Features Reduction using Wavelet and Discriminative Common Vector and Recognizing Faces using RBF

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ABSTRACT

Recognizing patterns by radial basis function network using reduced features obtained through wavelet transformation and discriminative common vector is proposed. Wavelet coefficients obtained after applying wavelet transformations on input patterns, are used to extract significant features from the samples. The discriminative common vectors are extracted using the within-class scatter matrix method from the wavelet coefficients. The discriminative common vectors are classified using radial basis function network. The proposed system is validated using three face databases such as ORL, The Japanese Female Facial Expression (JAFFE) and Essex Face database. The proposed method reduces the number of features, minimizes the computational complexity and provides better recognition rates.

General Terms
Face Recognition

Keywords
Feature extraction, Wavelet transformation, Discriminative common vector, Radial basis function network.

1. INTRODUCTION

Pattern recognition tasks are predominant all over the world and there have been growing interests on pattern recognition problems in the community of machine learning. Typical pattern recognition systems are designed using two steps. The first step is a feature extractor that finds features within the data which are specific to the task being solved. The second step is a classifier, which may use any general procedure or neural network for doing classification. The feature extractor typically requires most design effort, since it usually be based on what the application is trying to achieve.

In the past, many feature extraction approaches have been studied. Principal component analysis (PCA) is the typical method, by which faces are represented by a linear combination of weighted eigenvectors, known as eigenfaces [1]. In practice, there are several limitations accompanying PCA-based methods. In this, the pixelwise covariance among the pixels may not be sufficient for recognition. PCA usually gives high similarities indiscriminately for two images of a single person or from two different persons. The Linear Discriminant Analysis (LDA) method overcomes the limitations of the Eigenface method using Fisher linear discriminant Model [2, 3]. Cevikalp et al. have proposed a new face recognition method called the Discriminative Common Vector (DCV), in which one algorithm uses within-class scatter matrix of the samples in the training set while the other uses the subspace methods and the Gram-Schmidt orthogonalization procedure is used to obtain the DCV [4]. The Common Vector (CV) method has been originally proposed for isolated word recognition problem and then it was applied to the face recognition problem [5].

A novel face recognition approach based on kernel discriminative common vectors (KDCV) and RBF network is proposed. In this, kernel DCV (KDCV) algorithm is employed to generate discriminative common vector and DCV generated by the KDCV are used as the hidden-layer units of the RBF network [6] for recognizing the patterns. Boosting Kernel Discriminative Common Vector (BKDCV) [7] is used to further improve the overall performance of KDCV by integrating the boosting and KDCV techniques. Cevikalp et al. have proposed a DCV method with kernels, which first map all data samples to a higher dimensional feature space through a nonlinear mapping, and then, the DCV method is applied in the mapped space [8]. Carlos et al. have performed the feature reduction based on discriminative common vector which result in less load time and improved recognition rate [9].

The wavelet techniques are applied to solve many real world problems, particularly in image processing and face recognition [10, 11]. A new face recognition method based on wavelet transform and radial basis function fusion network is proposed in which an image is decomposed with wavelet transform (WT) to three levels and the Fisherface method is applied to three low-frequency sub-images [12]. Chengjun Liu and Harry Wechsler [13] have introduced a novel Gabor-Fisher Classifier (GFC) for face recognition. The GFC method, which is robust to changes in illumination and facial expression, uses the Enhanced Fisher linear discriminant Model (EFM) to an augmented Gabor feature vector derived from the Gabor wavelet representation of face images. Chien and Wu [14] have proposed a hybrid approach, in which, the multiresolution wavelet transform is applied to extract waveletface and the linear discriminant analysis is on waveletfaces to reinforce discriminant power, then the nearest feature plane (NFP) and nearest feature space (NFS) classifiers are explored for robust decision in presence of wide facial variations. Shen et al. [15] have presented a frame work based on a combination of Gabor wavelets and General Discriminant Analysis for face identification and verification. Guang Dai et al. [16] proposed an enhanced kernel discriminant analysis (KDA) algorithm called kernel fractional-step discriminant analysis (KFDA) for nonlinear feature extraction and dimensionality reduction. To further strengthen the overall performance of KDA algorithms for face recognition, they have proposed two new kernel functions: cosine fractional-power polynomial kernel and non-normal Gaussian RBF kernel.

Radial Basis Function Neural Network is a special type of artificial neural network suitable for classification, time-series forecasting and so on. The principle of back propagation is used to tune the RBF network [17, 18]. Balasubramanian et al. [19] have presented a method for automatic real time face and mouth in video sequences recognition using radial basis function neural networks (RBFNN). Bicheng Li and Hujun Yin have presented a face recognition system using radial basis function neural network and wavelet transformation [20]. RBF neural network with a new incremental learning method based on the regularized orthogonal least square (ROLS) algorithm is proposed by Yee Wan Wong for face recognition [21].

In this paper, a face recognition system which extracts features in reduced dimension namely discriminant common vectors using within class scatter matrix from the wavelet coefficients is proposed. The features, discriminative common vectors are recognized by the radial basis function neural network. The paper is organized as follows: Section 2 describes feature extraction using wavelet transform and the discriminative common vector. Section 3 presents recognition process using radial basis function network. Section 4 describes the data set and experiment results along with discussions.

2. FEATURE EXTRACTION

Feature extraction in the sense of some linear or nonlinear transform of the data with subsequent feature selection is commonly used for reducing the dimensionality of the patterns. The wavelet transformation is applied and then discriminant common vectors are obtained from the wavelet coefficients during feature extraction. This proposed work comprises of an effective face representation using wavelet transformation and DCV and is recognized using RBF network. In the first step, we used Wavelet transformation on the face images in order to get a dimensionally reduced face features. In the second step of the proposed work, the DCV values are obtained from the wavelet coefficients using the within class scatter matrix method.

2.1 Wavelet transform

Wavelet transform can result in robust representations with regard to lighting changes and be capable of capturing substantial facial features while keeping computational complexity low [10]. In the proposed work, wavelet transform is created by passing the face image through a series of filter bank stages. In the level-1 of wavelet transformation, the face image is applied to low pass and high pass filter and the values are down sampled by a factor in the horizontal direction. In the level-2, the filtered output of level-1 is then filtered by an identical filter pair in the vertical direction. The decomposition of the image into four wavelet frequency subbands is denoted by approximation (LL) and detailed coefficients (HL, LH, and HH) [22]. Each of these subband can be thought of as a smaller version of the image representing different image properties. The approximation wavelet coefficient is known as low frequency subband and the changes in pose or scale of a face affect only their low-frequency spectrum. In this proposed work, the low frequency approximation wavelet coefficients are only considered for further processing. The 2D wavelet transform is shown in Fig. 1[10]. The original image and the output of wavelet decomposition after level-2 are shown in Fig.2.

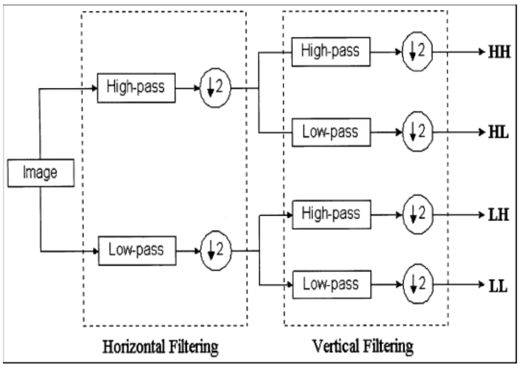

Fig 1: 2-D Wavelet Transformation

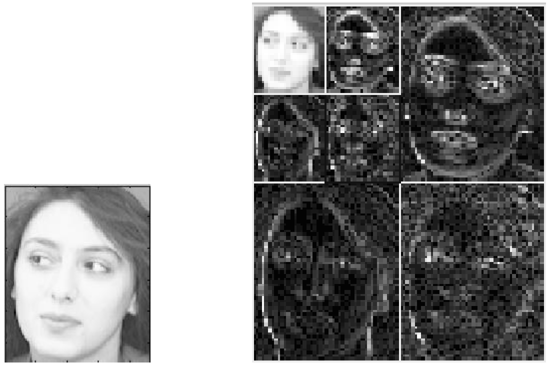

Fig 2: Original image and 2-level wavelet decomposition

2.2 Discriminative common vector

Wavelet coefficients can be applied directly in most of the applications. The direct use of wavelet coefficients may not extract the most discriminative features for two reasons such as there is much redundant or irrelevant information contained in wavelet coefficients and it cannot recover new meaning underlying features which have more discriminative power. In order to overcome the deficiency of direct use of wavelet coefficients, it is proposed to construct discriminant features from the wavelet coefficients using within-class scatter matrix method. A common vector for each individual class is obtained by removing all the features that are in the direction of the eigenvectors corresponding to the nonzero eigen values of within-class scatter matrix of all classes. The new set of vectors, called the discriminative common vectors, are used for recognition.

Let the training set be composed of C classes, where each class contains N samples. Let x_m^i denotes m th sample of i th class. Within-class scatter matrix of the samples is constructed to obtain feature vectors, which is defined as [4]

$$S_w = BB^T \tag{1}$$

where the matrix B is given by

$$B = [x_1^1 - \mu_1, ..., x_N^1 - \mu_1, x_1^2 - \mu_2, ..., x_N^C - \mu_C] \tag{2}$$

where x_i^j is i^{th} sample of class j and μ_j is mean of the samples in the j^{th} class.

Let us define Q = $[\alpha_{1,\ldots,}\ \alpha_r]$, which is the set of orthonormal eigenvectors corresponding to the non-null eigenvalues of S_w and r is the dimension of S_w. Next choose an input sample and project it on the null space of S_w in order to get the common vectors, defined as:

$$\boldsymbol{x_{com}^i} = \boldsymbol{x_m^i} - \boldsymbol{Q\overline{Q}x_m^i} \qquad (3)$$

where m = 1…N samples and i = 1…C classes. Calculate the principal components of S_{com} (the eigenvectors w_k), which correspond to the non zero eigenvalues as defined as:

$$J(W_{opt}) = \arg\max_{W}[W^T S_{com} W] \qquad (4)$$

where S_{com} is computed as

$$S_{com} = B_{com} B_{com}^T \qquad (5)$$

where B_{com} is given by

$$B_{com} = [x_{com}^1 - \mu_{com} \ldots x_{com}^C - \mu_{com}] \qquad (6)$$

The Feature Vector of Training set is calculated as

$$\Omega_i = W^T x_m^i \qquad (7)$$

Similarly, to recognize a test image x_{test}, the feature vector of this test image is found by

$$\Omega_{test} = W^T x_{test} \qquad (8)$$

The above method is summarized as follows:

1. Compute nonzero eigenvalues and corresponding eigenvectors of S_w using the matrix BB^T, where B is computed using equation (2).
2. Choose an input sample from each class and project it onto the null space of S_w to obtain the common vectors. Compute $\boldsymbol{x_{com}^i}$ using equation (3).
3. Compute the eigenvectors w_k of S_{com}, corresponding to the nonzero eigenvalues, by using the equations (4) and (5).
4. The feature vector for training set and test set is obtained using equation (7) and (8) respectively.

The entire proposed work is summarized as follows.

1. Apply wavelet transformation and compute the wavelet coefficients for each pattern.
2. Compute the DCV Coefficients using the with-in class scatter matrix method.
3. Train the RBF network for recognizing DCV coefficients using algorithm in section 3.1.
4. Compute the DCV Coefficients for testing samples and find output of the RBF network.
5. Compute the recognition rate.

3. RECOGNITION BY RBF NETWORK

Radial Basis Function neural network (RBF) is used for recognition of discriminative common vectors which contains three layers: input, hidden and output layers. Fig. 3 displays the basic structure of the RBF network. The number of nodes in the input layer corresponds to the dimension of DCV coefficients. The *n* input neurons are normalized and then sent to each of the neurons in the hidden layer. The basis function of the hidden layer neurons are considered as Gaussian function and computed basis function output are passed to the output layer.

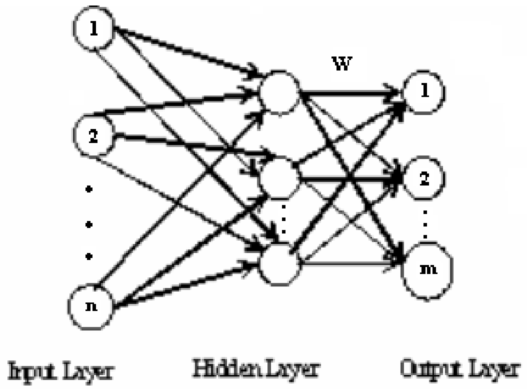

Fig 3: Structure of the RBF network

The hidden layer output (basis function) is computed as

$$\boldsymbol{\varphi_j}(\boldsymbol{X}) = \exp\left\{-\frac{\|\boldsymbol{X} - \boldsymbol{\mu}\|^2}{\boldsymbol{\sigma}^2}\right\} \qquad (9)$$

where $X = (x_1, x_2, \ldots x_n)^T$ is the normalized input vector, μ is the center and σ is the width.

The output of the output layer is computed as

$$y_i = \sum_{j=1}^{k} w_{ji} \varphi_j(X) \qquad (10)$$

where k is the number of hidden neurons, w_{ji} are the weights connecting the hidden layer neuron *j* and output layer neuron *i*. The weights are adjusted using the formula,

$$w(t+1) = w(t) + \lambda(d_i - y_i)\varphi_j(X) \qquad (11)$$

where λ is a positive learning rate parameter and *di* is the desired output.

3.1 Algorithm

The training algorithm of Radial Basis Function Network is given as follows [23].

Step 1. Generate random numbers to initialize the weights of the RBF network.
Step 2. Enter the input pattern (DCV coefficients) and expected output values.
Step 3. For each input pattern, compute hidden layer output using equation (9).
Step 4. Compute the output layer output using equation (10).
Step 5. Find the error as the difference between desired and obtained actual output.
Step 6. Adjust the hidden layer weights according to equation (11).
Step 7. Find output of the output layer.
Step 8. Compute sum of squared error of the network.
Step 9. Repeat steps 3-8 for all input patterns.
Step 10. Repeat steps 3-9 until the acceptable minimum error level is reached.

4. RESULTS AND DISCUSSIONS

The proposed work has been carried out using Matlab 7.1 on AMD Athlon processor with 1.81 GHz system and 640 MB RAM. The proposed work is tested on three face databases such as ORL, the Japanese Female Facial Expression (JAFFE) and Essex Face database. Better recognition is achieved when the classification is done using the radial basis function neural network. The RBF network is trained by considering different learning rate values and the network which is giving better results is discussed here. The centers of the basis function are selected randomly. 2-level wavelet transformation is used in the experiment as it gives better recognition rate.

The ORL face data base contains 40 faces of size as 112 x 92 and each face has 10 different facial views representing various expressions, small occlusion by glasses, different scale and orientations. Hence, there are 400 face images in the database. In the proposed method 5 different poses of 20 person's face are used for training and 5 different poses of 20 person's faces are used for testing the proposed method. The 5 poses for training and 5 poses for testing are considered sequentially. The Japanese Female Facial Expression contains different facial expressions posed by Japanese female models in which 5 different poses of 15 models are used for training and the other 5 different poses of 15 models are used for testing. The actual dimension of the image is 256x256. The Essex Face database is having faces of more than 150 male and female with 20 images per individual of University of Essex, UK with the size of 180 x 200. Table 1 shows the reduced size of the resultant wavelet coefficient, for different types of wavelet, after applying 2-level wavelet transformation.

Table 1. Size of the wavelet coefficients

Wavelet Name	Size of the wavelet Coefficients		
	ORL Database	JAFFE Database	Essex Database
Haar	28 x 23	64 x 64	45 x 50
Sym4	33 x 28	69 x 69	55 x 50
Sym8	39 x 34	75 x 75	61 x 56
Db4	33 x 28	69 x 69	55 x 50
Db6	36 x 31	72 x 72	58 x 53
Coif2	36 x 31	72 x 72	58 x 53
Coif4	45 x 40	81 x 81	67 x 62

The original face image and their corresponding wavelet representations after two levels wavelet decomposition are shown in Fig. 4. The original face image and their corresponding Discriminative Common vectors representations are shown in Fig. 5. Three level wavelet transform is applied on input patterns with dimension 112×92 and obtained 14x12 dimensioned image representations as a result.

Fig 4: Original image and the wavelet representations after 2-level decomposition

Fig 5: Original image, the discriminative common vectors

The recognition rate for different classes using RBF with wavelet coefficients is shown in Table 2 and RBF with DCV of wavelet coefficients is presented in Table 3. The chart given in Fig. 6 compares the recognition rate of RBF with Wavelet and RBF with Wavelet and DCV for different classes.

Table 2. Recognition rate of RBF with wavelet – ORL

Method	Classes	Recognition rate (%)
RBF + Wavelet	5	93.33
	7	95.24
	10	94.44
	15	96.67
	20	97.6

Table 3. Recognition rate of RBF wavelet and DCV - ORL

Method	Classes	Recognition rate (%)
RBF + DCV + Wavelet	5	94.44
	7	96.67
	10	95.24
	15	97.33
	20	98.4

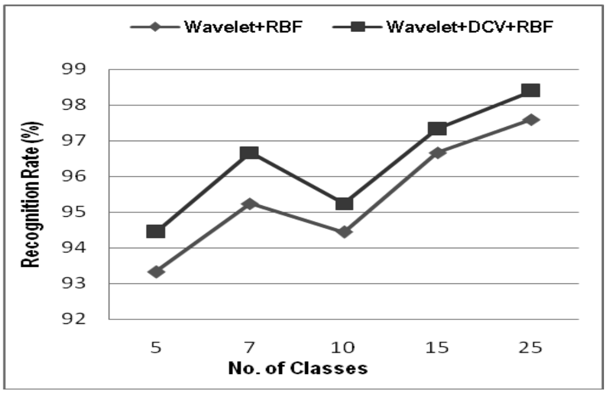

Fig 6: Comparison of Recognition Rates

Some sample faces of JAFFE database are shown in Fig.7. After applying 3-level wavelet transformation the size is reduced to 32x32 and the resultant images are shown in Fig.8.

Fig 7: Sample faces of JAFFE database

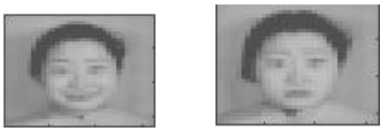

Fig 8: After 3-level decomposition

The wavelet coefficients are obtained from the samples and recognition process proceeded with the obtained Wavelet coefficients and DCV of wavelet coefficients. The sample images from Essex database and its corresponding wavelet coefficients at various levels with the dimensions are shown in Fig. 9. The image corresponding to discriminative common vector obtained for the Essex data base is shown in Fig.10.

Fig 9: Wavelet decomposition at various levels

Fig 10: Sample face and its discriminative common vector

Training and then testing process are carried out for 25 different times. The recognition rates discussed here are the average of 25 different trials. The recognition rates of the three databases for different wavelets namely Haar, Sym4, Sym8, Db4, Db6, Coif2, Coif4 are shown in Table 4. The RBF network is trained by setting different learning rate. The epoch, training time and recognition rate for various classes with different learning rate are listed in the Table 5 for ORL database. The Time complexity of both the methods such as RBF with wavelet and RBF with wavelet and DCV are compared and listed in Table 6. The recognition rate obtained for Haar wavelet after applying 3-level decomposition is shown in Table 7. It has been observed that recognition rate of 3-level wavelet transformation is lesser than 2-level wavelet transformation. Table 8 is the comparative table of the recognition rates obtained for three different databases. The recognition rate 97.54% is obtained by the method Push-Pull Marginal Discriminant Analysis on ORL database. The MLA+NM method has the recognition rate of 97% on JAFFE database. When Essex database is used, the recognition rate of 97.2% has been achieved by Curvelet with SVM. Eigen face, wavelet face and SVM methods have better results when combined with neural networks (NN) or convolution neural networks. The sum of square error curves for the proposed method RBF with wavelet and RBF with wavelet and DCV are shown in Fig. 11 and Fig. 12 respectively.

Table 4. Recognition rates for three databases

Wavelet Name	Recognition Rate (%)		
	ORL Database	JAFFE Database	Essex Database
Haar	98.0	98.4	98.45
Sym4	97.0	97.33	97.67
Sym8	96.67	96.67	96.45
Db4	96.66	97.0	96.5
Db6	97.0	96.67	97.0
Coif2	95.67	96.0	98.0
Coif4	96.0	97.0	96.33

Table 5. Epoch, training time and recognition rate for different learning rate

No. of classes	Learning rate	Epoch	Training Time (in sec)	Recognition Rate (%)
3	0.1	23	0.435	100
3	0.01	308	8.60	100
6	0.1	28	0.50	100
6	0.01	284	9.28	100
10	0.1	36	1.80	98
10	0.01	374	18.07	98

Table 6. Training time

Method	Training Time in Seconds					
	3 classes		6 classes		10 classes	
	μ=0.1	μ=0.01	μ=0.1	μ=0.01	μ=0.1	μ=0.01
RBF + Wavelet	0.435	8.60	0.50	9.28	1.80	18.07
RBF+ DCV + Wavelet	0.1721	4.47	.0.253	5.141	1.33	10.29

Table 7. Recognition rate for 3-level Wavelet transformation

Wavelet Name	ORL	JAFFE	ESSEX
Haar – 3 Level	90.08%	90.14%	90.32%

Table 8. Comparison of recognition rates

Method	ORL	Method	JAFFE	Method	Essex
Eigen faces	89.5%	MLA + NN	91.14%	Wavelet + HMM	84.2%
Direct LDA	90.8%	LDA + SVM	91.27%	DWT+ PCA	86.1%
Eigen faces + NN	91.2%	SVM	91.6%	PZM	88.02%
2DPCA	96%	Adaboost	92.4%	Gabor + SHMM	88.7%
DCV method	96.2%	LBP +SVM	92.0%	DM	91.72%
Discriminant wavelet+ Nearest feature	96.4%	PCA + SVM	93.43%	Fisher faces	92.62%
Push-Pull Marginal Discriminant Analysis	97.54%	MLA + NM	97.0%	Curvelet + SVM	97.2%
Proposed Methods					
RBF+ Wavelet	97.6%	RBF+ Wavelet	98.0%	RBF+ Wavelet	97.33%
RBF+ Wavelet +DCV	98.0%	RBF+ Wavelet+ DCV	98.4%	RBF+ Wavelet+ DCV	98.45%

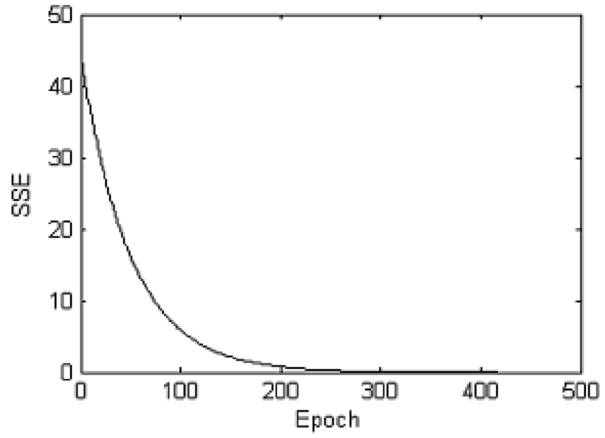

Fig 11: SSE curve for the RBF+wavelet method when μ=0.01 and epoch =418

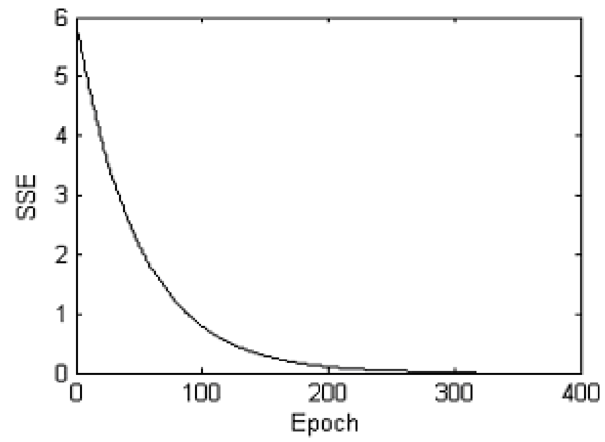

Fig 12: SSE curve for the RBF+wavelet +DCV method when μ=0.01 and epoch =327

5. CONCLUSION

A pattern recognition system comprised of radial basis function network using wavelet transformation and discriminative common vector is proposed. The features are reduced and extracted using wavelet transformation and DCV method. The proposed work uses only the low frequency wavelet coefficients of 2-level wavelet transformation and it is observed that only those low frequency components are sufficient for the better recognition process. It has been found that the execution time of RBF is minimized when the wavelet and discriminative common vectors are used in a combined way. The recognition rate is improved due to the significant discriminative common vectors obtained from the wavelet coefficients.

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