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Personal Identification System Based on Palmprint

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Abstract: The need for a secured personal identification system has led researchers into the field of biometrics. Currently a lot of research work is carried out in this area. One of the most promising traits is the palmprint which is widely used because of the ease with which it can be acquired, accuracy and stability. The palmprint contains principal lines, ridges and wrinkles which can be used to uniquely identify a person. It is user friendly, contains larger surface area and more features can be extracted using low resolution images. Also it is highly discriminative and even identical twins have different palmprint. In this proposed study, features are extracted from palmprint based on local gabor XOR pattern and principal component analysis. Each of these features is extracted and matched using Euclidean distance measure. Finally the scores generated by the individual matchers are combined using score level fusion. This fusion technique improves the performance of the biometric system and is found to provide low error rates and high recognition accuracy.

Key words: Palmprint recognition, texture feature, local gabor XOR pattern, principal component analysis, fusion

INTRODUCTION

A biometric system is essentially a pattern recognition system which identifies a person based on the physiological or behavioral characteristics possessed by the person (Jain *et al*., 1999). Biometric features have been widely used in personal authentication system because it is more reliable when compared to conventional methods like knowledge based methods e.g., password, PIN number and token based methods e.g., passports, ID cards. Different physical or behavioral characteristics like fingerprint, face, iris, palmprint, hand geometry, voice, gait, signature etc., have been widely used in biometric systems. Among these traits hand based biometrics such as palmprint, fingerprint and hand geometry are very popular because of their high user acceptance. The most widely used feature is the fingerprint. It has several advantages of small chip size, easy to acquire and highly accurate, making it the most popular biometric technology. But it is difficult to extract features from damaged fingers and also has less user acceptability since people associated with police process (Zhang, 2004). Hand geometry has advantages like small feature size and low computation complexity but it has the disadvantage of high cost and low accuracy (Fung *et al*., 1997). Palmprint contain many features like principal lines, wrinkles, ridges, datum points and minutiae features. It is highly unique and even identical twins have different palmprints (Kong *et al*., 2006a, b). It is also rich in texture and in the proposed study Gabor filters are used for texture feature extraction. Also principal component analysis is used to extract the global features from the palmprint. Finally the matching scores of the above features are combined using Minimum Distance Rule (MDR).

Personal identification based on palmprint has been the area of research for the past ten years. There are a number of algorithms proposed in the literature using palmprint and they may be classified as:

- Line based methods (Wong *et al*., 2008; Li and Leung, 2006; Wang and Ruan, 2006a; Yang *et al*., 2009)
- Subspace based methods (Yu *et al*., 2010; Wang and Ruan, 2006b; Guo *et al*., 2010; Lu *et al*., 2008)
- Statistical methods (Jin and Kang, 2005; Han *et al*., 2009; Wu *et al*., 2004; Liu *et al*., 2008)

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- Coding methods (Zhang *et al*., 2003; Kong and Zhang, 2004; Guo *et al*., 2009; Jia and Huang, 2007; Zhao *et al*., 2010)
- Hybrid methods (Yang *et al*., 2008; Xu and Guo, 2010; Zhu and Xing, 2009; Zhang *et al*., 2010; Zhu *et al*., 2008)

Many researchers have extracted the palm lines for personal identification. Mainly edge detection methods are used for this purpose. The lines may be matched directly or represented in other formats for matching. Wong *et al*. (2008) used Sobel operators with different orientations to extract the line information from the normalized palmprint images. The feature vectors are either zero or one and Hamming distance is used for matching. Wang and Ruan (2006a) used two stage steerable filters for global and local filtering. In the first stage, steerable filters are used on the whole image to extract the palm lines and approximate directional angles. In the second stage, they extract palm lines and connect the broken lines in local regions of the same palmprint image. The proposed method is claimed to be effective and fast in extracting the palm lines from online images.

The subspace methods like Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and independent component analysis are the techniques adopted in the literature for feature representation and also in dimensionality reduction. The coefficients obtained in the subspace are used as features and distance metric and other classifiers are used for matching. Instead of applying the subspace methods directly, they may also use Gabor filters, Discrete Cosine Transform (DCT), wavelets in their methods. The subspace feature extraction methods have strong representations, low computation, easy to implement and good separation, so they are widely used in many fields like face, palm print recognition and so on.

The statistical features can be easily extracted and represented for identification. Local or global statistical features can be obtained. In local statistical method the image is transformed into some other domain. The transformed image is then sub divided into small regions and mean, variance of these regions is stored as feature vectors. The image transforms such as fourier transforms, Gabor and wavelet transform techniques are used. Lu *et al*. (2002) use histograms of local binary patterns as features. Global statistical methods compute the global features such as moments and center of gravity directly obtained from the transformed images moments. Wu *et al*. (2004) used fuzzy directional element energy features, a statistical feature containing some line structural information about palm prints. Euclidean distance is used for matching.

Different coding algorithms are proposed in the literature and they provide high recognition rates. Kumar and Shen (2004) used the Real Gabor Function (RGF) on palmprint. The RGF filter was implemented using 13X13 spatial masks with six different orientations. They extracted circular ROI and for each of the circular concentric band, the mean and variance was estimated. The ordered set of feature vectors is called as the palmcode. Competitive coding scheme was developed by Kong and Zhang (2004) which takes in to account, the orientation field of the palmprint constituted by the palm lines. 2D Gabor filter is used to extract the orientation field and a novel coding scheme is used to generate a bitwise feature representation and bit wise angular distance is used to compare the two feature codes. Better performance was achieved in comparison to palm code and fusion code.

The hybrid methods combine different image processing techniques for feature extraction in palmprint and they employ some classifiers like neural network. Zhu and Xing (2009) proposed a new hierarchical palmprint recognition method. First, major lines are extracted by Canny detectors on four gradient images. Then dual tree complex wavelet is applied to the palmprint image to extract texture features. The two features are shown to complement each other and a recognition rate of 97.82% is achieved. Zhang *et al.* (2010) used multispectral palmprint images to acquire more descriptive information. A data acquisition device was designed to capture palmprint images under blue, green and red and Near Infra Red (NIR) illuminations. The method employed orientation based coding texture features.

MATERIALS AND METHODS

Palmprint is one of the important biometric traits used among the people. Any palmprint recognition process has the following major steps: (1) Image preprocessing, (2) Feature extraction and (3) Matching. In our proposed method, the input image is enhanced using median filter. Then the central palm area is extracted. After that the features are extracted from the selected ROI of palm image. Here, the texture feature and the global PCA features are extracted. Finally, based on the feature extracted the palm image is recognized using Euclidean distance measure. The block diagram of the proposed work is shown in Fig. 1.

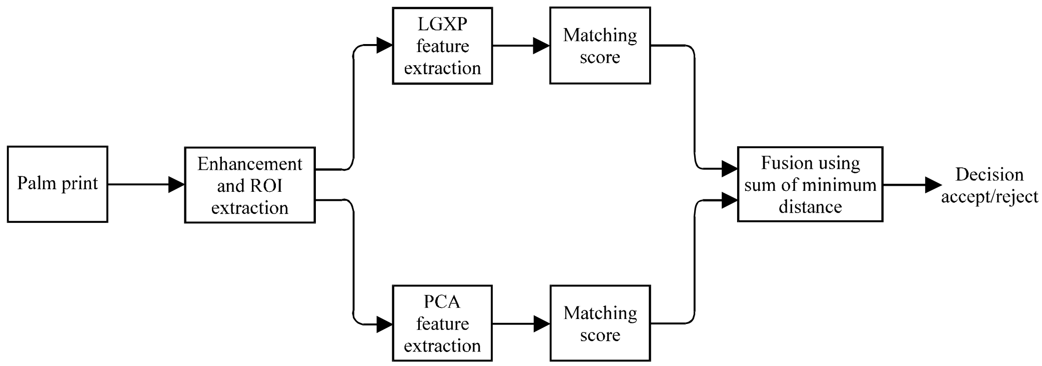

Fig. 1: Block diagram of the proposed system

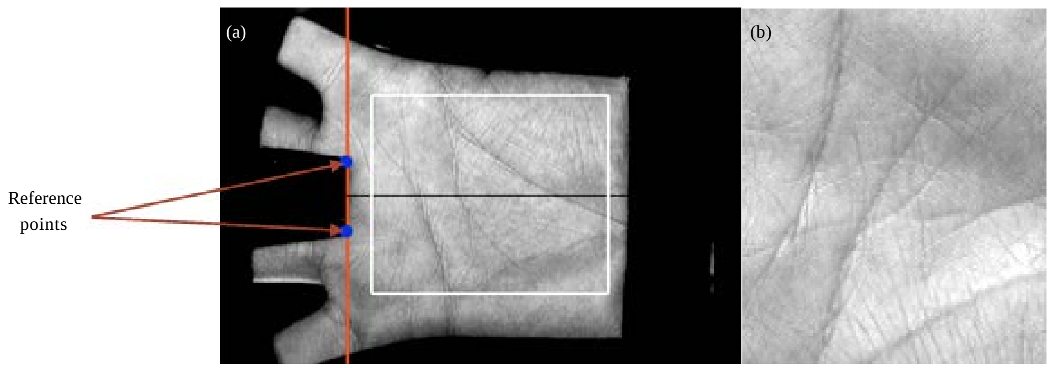

Fig. 2(a-b): (a) ROI selection-poly U database and (b) Extracted ROI

The description of the different blocks is explained as below.

Preprocessing: The first step in any biometric authentication system after capturing the image is preprocessing. Preprocessing is used to align different palm print images and to segment the central parts for feature extraction. Most of the preprocessing algorithms employ the key points between fingers to set up a coordinate system. Preprocessing involves generally five common steps: (1) Binarizing the palm images, (2) Extracting the contour of hand and/or fingers, (3) Detecting the key points, (4) Establishing a coordinate system and (5) Extracting the central parts. Initially the images in the database are filtered using median filter. This serves to enhance the edges in the palmprint images. The entire palmprint is not used for feature extraction but a Region of Interest (ROI) is extracted from the enhanced palmprint image. The Fig. 2 shows the reference points used and the extracted central palm area. The detailed steps are explained in the previous study (Rani and Lakshmi, 2012).

Feature extraction: Feature extraction plays an important role in image identification and verification. The palmprint contains principal lines that can be used to represent features but these lines are not sufficient to uniquely represent a person because the principal lines in some people are similar (Zhang *et al*., 2003). Hence, the texture features are extracted from the palmprint using Gabor filter.

Local gabor XOR pattern (LGXP): The circular Gabor filter (Zhang *et al*., 2003). is most suitable for texture analysis and has the form as shown in Eq. 1:

$$G(x,\ y,\ \theta,\ u,\ \sigma) = \frac{1}{2\pi\sigma^2}\exp\left\{\frac{-x^2+y^2}{2\sigma^2}\right\}\exp\{2\pi i(ux\cos\theta + uy\sin\theta)\} \tag{1}$$

where, $i = \sqrt{-1}$; u is the frequency of the sinusoidal wave; θ is the orientation of the function and σ is the standard deviation of the Gaussian envelope. Such Gabor filters have been widely used in various applications like fingerprint recognition, face recognition and texture analysis.

The Gabor filter $G(x, y, \theta, u, \sigma)$ forms the complex valued function. Decomposing $G(x, y, \theta, u, \sigma)$ into real and imaginary parts gives Eq. 2:

$$G(x, y, \theta, u, \sigma) = R(x, y, \theta, u, \sigma)+jI(x, y, \theta, u, \sigma) \quad (2)$$

where, $R(x, y, \theta, u, \sigma)$ and $I(x, y, \theta, u, \sigma)$ represent the real and imaginary parts of the Gabor filter. In order to provide more robustness to brightness variation a zero mean Gabor filter is necessary. The mean value of the imaginary part of the Gabor filter is automatically zero because of the odd symmetry of the sine function but the mean of the real part of the filter is not zero because of the even symmetry of the cosine function. A zero mean Gabor filter is obtained using Eq. 3 given below:

$$G^{ZM}(x, y, \theta, u, \sigma) = G(x, y, \theta, u, \sigma) - \frac{\sum_{i=n}^{n}\sum_{j=n}^{n} G(x, y, \theta, u, \sigma)}{(2n+1)^2} \quad (3)$$

where, $(2n+1)^2$ represents the size of the filter. The magnitude and phase part are then computed using the Eq. 4 and 5:

$$M(x, y) = \sqrt{G*I(x, y)\times \overline{G*I(x, y)}} \quad (4)$$

$$P(x, y) = \tan^{-1}\left\{\frac{\overline{G*I(x, y)} - G*I(x, y)}{G*I(x, y) + \overline{G*I(x, y)}}\right\} \quad (5)$$

The phase values are then quantized and the LXP operator is applied to the quantized phases of the central pixel and each of its neighbors and finally the resulting binary labels are concatenated together as the local pattern of the central pixel as shown in Fig. 3.

The pattern map described above for a 3×3 sub image is calculated and same is obtained for n number of the sub image. Finally the concatenated pattern map for the filtered image is given as Eq. 6:

$$LGXP = [LGXP_1, LGXP_2 \ldots\ldots LGXP_n] \quad (6)$$

Principal component analysis: Next the PCA feature is computed. PCA is also known as Karhunen-Loeve (K-L) transform. PCA is a classic appearance-based technique used to extract global features in many applications such as iris recognition face recognition and image compression. It is a way of identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences. The objectives of PCA are to reduce the dimension of the data set and identify new meaningful underlying variables. The key idea is to project the objects to an orthogonal subspace for their compact representations. It usually involves a mathematical procedure that transforms a number of correlated variables into a smaller number of uncorrelated variables which are called principal components. The basic approach is to compute the eigenvectors of the covariance matrix and approximate the original data by a linear combination of the leading eigenvectors. The personal identification using PCA is found in (Lu *et al*., 2003).

RESULTS

Three experiments were conducted and the identification results are compared. The experimental results are evaluated on the polyU database that contains 7752 grayscale images corresponding to 386 different palms in BMP image format. Around twenty samples from each of these palms were collected in two sessions where around 10 samples were captured in the first session and the second session, respectively. The average interval between the first and the second collection was two months.

LGXP feature: In the experiment 4 samples of each 150 persons captured during the first session are used in training set and remaining samples are used in the testing phase. The success of 2D Gabor phase coding depends on the selection of the Gabor filter parameters, θ, σ and u. The optimized parameters of the Gabor filter are given as, $\theta = 30°$, $\sigma = 5.5$ and $u = 0.091$ (Zhang *et al*., 2003).The dimensions of the PCA feature is selected as 100. In the training phase the LGXP feature is obtained for above parameters and stored in the database as master template. In the testing phase, the LGXP feature is obtained for the test image and matching is done using Euclidean distance. Since, the database contains four

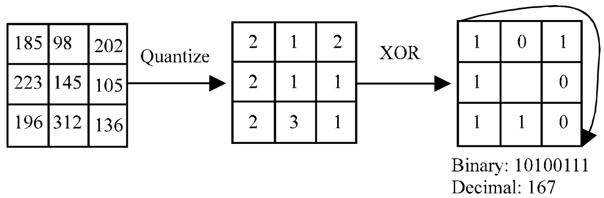

Fig. 3: Encoding method of LGXP

images of each person, for each test image four matching scores are generated by the matcher. The minimum of these distances is taken as the matching score and thus the name Minimum Distance Rule (MDR). After calculating the distance, the image can be recognized by using the thresholding technique which is described in the following pseudo code.

```
Thresh←t; // t is the average distance value
If min(dist)< Thresh Then
      Assign ismatch is True;
Else
      Assign ismatch is False;
End if
```

MOLGXP feature: In the above experiment only single orientation was used and selected to be $\theta = 30°$ but here the value of the LGXP features are obtained for six different orientations of θ = 30, 60, 90, 120, 1500 and 180°. They are concatenated to form the total feature set. This feature set is called as multiple orientation LGXP feature (MOLGXP).

MOLGXP and PCA feature: In addition to the MOLGXP the PCA feature is also computed for each of the palmprint image. In the testing phase the minimum Euclidean distance is computed for MOLGXP feature and PCA feature. Let m_1 represent the matching score from the MOLGXP matcher and m_2 from the PCA matcher. The combined score m using the sum rule (Ross *et al*., 2006) is given by:

$$m = m_1+m_2$$

The Fig. 4a and b shows the real and imaginary parts of the filtered palmprint image and Fig. 5a and b shows the magnitude and phase part of the filtered image for different orientations.

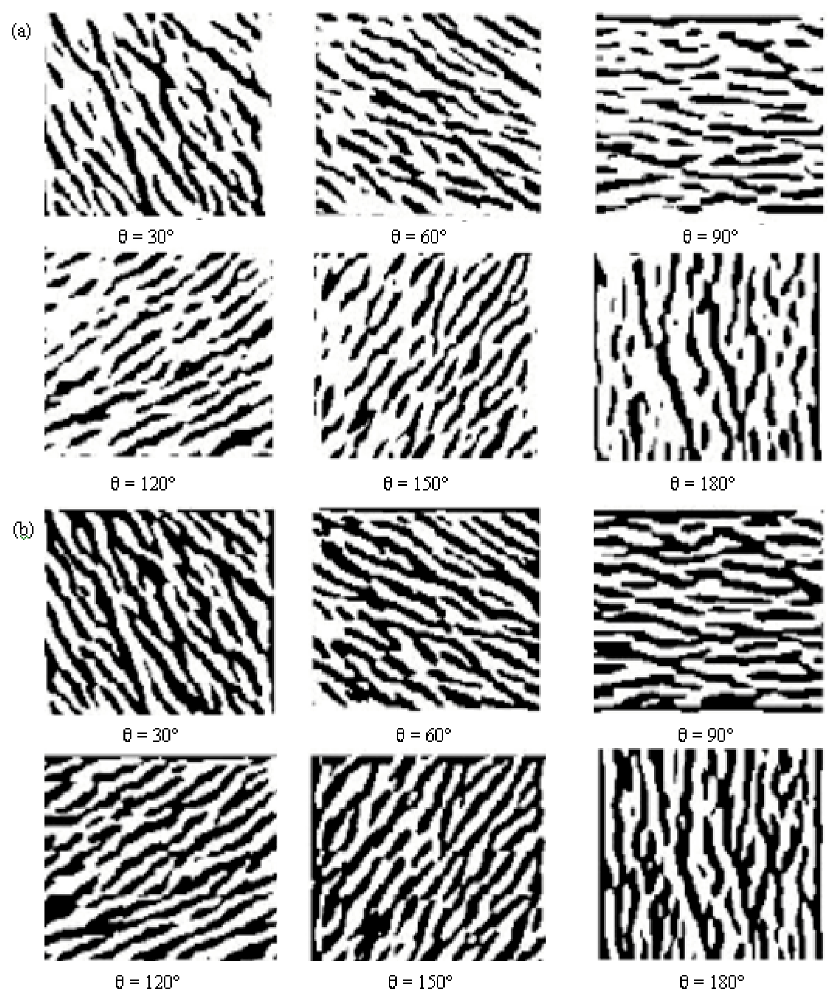

Fig. 4(a-b): (a) Real part and (b) Imaginary part for different orientations

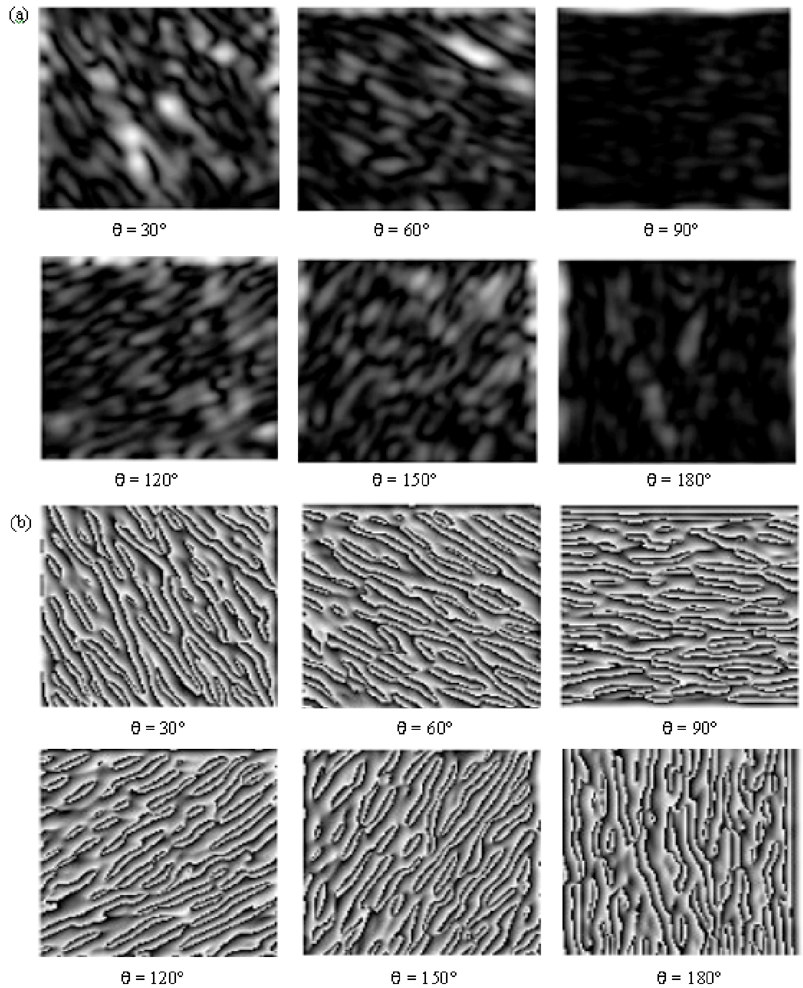

Fig. 5(a-b): (a) Magnitude part and (b) Phase part for different orientations

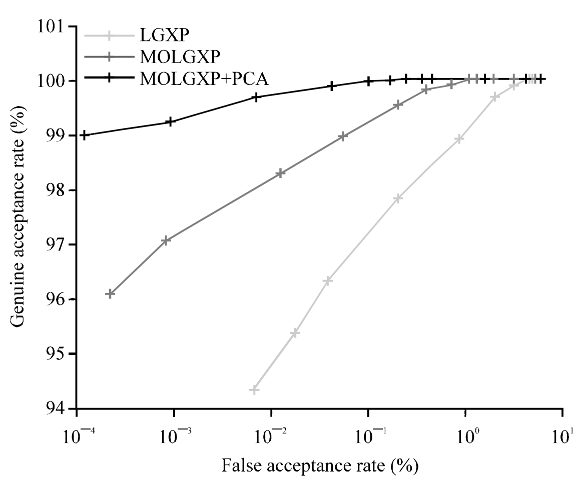

Fig. 6: Receiver operating characteristics

The Fig. 6 shows the Receiver Operating Characteristics (ROC) as a plot of genuine acceptance rate against the false acceptance rate at different threshold values for all the three experiments.

COMPARATIVE ANALYSIS

This sub section presents the comparative analysis of the proposed approach. We have compared the recognition accuracy of the proposed approach with some existing approaches. Computing the False Acceptance Rate (FAR) and False Rejection Rate (FRR) is the common way to measure the biometric recognition accuracy. FAR is the percentage of incorrect acceptances i.e., percentage of distance measures of different people's images that fall below the threshold. FRR is the percentage of incorrect rejections-i.e., percentage of distance measures of same

Table 1: Performance measure for the proposed and the existing methods

Method	FRR (%)	FAR (%)	EER (%)	GAR (%)
LGXP	5.860	0.00650	1.14	94.14
MOLGXP	3.500	0.00022	0.19	96.50
MOLGXP+PCA	1.030	0.00012	0.12	98.97
Competitive code	1.336	0.00010	-	98.66
Fusion code	4.560	0.00691	-	95.44

people's images that exceed the threshold. Genuine Acceptance Rate (GAR) gives the recognition rate and is given by GAR = 1-FRR. Table 1 gives the percentage of the recognition rates and the accuracy rates. The performance measure for the proposed and the existing methods are described in the Table 1.

CONCLUSION

In this study, we have proposed a palmprint recognition system based on LGXP and principal components features. Different experiments have been conducted. In the first case the LGXP feature for a single orientation is alone considered. A recognition rate of 94.34% is achieved and it is improved to 97.08% when the same LGXP feature is considered for six different orientations with the features being concatenated. In the third case principal component features are extracted and the matching score is combined with score of MOLGXP feature using the score level fusion. This further improved the recognition rate to 98.97%. The proposed technique is found to perform better when compared to the competitive code and fusion code.

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