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Face Recognition through Symbolic Modeling and Analysis of Segmented face images using Savitzky Golay filter features

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Abstract—**Face biometrics has become an important technology for person identification and verification and large amount of work has been reported in this direction. But many issues still need to be addressed to build a robust face biometric system for person identification. A few of such issues includes dealing with changes in expression, varying light conditions and presence of occlusion in the face images. The proposed work introduces a novel robust symbolic data modeling approach to face recognition technique, which use minimal set of face features to handle listed issues of face recognition. In this approach, initially face parts such as eyes, nose and mouth parts are cropped from the original face image using Viola-Jones algorithm. Further extracted face parts are converted into gray scale image of size 64 x 64 pixels. From each face part, optimal set of features are computed by using the Savitzky-Golay filter. The extracted features of face parts are represented as a symbolic data objects. Further, during the recognition phase newly devised symbolic similarity measure is employed to compute similarity between test objects and trained objects of face parts. The object is identified as belonging to the class with maximum similarity. The performance of the method has been evaluated by conducting experiments on AR face database and an average efficiency of 95.58% is obtained by considering all the face parts of face image**

Index Terms— **Symbolic Data, Savitzky-Golay filter, Face Recognition, Similarity Measure.**

I. Introduction

In the last few decades, face recognition has been one of the most active research topic due to its wide range of applications ranging from entertainment to information securities. Several biometric systems have been developed for person identification and recognition based on face biometric. To develop such biometric systems, several researchers have proposed various methods for face feature extraction and classifications, among which the representatives include subspace learning methods (e.g. Eigenface , Fisherface, Laplacianfaces), subspace learning from image gradient orientations (IGO) [1], kernel-based subspace learning methods [2], local directional pattern[1], local binary pattern (LBP), and local ternary patterns[3] methods, Gabor feature-based classification methods [4] so on. While performance of such method is greatly influenced by various factors such Illumination conditions, varying of facial expression, pose and occlusions from controlled environment to uncontrolled environment. Most of these methods in controlled conditions have already achieved impressive performance over large-scale face databases but there exist many challenges for face recognition in uncontrolled environments. The extraction of features from varying face images and representation of those extracted features in lower dimension feature space is a challenging task for face recognition. The proposed work use Savitzky–Golay [5] moving filter for feature extraction. The extracted features represent such variations of face images in an efficient manner.

Savitzky–Golay filter was originally used for smoothing the noisy data obtained from chemical spectrum analyzers [5]. To minimize the mean-square error, for a given data set least-square fit is adopted [6]. The major advantages of the Savitzky–Golay filter is, it can be used to simultaneously compute higher order derivatives along with smoothing i.e. it preserves higher order statistics such as edges/lines present in the input data. Hence in the proposed symbolic approach to face recognition, Savitzky-Golay filter is used to compute an optimal set of face features, which reflects variations of face image. Another challenge for face recognition is representation of such face features in lower dimension in order to reduce the amount of computation time required for classification. Larger the dimensionality, more sever is the problem of storage and analysis [7] leading to larger amount of computation time. In this direction a new symbolic modeling approaches for classification, clustering and other applications [8] are introduced. Hiremath and his co-authors propose a PCA [7], LDA [9], KPCA+LDA [10], features based face recognition using symbolic modeling techniques for dimension reduction.

Even though little effort has been made in the applications of face recognition through symbolic approach, complete advantages of symbolic data modeling technique has not been explored. Hence, it is necessary to build an efficient and robust face recognition system that uses minimal set of face features for recognition through symbolic modeling approach. The proposed methodology aims for face recognition by using the concept of symbolic data analysis. In which each class consists of N number of assertion objects which are represented by two variables Dx and Dy as they represent optimal set of face features in the vertical and horizontal directions respectively, which stand for knowledge base for classification. Further, each class of face image is represented by a single synthetic object. Each synthetic object consists of four Hoard objects. The Hoard objects represent left eye, right eye, nose and mouth parts of each face class and are represented with maximum and minimum values of Dx and Dy. During the evaluation, test synthetic symbolic object is measured with all the trained synthetic objects. The object which represents the maximum similarity score is treated as recognized object or recognized face class.

The rest of the paper is organized as follows: Section II describes the proposed methodology. Section III describes steps involved in symbolic representation and data modeling techniques for face recognition. Section IV describes procedure involve in similarity analysis between symbolic knowledge base and test object. Section V gives experimental results. Section VI presents concluding remarks.

II. Proposed Methodology

The purposed methodology presents a new symbolic modeling technique for face recognition based on optimal set of face features, which are extracted by using Savitzky-Golay filter. To overcome the complexity of using texture features on entire image, it divides the face into four parts namely eyes, nose and mouth and from each face part extracts the features in the vertical and horizontal directions respectively. The extracted features from each face part are represented as symbolic object which are further used for face recognition. The overall process involved in the proposed methodology is depicted in fig.1.

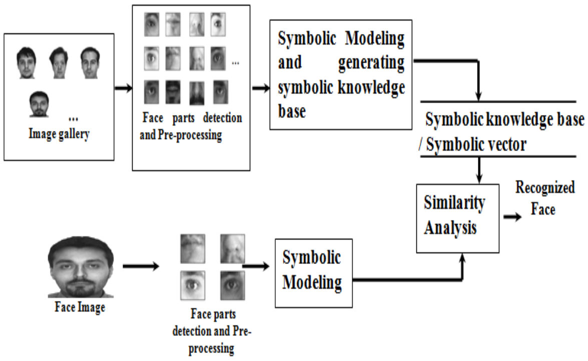

Figure1. The process involved in the proposed system

For face recognition, images from a database (drawn from AR database [11]) are taken and face parts are extracted using Viola-Jones algorithm [12]. The cropped face parts are rescaled to 64 x 64 pixels and converted into gray scale. Form each face part, optimal set of features are extracted by using Savitzky-Golay filter. Further, extracted features from face parts such as eyes, nose and mouth are represented as independent symbolic data objects which are used as symbolic knowledge base. Further, symbolic objects of eyes, mouth and nose belonging to a same face class are represented as a synthetic object. Using modified form of content based similarity measure, symbolic similarity between synthetic symbolic model of symbolic knowledge base and symbolic data model of test face parts images are computed. Synthetic object class that has maximum similarities to the test object is the recognized class of the test object.

III. Symbolic Representation and Data Modeling

This section describes the feature extraction technique and representation of features as symbolic faces.

A. *Features for Symbolic Representation*

In the proposed system, features required for face recognition are computed using Savitzky-Golay filters. The Savitzky-Golay filter is a particular type of low-pass filter which removes high frequency noise from the input data and is particularly suited for smoothing noisy data. The main advantage of Savitzky-Golay filter approach is that it tends to preserve features of the distribution such as relative maxima, minima and width, which are usually neglected by the other averaging techniques (like a moving average filter, for example).

Savitzky-Golay filters are widely used to fit one dimensional polynomial and compute its numerical derivatives. However, an image is a function of two variables; thus, 1D Savitzky-Golay differentiator need to be generalized to two dimensional to include both the x and y values [13]. The second order 2D polynomial f(x, y) employed in this work has the following form:

$$f(x,y) = c_{00} + c_{10}x + c_{01}y + c_{11}xy + c_{20}x^2 + c_{02}y^2 \quad (01)$$

where x and y are the two dimensional coordinates of a data point of f. c is column vector of polynomial coefficients.

The least-squares method can be used to estimate the coefficients of f accurately, hence in simpler way equation (01) can be described as:

$$d = M*c \quad (02)$$

Where d= [d_1, d_2..... d_F] ^{T} denotes the calculated magnitude points in the filter window, M = [m_1, m_2,....m_r]^T denotes the coefficient vector of the polynomial function and c is column vector of polynomial coefficients. In the proposed work order of the polynomial r(=2) and the template size F(=5) are determined empirically.

The overall process involved in the computation of face features is shown in fig.2.

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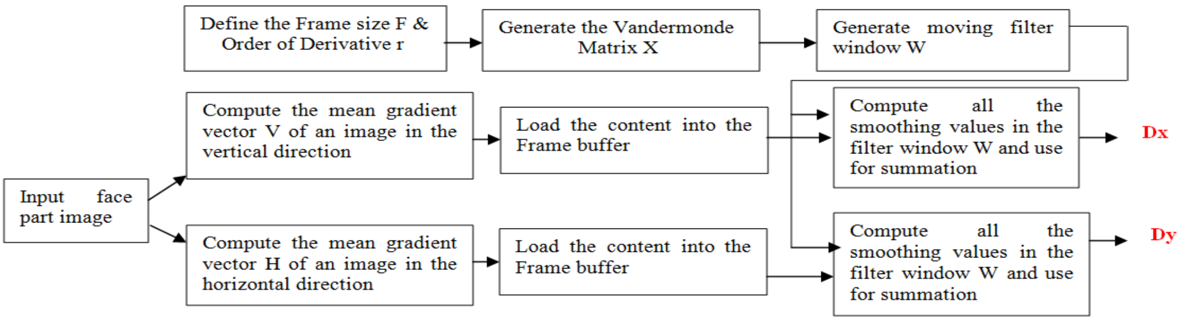

Figure 2. Computation of Dx and Dy features

Generate Vandermonde Matrix X with empirically chosen F=5 frame points. Further generate moving filtering window W using Vandermonde Matrix X of size F * (r+1). The matrix W denotes the moving window's coefficient matrix that can be used to estimate Dx and Dy features of given gray scale N x N size image f(x, y). In order to estimate the optimal set of features from face parts images using Savitzky-Golay filter, template W is defined. This template is used to compute optimal set of face features from face parts which are required for face recognition.

Further, calculate mean gradient vector I_{av_v} of face image f(x, y) in vertical direction as:

$$I_{av\_v} = \text{mean}(f) \tag{03}$$

Similarly, calculate mean gradient vector I_{av_h} of face image f(x, y) in horizontal direction as:

$$I_{av\_h} = \text{mean}(f) \tag{04}$$

Then, load I_{av_v} in to the frame buffer block I_{av_bv} (p,q) and I_{av_h} in to frame buffer block $I_{av\_bh}(p,q)$ so that the block redistribute the data in each column of the input to produce an output with a frame size 5 x 5.

Further, using 2D template $W^{(r)}(s,t)$ and equation (02), all the smoothing values in vertical and horizontal directions in the filter window W can be calculated by

$$I^{r}_{av\_bv}(p,q) = \sum_{s=-N}^{N}\sum_{t=-N}^{N} W^{r}(s,t) I_{av\_bv}(p-s, q-t) \tag{05}$$

and

$$I^{r}_{av\_bh}(p,q) = \sum_{s=-N}^{N}\sum_{t=-N}^{N} W^{r}(s,t) I_{av\_bh}(p-s, q-t) \tag{06}$$

Where t = N, r = 2 and W is the value of the template.

The smoothed points of $I^{r}_{av\_bv}(p,q)$ and $I^{r}_{av\_bh}(p,q)$ are found by replacing each point with the values of its fitted polynomial. Using the equations (05) and (06) the features Dx and Dy are computed as described in equations (07) and (08):

$$Dx = \sum_{i=0}^{N-1} I^{r}_{av\_bv}(p,q) \tag{07}$$

$$Dy = \sum_{i=0}^{N-1} I^{r}_{av\_bh}(p,q) \tag{08}$$

Further, these extracted Dx and Dy features are used for symbolic data modeling for face recognition.

B. *Symbolic Data Modeling*

Let the face image database consists of N number of face image classes and each class of face image consists of M number of face images that vary in expression, occlusion and illuminations (Images are drawn from AR database).

Let $\Omega = \{ \Psi_1, \Psi_2, \Psi_3 \ldots \Psi_M \}$ be a set that represents M images of a face class, which are used for training.

Let mouth, nose, left eye, right eyes are the four parts extracted form j^{th} face image Ψ of i^{th} class and may be represented as

$$\psi_j^{\,i} = \{ \text{mouth}_j\, i, \text{nose}_j\, i, \text{left\_eye}_j\, i, \text{right\_eye}_j\, i \} \tag{09}$$

In general all face image classes can be represented as

$$U = \{ \Omega_I \} \; \forall\, i=1 \text{ to } N \tag{10}$$

In this work, each face part such as nose, mouth and eyes is represented by a single assertion object, which consists of two features Dx and Dy. Each face part class of M samples is represented by a single Hoard object. The Hoard object indicates the minimum and maximum feature values of M assertion objects of each face part. Further, entire face class is represented by a single synthetic object which consists of four Hoard objects namely HO_Nose, HO_Mouth, HO_Lefteye, and HO_Righteye of nose, mouth, left eye and right eye parts of face images respectively.

The symbolic synthetic object of i^{th} face class of training images can be represented as:

$$SO^{(i)}=[\{ HO\_Nose^{(i)}\},\{HO\_Mouth^{(i)}\},\{ HO\_Lefteye^{(i)}\}, \{ HO\_Righteye^{(i)}\}] \tag{11}$$

Where $\forall\, i=1 \text{ to } N$ and

$HO\_Nose^{(i)} = [\{ \min(DxN)^{(i)}, \max(DxN)^{(i)} \}, \{ \min(DyN)^{(i)}, \max(DyN)^{(i)} \}]$

$HO\_Mouth^{(i)} = [\{ \min(DxM)^{(i)}, \max(DxM)^{(i)} \}, \{ \min(DyM)^{(i)}, \max(DyM)^{(i)} \}]$

$HO\_Lefteye^{(i)} = [\{ \min(DxLE)^{(i)}, \max(DxLE)^{(i)} \}, \{ \min(DyLE)^{(i)}, \max(DyLE)^{(i)} \}]$

$HO\_Righteye^{(i)} = [\{ \min(DxRE)^{(i)}, \max(DxRE)^{(i)} \}, \{ \min(DyRE^{(i)}, \max(DyRE)^{(i)} \}]$

The symbolic Assertion object of i^{th} face class used for training can be represented as:

$$AO^{(i)} = [\ \{ DxN(nose_j\, i), DyN(nose_j\, i) \}, \{ DxM(mouth_j\, i), DyM(mouth_j\, i) \}, \{ DxLE(left\_eye_j\, i), DyLE(left\_eye_j\, i) \}, \{ DxRE(right\_eye_j\, i), DyRE(right\_eye_j\, i) \}\ ] \text{ for all } j = 1 \text{ to } M \quad (12)$$

Where $\forall$ i = 1 to N and $\forall$ j=1 to M

Similarly, symbolic representation of test face image can be represented as

$$\Psi = \{ TAO\_nose, TAO\_mouth, TAO\_left\_eye, TAO\_right\_eye \} \quad (13)$$

Where
TAO _ nose= { TDx, TDy }, TAO_ mouth = { TDx, TDy },
TAO_ left_eye = { TDx, TDy}
and TAO_ right_eye = { TDx, Dy}

The symbolic similarity analysis can be done by considering $SO^{(i)}$, $AO^{(i)}$ of trained objects and test symbolic object.

IV. Symbolic Similarity Analysis for Face Recognition

The similarity measure gives the similarity of the input face image to possible face classes [8] [14] [15]. To compute similarity/distance the measures described in [8] made up of three components namely span, content and position is employed after appropriate modification. As a face object has only quantitative and interval type values of Dx and Dy ie max-min values of Dx and Dy, the content similarity measure is modified and used in this work. The content similarity measure is used to assign test face image to trained face classes.

To define modified content based similarity between two quantitative and interval type values of object A_i, and object B_i

Let

a_lower = lower limit of object A_i (minimum value)

a_upper = upper limit of object A_i (maximum value)

b_lower = lower limit of object B_i (minimum value)

b_upper = upper limit of object B_i (maximum value)

inters = number of common elements between A_i and B_i objects and ls=span length of A_i and B_i

In the proposed work, for test object the lower limit is equal to the upper limit i.e. b_lower = b_upper

In general, the similarity component due to content between two symbolic objects $SO^{(i)}$ and Ψ of i^{th} class can be defined as

$$S^{(i)}(SO^{(i)}, \Psi) = inters^{(i)} / ls^{(i)} \quad (14)$$

Where $ls^{(i)} = |\max(SO^{(i)}_{upper}, \Psi_{upper}) - \min(SO^{(i)}_{lower}, \Psi_{lower})|$

$inters^{(i)} = \sum_{j=1}^{M} CMP(AO^{(i)}, \Psi) \quad \forall i = 1 \text{ to N and } \forall j = 1 \text{ to M}$, in which $inters^{(i)}$ is computed using overlap measure technique. Overlap measure technique assigns a similarity of 1 if the two values are approximately equal otherwise assigns similarity as 0. Hence, Overlap measure between $AO^{(i)}, \Psi$ at i^{th} class can be computed as:

$$CMP(AO^{(i)}, \Psi) = \begin{cases} 1 & \text{if } Dx(\Psi^i_j) \cong Dx(\Psi),\ Dy(\Psi^i_j) \cong Dy(\Psi) \\ 0 & \text{otherwise} \end{cases} \quad \forall i = 1 \text{ to N and } \forall j = 1 \text{ to M}$$

The similarity measure gives the similarity of Ψ (TAO _ nose / TAO_ mouth / TAO_ left_eye / TAO_ right_eye) of the test input face object with various assertion objects/synthetic objects $AO^{(i)}$ / $SO^{(i)}$ of ith trained face objects $S^{(i)}$ ($SO^{(i)}$,Ψ) can be calculated using the equation(14) as

$$S^{(i)}(SO^{(i)}, \Psi) = Net\_inters^{(i)} / Net\_ls^{(i)} \quad (15)$$

Where

$$Net\_inters^{(i)} = (inters^{(i)}_{nose} + inters^{(i)}_{mouth} + inters^{(i)}_{left\_eye} + inters^{(i)}_{right\_eye}) \text{ and}$$

$$Net\_ls^{(i)} = (ls_{nose} + ls_{mouth} + ls_{left\_eye} + ls_{right\_eye})$$

Further the net similarity of test object Ψ with all the N face classes can be represented as a 1 x N vector.

$$Netsim = [S^{(i)}], \forall i = 1 \text{ to } N \quad (16)$$

The find the identity of person class, class with max similarity is found in equation (17)

$$Face\_class\_ID = \max(Netsim) \quad (17)$$

In equation (17), max (Netsim) returns the index of the trained face class.

The results obtained from the proposed symbolic approach for face recognition are discussed in experimentation and analysis section.

V. Experimentation and Analysis

Performance of the proposed method is tested and evaluated using AR database [11]. There are face images of 120 persons in the AR database. The results of the proposed method indicate that it is robust against partial occlusions, expressions and

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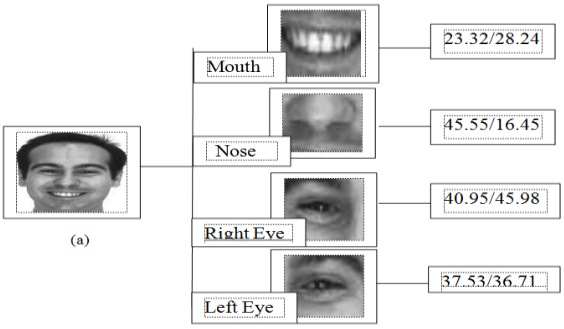
nonlinear lighting variations because face images are represented as symbolic objects as they are represented with minimum number of face features. Hence there is a minimum comparison involved in comparison between trained symbolic objects and test symbolic object. Some of the cropped face parts and their corresponding Dx and Dy face features are shown in fig.3.



(b) (c)

Figure 3. Sample AR Database image (a), corresponding cropped images (b), and extracted Dx and Dy values(c)

In order to evaluate the effectiveness of the proposed symbolic modeling approach, 1200 images of 120 persons from AR database is considered. 1200 face images are categorized into five unequal categories. The category C1 contains face images that vary in illumination, C2 contains some of the face images that vary in expression, C3 contains images of persons wearing sunglass and scarves, C4 contains face images of persons wearing sunglass in nonlinear light conditions and C5 contains person images wearing sunglass in non uniform light condition. The results obtained from experimentation are tabulated in table 1.

Fig.4 shows the average of the classification rates of the proposed symbolic approach to face recognition. All the results are obtained on an Intel® B960 processor (2 GHz) PC with the MATLAB R2014a tool. The average execution time for the proposed symbolic approach to face recognition is 0.827 sec per test image (considering all four face parts).

Table 1: Recognition results on C1 to C5

Individuals /Labels	**Total no. samples**	**No. of samples recognized correctly**	**No. of samples misclassified**	**Accuracy in %**
Illumination Variation(C1)	336	332	04	98.81
Expression (C2)	552	542	10	98.19
Occlusion(Scarves + Sunglasses) (C3)	(91+14)=105	87	(7+11)=18	82.86
Scarves- Illumination(C4)	197	180	17	91.37
Sunglasses- Illumination(C5)	10	06	04	60.00
Total number of images (C1+C2+C4+C5)	1200	1147	53	95.58

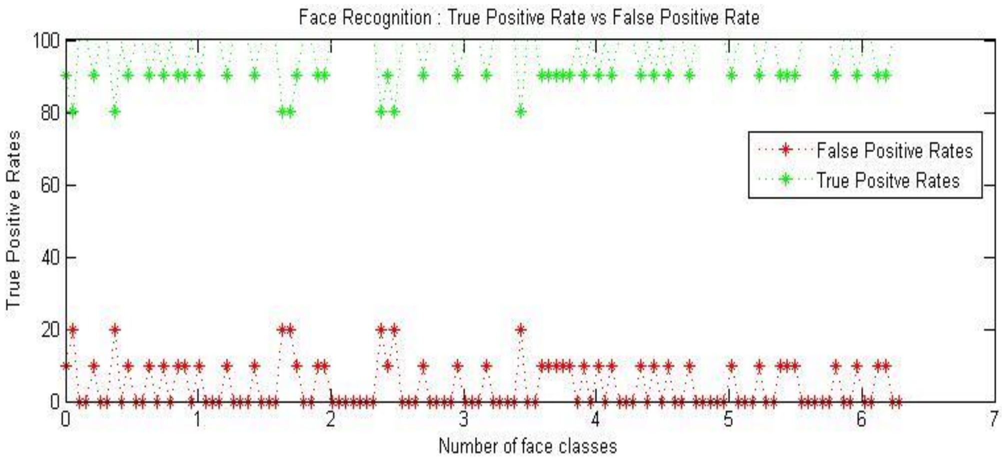


Figure 4. Recognition Rate: True Positive vs False Positive Rate

In the real world face recognition problem, sometimes it is not possible to extract all face parts due to occlusions, vary light conditions and expression changes. Therefore entire face image representation is severely affected when these regions vary or are not available for face recognition. However, face recognition system has to work well with available information. By keeping this fact, the performance of the proposed method is evaluated by considering single/combination of different face parts of face images of AR database. The experimental results obtained from the proposed method by considering different combination of face parts are tabulated in table 2.

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Table 2: Recognition rate of different face features with face parts

Face parts	Mouth + Nose + Eyes	Eyes + Mouth	Eyes + Nose	Nose + Mouth	Only Eyes	Only Mouth	Only Nose
Recognition rate in %	**95.58**	**93.33**	**89.83**	**78.92**	80.33	50.17	38.92

Form the table 2 it is noticed that, the proposed method achieves higher recognition rate about 95.58% when all face parts are considered for evaluation because eyes, mouth and nose represents higher order informative regions in ascending order. When only eyes and mouth parts are considered for face recognition, the recognition rate goes to about 93.33 % due to the fact that; eyes and mouth regions contribute more informative information compared to nose during face recognition. Further performance of the proposed method reduces to 89.83 % to 78.92% when either eyes and mouth information is not available. It also noticed that; when considered presences of single face part during recognition, the recognition vary from 80.33 % to 38.92%.

VI. Conclusion

In this paper, a robust symbolic approach for face recognition is presented; that uses smoothing coefficients values of Savitzky-Golay filter as features for classification. For the purpose of feature extraction, instead of considering entire face image, face parts are extracted from the original face image using Viola-Jones algorithm. From the cropped images optimal set of features are calculated using Savitzky-Golay moving filter. Further, extracted features of each face part are represented as independent symbolic objects. During the symbolic analysis, modified content based similarity measure is employed to compare trained symbolic data objects of eyes, mouth and nose and test symbolic objects. The representation of face as symbolic object utilizes a very low dimensional feature space, which ensures lower computational burden. It has been found that the proposed method provides high recognition accuracy of 95.58 % even for images that vary in expression, occlusions and are affected due to nonlinear lighting variations.

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