Research and Application of Facial Recognition Technology Based on AI Recognition System and Information Privacy Protection

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Abstract. Currently, cross modal model algorithms are commonly used in facial recognition, which are susceptible to the influence of the confidence level of facial key points, resulting in low recognition accuracy. Therefore, the research and application of facial recognition technology based on AI recognition system and information privacy protection are proposed. Utilizing the sensitivity of AI recognition systems to feature perception and analysis, contour detection and alignment of faces are carried out. The confidence of facial key points is calculated using the pre-selected box scale function of the face, combined with pixel transformation matrix and decision matrix to extract facial feature points, and a set of feature vectors is constructed. Based on this, information privacy protection mechanisms are used to calculate the prediction probability of facial images, thus achieving facial recognition. The comparative experimental results show that the designed method can more accurately identify the samples to which the facial image belongs, and the recognition effect is better.

Keywords: AI identification system; information privacy protection; face recognition

1 Introduction

Face recognition is a means to authenticate users using key facial information by combining advanced technologies such as image pre-processing and feature detection. Face recognition has been widely used in the fields of transportation, enterprise management and qualification, and has achieved many results. Currently, with the rapid development of artificial intelligence technology, the scale of face recognition is also expanding. However, the accuracy of facial recognition is greatly hindered by factors such as complex and variable lighting environments and different blurring rates of facial images. In order to effectively improve the recognition effect of face recognition technology, it is necessary to conduct an in-depth research on it.

Some studies use fusion dual attention mechanism to add information entropy sub-blocks to achieve reconstruction of image pixels during refinement feature ex-

C. Chen et al. (eds.), *Proceedings of the 3rd International Conference on Digital Economy and Computer Application (DECA 2023)*, Atlantis Highlights in Computer Sciences 17,
https://doi.org/10.2991/978-94-6463-304-7_30

traction and combine feature weights to complete face recognition [1]. However, this method ignores the spatial relationship between the feature maps of the key regions of the face, which makes the feature fusion ineffective and thus affects the recognition performance; there is also a study that uses domain adaptive mean network to calculate the spatial distance between two images by reducing the dimensionality and weighting coefficients of the original image features and using the backbone network to achieve face recognition [2]. However, this method does not take into account the multi-scale covariates when setting the distance discrimination threshold, which leads to a low overall recognition accuracy.

Based on the above analysis, this paper designs face recognition technology using AI recognition system and information privacy protection mechanism, which is an intelligent recognition detection system that inputs the target's feature information into the backend computer for processing and analysis and outputs the target's biometric features [3]; and information privacy protection mechanism is an information data distribution anonymity protection technology. The advantages of both are combined to analyze and study the face recognition technology in order to further optimize the recognition performance of face recognition technology.

2 Face Recognition Technology Development and Design

2.1 Face Alignment Based on AI Recognition System

In the process of face recognition, due to the different distance and angle of the face image, the size of the face in the image is not fixed, and there is a skewed situation. Therefore, in order to better achieve face recognition, the face image should first be corrected to achieve face alignment.

In this paper, AI recognition system is used to complete image face alignment through three core modules of business application, intelligent analysis and target perception, according to the functional deployment of recognition technology. The process of face alignment based on AI recognition system is shown in Figure 1.

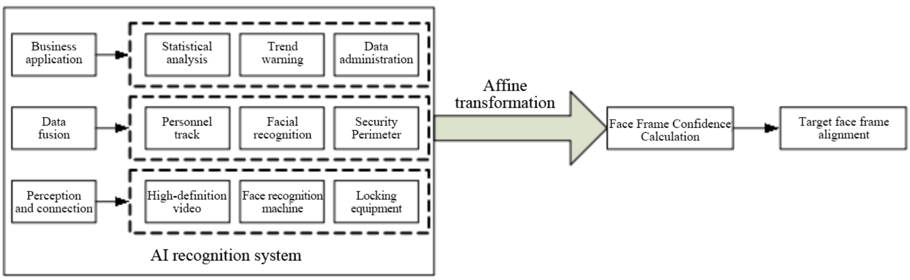

Fig. 1. Face alignment process based on AI recognition system

Target face alignment requires not only detecting the face contour in the image but also determining the specific position of the face in the image [4]. Usually, AI recognition systems can initially target several face window reference frames by scanning anchor points in the image, and then calculate the offset of the face position by regression calculation between the target frame and the reference frame, followed by data construction using the faces in the face recognition database to analyze the compliance of the face to be detected and form the base data, and finally control the recognition process by data sensing and fusion and perform change trend prediction [5], and intelligent analysis of preauthorized face recognition and feature recognition to generate continuous dynamic feature information for face frame confidence conversion, and finally achieve target face alignment. The specific calculation process is as follows.

Assuming that the size of the feature image is 3x3, the square on the left side of the image indicates the 9 feature points in the feature map, and the right side indicates the pre-defined reference frame of different sizes corresponding to each feature point, a $3 \times 3 \times k$ reference frame is generated [6], as shown in Figure 2.

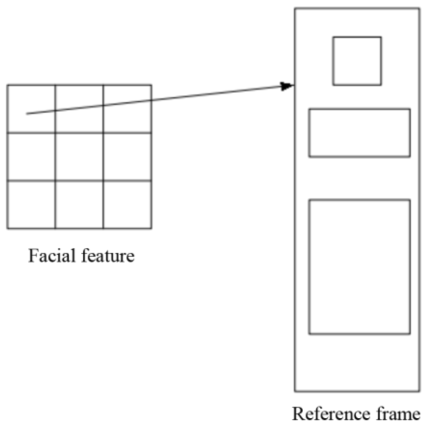

Fig. 2. Face feature map and alignment reference frame

Since the face size and aspect ratio in the image are not fixed, for better face alignment, it is necessary to extract the face feature size and build a feature pyramid to obtain the pre-selected frame offsets in the horizontal and vertical directions of the image [7], which is calculated as follows:

$$\begin{cases} R_x = p_w q_x(p) + p_x \\ R_y = p_h q_y(p) + p_y \end{cases} \tag{1}$$

In the above equation, R_x and R_y denote the horizontal and vertical offset of the preselected box, respectively; p_w and q_x denote the width and height of the preselected box, respectively; $q_x(p)$ and $q_y(p)$ denote the parameters of the AI recognition system, respectively; p_x and p_y denote the center coordinates of the preselected box.

After obtaining the information of face preselected boxes, multiple preselected boxes are filtered with the aim of eliminating overlapping preselected boxes, and the original output preselected boxes are refined using a multi-scale detail enhancement method [8] to obtain fine-scale face boxes, i.e:

$$B_1 = g_1 \times I_1 + \left(R_x + R_y\right) \tag{2}$$

In the above equation, B_1 denotes the preselected box fine scale parameter; g_1 denotes the Gaussian kernel function; and I_1 denotes the input original face image.

The scale parameters of each preselected box are calculated separately using the above equation and superimposed and merged [9] to generate the final detailed preselected box, i.e:

$$B^* = \left(1 - w_1 \times \operatorname{sgn} B_1\right) + \sigma_1 \tag{3}$$

In the above equation, B^* denotes the fine scale parameter of the fused preselected frame; w_1 denotes the image suppression saturation factor; $\operatorname{sgn}(.)$ denotes the sign function; and σ_1 denotes the Gaussian coefficient.

To achieve dynamic adjustment of the image pixel changes, the gradient matrix is used to bias correct the face image features [10], which makes the parameter changes of the pixels relatively smooth and is calculated as follows:

$$m_1 = \beta_1 \times m_\alpha + \left(1 - \beta_2\right) \times B^* \tag{4}$$

In the above equation, β_1 denotes the image super-resolution; m_α denotes the gradient coefficient; β_2 denotes the pixel correction step; and m_1 denotes the amount of face feature bias change.

To better accomplish the alignment of the target face, the original color image is converted into a grayscale image [11], which can be expressed as:

$$G_r = 0.256 * r_1 + 0.214 * t_1 + m_1 \tag{5}$$

In the above equation, G_r denotes the grayscale image; r_1 denotes the luminance component; and t_1 denotes the luminance component.

For cross-modal segmentation of the image the pixel difference loss values obtained are

$$L_s = G_r \sum L_1 + L_2 \tag{6}$$

In the above equation, L1 and L2 denote the estimation matrices of the image subject modality and the auxiliary modality, respectively.

Taking the grayscale image subject modality as an example, the internal difference loss between its preselected frame and reference frame is:

$$\alpha_t = \frac{}{M}\left(L_s + \log\left(p_i\right)\right) \tag{7}$$

In the above equation, M denotes the number of image pixels; p_i denotes the cross entropy of pixel points.

Then the transformation alignment of image faces can be achieved using the following equation, i.e:

$$I^{'} = I \times \cos\theta \times \alpha_t \tag{8}$$

In the above equation, $I^{'}$ denotes the image after face alignment; θ denotes the rotation angle needed for the original image.

Using the conversion matrix between the key points of the face to be recognized and the standard face key points and the internal modal loss function, the data fusion and perception layer of the AI recognition system is used to perform an affine linear transformation on the face features to find out the angle at which the image needs to be rotated, thus realizing the face alignment, and this step lays the foundation for the next face feature extraction.

2.2 Face Feature Extraction

Based on face detection and alignment, key face features are next extracted for future accurate recognition [12]. Since facial images are distorted during the acquisition process and thus undergo a series of distortion, blurring, downsampling and adding noise to form a low-resolution image, then the degradation model of the image can be expressed as：

$$I_1 = d_1 b_1 f_1 I + n_0 \tag{9}$$

In the above equation, d_1 denotes the downsampling matrix; b_1 denotes the blurring matrix; f_1 denotes the displacement matrix; I denotes the original input image; and n_0 denotes the additional noise.

In order to completely correspond to each pixel between the input image and the label image, the pixels of the original input image are reconstructed to scale the input image to the size of the label image [13], and the transformation equation is as follows:

$$m_r = \frac{I^{'} I_1}{1-\alpha_1} \tag{10}$$

In the above equation, m_r denotes the pixel transformation matrix; $I^{'}$ denotes the face-aligned image; and α_1 denotes the transformation step size.

The classification boundaries of different classes are determined according to the fully connected layers of the depth image [14], and the inter-class distances of different face images in a binary classification scenario can be expressed as:

$$L_1 = -\frac{1}{b_2}\sum \log\left(m_r \times y_\theta\right) \tag{11}$$

In the above equation, b_2 denotes the decision boundary margin; y_θ denotes the weights of the feature vectors.

The matrix differences of the pixel points in the image are calculated, from which the thickness of each layer of the feature map is obtained, i.e:

$$G_l = \sum_{i=1}^{m_1} L_1\left(f_l + k_l\right) \tag{12}$$

In the above equation, G_l denotes the thickness of the feature map of a single layer of pixels; m_1 denotes the number of pixel points; m_1 denotes the feature information of the first layer; and k_l denotes the style information of the image.

The style loss function of the image is as follows:

$$\eta_l = \left\|G_l - g_1\right\|^2 / A_0 \tag{13}$$

In the above equation, g_1 denotes the pixel correlation coefficient; A_0 denotes the pixel structure matrix.

The pixel matrix of the original image is normalized [15] to obtain the normalized pixel grayscale values, i.e:

$$\lambda_i = \frac{x_i}{\sqrt{\sum_{J=1}^{D'} \eta_l}} \tag{14}$$

In the above equation, λ_i denotes the grayscale value of the i th pixel point; D' denotes the number of valid pixel points.

The configuration vector of image pixels is obtained by convolution operation [16] using convolutional network for low-resolution images, which can be expressed as

$$\rho_0 = \max \lambda_i \times w_1 \times B_2 \tag{15}$$

In the above equation, w_1 denotes the convolution parameter; B_2 denotes the convolution kernel size.

After the initial convolution operation, multidimensional feature vectors are extracted for each image block, and then the feature vectors are nonlinearly mapped [17] to obtain the new low-dimensional feature vectors, i.e:

$$\rho_1 = f(x) + \frac{\rho_0}{\sqrt{w_2 \times \kappa_1}} \tag{16}$$

In the above equation, $f(x)$ denotes the activation coefficient; w_2 denotes the unit left-shift operator; and κ_1 denotes the unit up-shift operator.

Next, a quadruple deconvolution operation is performed on the low-dimensional feature map, as shown in Figure 3.

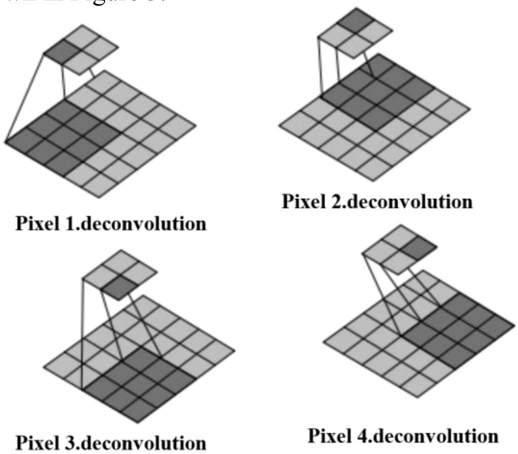

Fig. 3. Image feature vector deconvolution operation

The output high-resolution image is the input image of the fourth convolutional layer of the new network, while the output is the output of the nonlinear mapping layer of the original network [18]. After four deconvolution operations, the extracted face features are:

$$K_1 = \frac{1}{n''} \sum \rho_1 |P_1|^2 \tag{17}$$

In the above equation, n'' denotes the number of convolutional network layers; P_1 denotes the feature down-sampling multiplier; K_1 denotes the face feature vector.

According to the image degradation model, the face feature vector is up-sampled, combined with the pixel displacement transformation matrix, the inter-class distance of the image is calculated, and the extraction of face features is completed by the de-convolution operation of pixels, which provides favorable conditions for the next implementation of face recognition.

2.3 Face Recognition Based on Information Privacy Protection

The extracted high-dimensional face feature vectors, either for distance binary classification or recognition comparison verification, require matching search on the feature vectors and calculating their similarity to the original images in the face database [19]. For this reason, this paper uses an information protection mechanism to accomplish face recognition. The face recognition process based on the information privacy protection mechanism is shown in Figure 4.

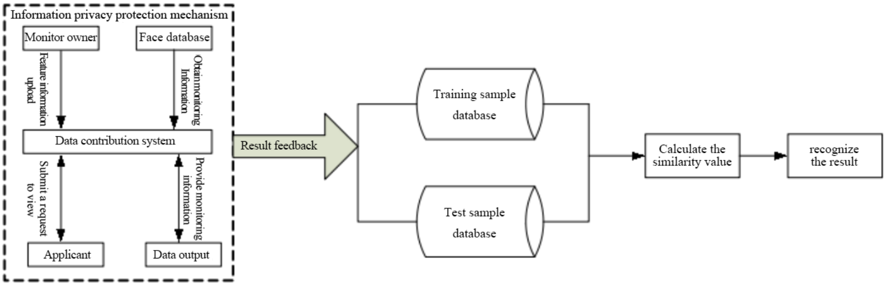

Fig. 4. Face recognition based on information privacy protection mechanism

For the input face sample to be recognized, the predicted deviation value from the nearest labeled privacy module [20-22] can be expressed using the following scale function:

$$Q_i = |q_1 - q_2|^2 + K_1 \tag{18}$$

In the above equation, Q_i denotes the scale function of the face feature vector; q_1 and q_2 denote the regression target value and the true target value of the output image features, respectively.

The extracted low-dimensional features of the face are localized with the source images in the database for key points, i.e:

$$w_2 = Q_i \times \frac{\xi_i + \alpha_j}{2} \tag{19}$$

In the above equation, ξ_i denotes the network weights of each layer; α_j denotes the feature fluctuation factor.

A difficult sample mining model is used to cluster part of the dataset in the face training classification process, i.e:

$$z_k = \frac{n_k m_k}{n_i w_2} \tag{20}$$

In the above equation, z_k denotes the mining function; n_k denotes the number of gray-level pixels; m_k denotes the pixel local perception; and n_i denotes the probability of pixel i becoming gray-level.

The transformed depth image samples are numerically transformed to obtain the normalized sample data, i.e:

$$T_k = \mathrm{int}\left[z_k \left(L_2 - 1 \right) + S_{rj} \right] \tag{21}$$

In the above equation, $\mathrm{int}(.)$ denotes the roughness function; L_2 denotes the image dimension; and S_{rj} denotes the random vector.

Describing the correlation between the original high-dimensional data points μ_1 and μ_2 as a conditional probability P_{12}, the key point matching between the to-be-recognized image and the source image is performed as follows:

$$\varpi_{12} = \frac{\exp\left(\mu_1 - \mu_2\right)/2\chi^2}{\sum \exp\left(\mu_2 - \mu_1\right)/2\chi^2} \tag{22}$$

In the above equation, ϖ_{12} denotes the face key point matching result; χ denotes the pixel point Gaussian distribution parameter.

The Gaussian distribution parameter χ is generally determined by the following equation, i.e:

$$\chi = \sum \log D_g\left(x\right) \tag{23}$$

In the above equation, $D_g\left(x\right)$ denotes a linear function.

Then the predicted probability of face recognition can be calculated using the following equation:

$$\Omega_{ij} = \log\left(\varpi_{12}\right) + \left(1 - \chi\right)^2 \tag{24}$$

In the above equation, Ω_{ij} represents the probability that the i th sample is predicted to be the j th face.

The feature vector of the sample to be recognized is input to the classifier, the feature prediction value of the input image is calculated, and the source image with the highest prediction probability and the image to be recognized are considered as the same face, thus realizing face recognition based on AI-based recognition system and information privacy protection.

3 Experimental demonstration

To verify the reliability of the proposed method for practical application in the face recognition process, comparative simulation experiments are designed to test the effectiveness of the designed method.

3.1 Experiment preparation

Three public face datasets dedicated to the study of face recognition, namely GitHub, Kaggle, Nvidia, and Setet91, were used in the experiments, as shown in Table 1.

Table 1. Experimental data set and description

Dataset	Category	Resolution	Number of pictures	Description
GitHub	Masking	Variation	5000	Real environment acquisition
Kaggle	Masking/Masking	103*200	1256/5630	Masking and masking generated by optimization algorithm
Nvidia	No Masking / Masking	Variation	1258/2333	Face key points are marked
Setet91	No Masking	None	1589	Baseline code provided

The images in the three datasets are in JPEG format and contain images of faces of different genders, ages, poses, expressions, and resolutions, as well as 12510 video frames. The size of these images ranged from 412x450 to 120x230, and all of them had relatively clear edges. A total of 1200 face images were retained after eliminating the smoothed images from the dataset before the experiment, and an example of the dataset is shown in Figure 5.

Fig. 5. Example of experimental data set

First, the images from the original training set are downsampled at a downsampling rate of multiplicity n to form high-feature images, and then, the feature images are cropped into low-dimensional feature subimages of step k, while the corresponding spatial-scale images are also cropped into low-dimensional feature subimages. These high-dimensional to low-dimensional feature sub-images corresponding to each other will be used as training samples

3.2 Experimental Description

The proposed method and the comparison method are implemented based on PyTorch, both using the Adagrad optimization method to optimize their control parameters. The batch size M for each mode is 48, resulting in a total of 120 small batches; the number of training rounds (epoch) is set to 1000, the initial learning rate is set to 0.02, the learning rate decays every 200 rounds with a decay factor of 0.1, and the edge parameter a is set to 0.3. Since more emphasis is placed on cross-modal matching recognition in the experiments, the learning rate decline rates between and within modes are different. Therefore, a larger edge parameter was set in the experiments to emphasize the differences between cross-modalities.

For the face alignment of the experimental dataset, the AI recognition system is used to detect the shadow proportion of the active image, after which the shadow change trajectory is recorded by applying dynamic continuous recognition coding, and finally the trajectory information of the face is compared with the regression frame to achieve face alignment. The main encoding of the part of capacity detection and alignment completed by using AI recognition system is shown in Figure 6.

```
      int main()
     {
  Mat src—unread(}}3.png}}, 0);
  //imshow("src"}   src);
  Mat dst;
    threshold(src}  dst}  100,    255, CV THRESH BINARY
CNV;//imshow("dst"}   dst);
  int nRows=dst.rows;
  int nCols=dst.cols;
  ofstream fout("data.txt");
  for Cint w—0;  w<nCols;   w++)
  {
    int sum=0;for Cint h—0;  h<nRows;  h++)
    }
Uchar *pRow-sum-dst.ptr<uchar> Ch}  w);
(*pBow);
if(sumC inr)
>0)
}
Gout<<" " cout-font
endl;
endl;
sum=n
break
}
```

Fig. 6. Part of the code for AI recognition system to implement aligned faces

First, the network is trained using the Set91 dataset and then fine-tuned using the NVIDIA dataset, which will converge earlier than if the two datasets were trained together directly from the beginning.

When training with the Set91 dataset, the learning rate of the convolutional layer is set to 0 100 and the learning rate of the transposed convolutional layer is set to 0.01. When fine-tuning with the NVIDIA dataset, the learning rate is reduced to 1/10 of the original.

3.3 Analysis of face recognition results

Based on the above experimental preparation and algorithm-related parameter setting, the test sample images in the dataset are recognized by applying the method designed in this paper. The samples to be recognized are input into the binary recognizer, and face recognition is completed by facial key point matching and feature extraction, and the recognition process is shown in Figure 7.

Fig. 7. Face recognition process

According to the face recognition process, the method designed in this paper is applied to multiple face images recognition, and the recognition accuracy of the algorithm is recorded, and the results are shown in Figure 8.

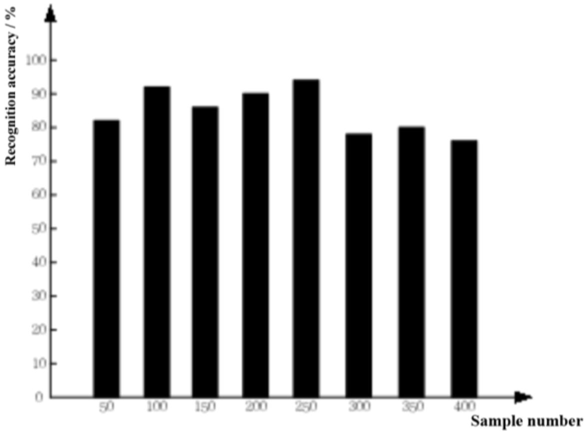

Fig. 8. Recognition accuracy results

From the above figure, it can be seen that the recognition accuracy obtained by using the method of this paper to recognize the experimental face images under different numbers of test samples is above 70%, and the overall recognition results basically remain stable. This can show that the recognition accuracy of the face recognition technology based on AI recognition system and information privacy protection designed in this paper is high and can meet the practical application requirements.

3.4 Experimental analysis of face structure similarity comparison

To further reflect the superior performance of this paper's method in face recognition accuracy, the literature [1] fused dual attention mechanism (method 1) and the literature [2] domain adaptive mean network (method 2) are used as the comparison methods of this paper's method, and the structural similarity index P_s is introduced to quantitatively evaluate the recognition effect of different methods, and the larger its value is, the more similar the two images are, the better the recognition effect is. The calculation formula is as follows.

$$P_s = 10\log\frac{255^2}{M_s} \tag{25}$$

In the above equation, M_s denotes the peak signal-to-noise ratio.

The three recognition methods are applied to face recognition in the Kaggle dataset respectively, and the structural similarity of the recognition results of different methods is calculated and compared, and the comparison results are shown in Table 2.

Table 2. Comparison of the structural similarity results of the identification results of different methods

Sampling magnification	Structural similarity		
	Method 1	Method 2	Methodology of this article
2	18.56	20.36	35.36
4	14.23	24.45	45.20
6	10.66	21.09	39.62
8	15.69	22.33	40.21
10	8.96	30.15	35.01

From the data in the above table, it can be seen that based on the different upsampling multipliers of the images, the structural similarity between the images recognized by this method and the source images is much higher than that of Method 1 and Method 2, which basically remains above 35. Method 1 has the lowest structural similarity because when the global feature parameters of the image are at the edge of the high-dimensional scale parameter value domain, the internal modal features extracted by this method are not conducive to pixel reconstruction, which in turn affects the final recognition effect; Compared with method 1, the recognition performance of method 2 has been improved, but the overall recognition effect is poor because the dataset contains large-scale materials from different fiber optic environments, which makes the bias vector of local feature fusion larger. The experimental comparison data can show that the face recognition method designed in this paper has high recognition accuracy.

4 Conclusions

To address the shortcomings of the current existing face recognition methods, this paper combines AI recognition system and information privacy protection mechanism based on and designed face recognition technology. Face recognition is achieved through face contour detection and alignment, and facial key feature extraction. After comparing the experimental results, the proposed method has higher recognition accuracy. However, the research in this paper has some limitations, and we can try to further optimize the technique by simulation in the future to expand its application scope.

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