a minimum error rate of 32.14 % when the wavelet decomposition level is three and the threshold level is 78.

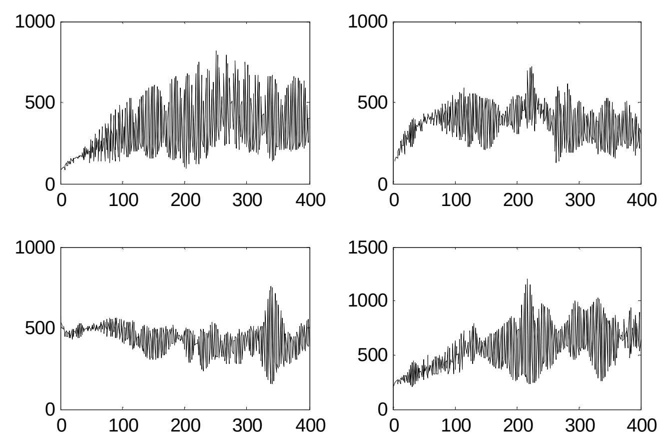

Figure 7: Average of approximation coefficients at level 6, for four iris classes (20 samples per class), using the dB1 wavelet.

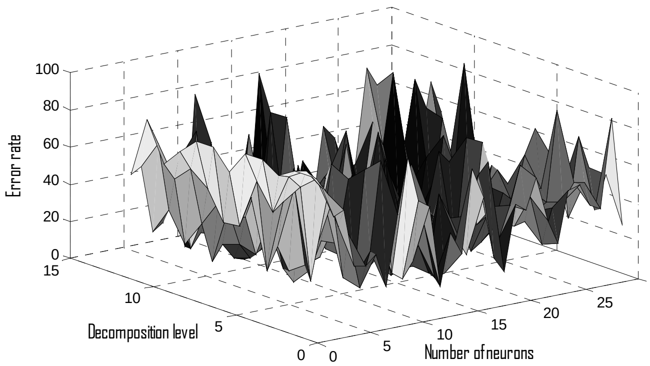

Figure 8: Error rate of the ANN system vs. decomposition level and number of neuron.

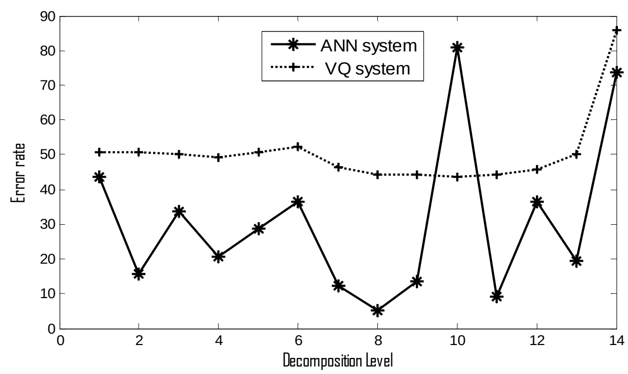

Figure 9: Error rate for the ANN and VQ systems versus decomposition level

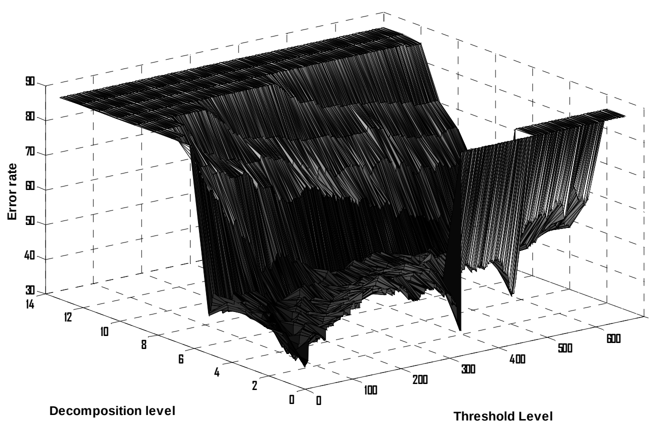

Figure 10: Error rate of the VQ system versus decomposition level and threshold level

5 Conclusion

Presented in this paper is a new approach to iris classification. In the proposed system, the iris is first extracted from the input eye image using the integro-differential operator. The isolated iris disc is converted to a 1-D vector and then normalized so that all the irises in the dataset have the same length. The 1-D WPD is used to transform the normalized iris vector in order to reduce its dimension and simplify the subsequent feature extraction stage. Relying on the fact that the low-frequency components of a signal carry most of the information about the signal, certain approximation coefficients are scanned as features using a novel thresholding technique that keeps the values and locations of the high-magnitude approximation coefficients. The selected features are then applied to an ANN for classification.

The proposed system has various configurations and parameters. In this study, we investigated the optimum ANN structure, the optimum WPD parameters, and the optimum threshold level for iris recognition. To show the robustness and the validity of the proposed system, its performance is compared to that of VQ, a minimum-distance classifier that employs the Euclidean distance. Both the proposed system and the VQ system receive the same feature vectors as input. Simulation results prove that the proposed ANN system produces a low error rate of 5% and always outperforms VQ system.

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