Application of adaptive MRF based on region in segmentation of microscopic image

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Abstract: - According to the characteristics of microscopic image, an adaptive MRF method based on region is provided for segmentation of microscopic image. Based on a series of filtering and de-noising, morphological gradient is implemented for image. Then a watershed algorithm is used for image's over-segmentation. In order to reduce the influence of noise, the mean gray value of regional block substitutes for each pixel value in this regional block. The fuzzy c-means algorithm is implemented for initial segmentation of image. In this processing, the mean value and variance of this region is feature value. Then MRF potential function is computed. Condition potential function is represented by membership of regional feature value on clustering center. The connection parameter of priori potential function is adaptively determined according to the connection degree between regional block and its adjacent blocks. The edge of the segmented regions with this algorithm is better than that algorithm in which fixed connection parameter is adopted. Because fuzzy c-means segmentation can get good initial state value, ICM with better real-time is employed to calculate the minimum potential function. Experiments show that this algorithm is better than OTSU, the traditional MRF and regional MRF with fixed connection parameter. This algorithm has better anti-noise ability and edge segmentation image. It has good robustness.

Key-Words: - Segmentation of microscopic image, Markov random field based on region, Watershed, Adaptive connection parameter, image processing, potential function

1 Introduction

In microscopic image, objects are enlarged and noise also is amplified, so there are much interference and noise in microscopic image. In different focus plane, objects' depth is inconsistent. Microscopic image's contrast is small so the segmentation is more complex and difficult. Microscopic image is widely used in micro-electromechanical system (MEMS), medical image and other important fields. In these fields in order to further implement image analysis and image recognition, image segmentation must be processed firstly. The image segmentation denotes a process that the image is segmented into the different regional blocks with special significance. These regional blocks do not intersect each other and each regional block should satisfy the consistency condition of a particular region[1]. Image segmentation is one of the most important problems in low level vision of computer vision's fields. It is the basis of image analysis, image recognition and image understanding. Image segmentation's result influences on the subsequent processing directly. It is a classical problem in computer vision. So far, there is not a universal method yet [2-7].

In this paper the improved adaptive markov random field (MRF) method based on region is provided. Because the traditional MRF is a statistical method which is based on pixels and it only considers the relationship of the pixel and the surrounding pixels, its processing result is bad for the microscopic image with much noise. When calculating the priori potential function, the fixed connection parameter is used which no considering the close degree of connection between the pixel and its neighborhood pixels. Then the effect of edge segmentation of the traditional MRF is not good and at the same time the amount of computation is relatively high[8-12]. The adaptive Markov random field (MRF) method based on region is provided in this paper. Firstly the over-segmentation of watershed algorithm is adopted and image is segmented into small regions. Then feature values of each region are extracted in order to process fuzzy classification. The condition potential function and the priori potential function are calculated later. When calculating the priori potential function, the connection parameter is calculated by adaptive algorithm according to the close degree of connection between each regional block and surrounding regional blocks. Then the priori potential function can more accurately reflect the relationship between the regional block and surrounding regional blocks. Thus this algorithm is more accurate and better segmentation effect is obtained. Because of watershed over-segmentation, the final segmentation is optimized by morphological opening-and-closing operation which can fill holes and remove little burr. The experiments show that the proposed algorithm is more effective.

2 Traditional MRF model

MRF is a probability theory to analyze the spatial correlation. The image is viewed as a two-dimensional random field X in MRF.

$$X = \{x_s, s \in S\} \tag{1}$$

Where S represents the image position sets.

$$S = \{(i, j) \mid 1 \le i \le M, 1 \le j \le N\} \tag{2}$$

Where M represents the number of rows; N represents the number of columns.

Image satisfies positive probabilistic and Markov property, so image can be viewed as a random field. Label field is Y and classification number of image is L.

$$Y = \{y_i, (i) \in \{1,2,\cdots L\}\} \tag{3}$$

The relationship between the Gibbs distribution and MRF is given in Hammers-Clifford theorem[13]. The equivalent condition of Gibbs distribution and MRF is that a random field is MRF about neighborhood system and the random field is Gibbs distribution about neighborhood system. Then a research of a priori probability model is transformed into a research on the potential function. Gibbs distribution and MRF can be connected. The equivalent form between MRF and Gibbs distribution about neighborhood system $\delta(s)$ is defined as

$$p(X = x) = \frac{1}{Z}\exp\left(\frac{-U(x)}{T}\right) \tag{4}$$

Where Z is a normalized constant; T is temperature constant.

$$Z = \sum \exp\left[\frac{-U(x)}{T}\right] \tag{5}$$

$$U(x) = \sum_{c \in C} V_c(x) \tag{6}$$

$V_c(\bullet)$ is a potential function which is defined in clique c. It only depends on the neighborhood $\delta(s), s \in c$.

The formula (4) solves the problem of probability distribution for MRF which is transformed into the research on potential function $V_c(\bullet)$. The equivalent relation is established between Gibbs distribution and potential function. It is an important milestone for the study of MRF.

Image segmentation based on traditional MRF is a process to distribute a sub-image label for each pixel which is based on region attribute and feature attribute of pixels. Region attribute is described by the label random field of priori distribution. Feature attribute is described by likelihood function. The total number of image classification is L. Then $Y_i = l(l = 1,2,\cdots,L)$. A given image is an implementation of a random field. That is $X = x$. Segmentation process is to estimate Y in terms of X. According to the MAP estimation, best realization y^* for label field Y is what makes a posterior probability distribution $p(Y = y / X = x)$ maximize. The problem of image segmentation is transformed into the problem of MAP estimation to decide the category of image pixels. It is defined as

$$\begin{aligned} \hat{y} &= \arg\max p(Y = y / X = x) \\ &= \arg\max[p(X = x / Y = y) \bullet p(Y = y)] / p(X = x) \\ &\propto \arg\max p(X = x / Y = y) \bullet p(Y = y) \\ &\propto \arg\max \ln p(X = x / Y = y) + \ln p(Y = y) \end{aligned} \tag{7}$$

For a given image x, $p(X=x)$ is a constant in the formula (7). So when $p(X = x / Y = y) \bullet p(Y = y)$ maximize, the best segmentation of image is obtained.

3 MRF model based on Region

The traditional MRF algorithm based on pixels has a high computation cost. In order to reduce the amount of computation, MRF based on region is adopted which can reduce the amount of processing units. The segmentation method of MRF based on region can reduce the influence of noise. Noise makes local correlation of the image abate. Conventional image segmentation methods based on gray can not effectively overcome noise influence on segmentation result [5]. MRF segmentation method is based on the local correlation of image data and has a certain ability to eliminate noise and protect edge. But if the image has low signal noise ratio(SNR), traditional MRF approach is difficult to consider the noise and the edge simultaneously. The ability of traditional MRF segmentation method to eliminate noise and protect edge depends on the neighborhood system. When the neighborhood system is relatively complicated, the ability to eliminate noise is stronger but the image edge is excessively smoothed. Conversely when the neighborhood system is simple, edge can be effectively kept but the noise influence on the segmentation result can not be effectively controlled. In this situation, the algorithm of MRF based on region can solve the contradiction between edge protection and noise reduction. Firstly, the image is segmented by watershed algorithm. Image is divided into many regional blocks, each regional block with similar gray and good edge. The gray value of each pixel in a region is substituted by the mean gray value of its regional block. On the one hand, noise can be adaptively reduced and local correlation can be strengthened. On the other hand, the mean gray value of each regional block can better express real gray value of the image and then anti-noise ability is improved. Because each region has good edge, the final segmentation edge is obtained by connecting the edge of each region. The obtained final edge is closer to the real edge of an image[14][15].

Regional blocks instead of pixels are as input, so MRF is defined between regional blocks and optimally objective function is obtained based on regional blocks.

4 Improved adaptive MRF model based on region

The microscopic image is enlarged and noise of microscopic image is enlarged too. In order to reduce the noise influence on watershed segmentation, image is processed with open morphological filter firstly in case much more regional blocks is produced by over-segmentation. Open morphological filter can eliminate some little noise. Shot noise and Gaussian noise exist in image, so image is processed with median filter and bilateral filter. Median filter can reduce shot noise and bilateral filter can reduce Gaussian noise. Then image is processed with morphological gradient. The image of morphological gradient is as input as shown in Fig.1. Edge positioning of morphology gradient is better and its speed is relatively faster.

The image of morphological gradient is over-segmented by watershed algorithm. The mean gray and variance are extracted from each obtained regional block. The mean gray and variance are feature value of each regional block. The fuzzy c-means algorithm is adopted to complete the initial segmentation.

The initial segmentation image is re-segmented by MRF. That is to calculate the maximum of posterior probability. According to Hammers-Clifford theorem, calculating the maximum of posterior probability is equivalent to calculating the minimum of potential function.

For MRF model based on region, the form of probability is defined as

$$p(y / x) \propto \ln p(X = x / Y = y) + \ln p(Y = y) \tag{8}$$

where

$\ln p(X = x / Y = y)$ -- conditional probability;

$\ln p(Y = y)$ -- priori probability.

For conditional probability, potential function of each image block is represented by relevant Gaussian function. In general, the distribution of each image block of watershed segmentation can be viewed as Gaussian distribution, so the potential function of each image block can be expressed by relevant Gaussian function.

$\varphi(x_i / y_i)$ represents the membership function of each regional block to the center. $-\varphi(x_i / y_i)$ represents the conditional potential function of each regional block. $\varphi(x_i / y_i)$ is computed by Gaussian membership function. Regional mean value and standard deviation are extracted from each region of

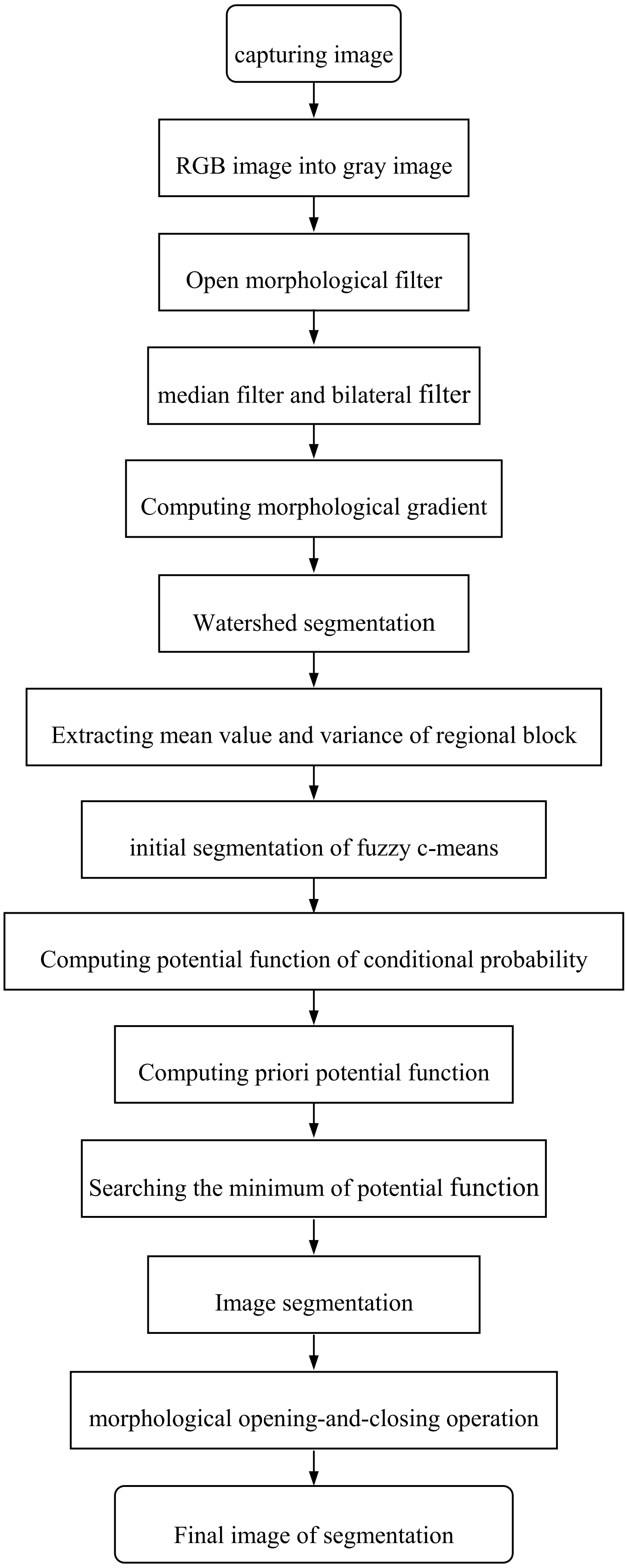


Fig.1 Image segmentation dataflow diagram

watershed segmentation. Regional mean value and standard deviation are feature values.

The Gaussian membership function is calculated by feature values, which is defined as

$$\varphi(x_i / y_i) = e^{-\frac{(x_i - m_i)^2}{2\sigma_i^2}} \tag{9}$$

Where m_i --- the mean of regional block i;

σ_i ---the standard deviation of regional block i.

The priori probability is as shown in the formula(10). The formula (10) represents the priori potential function of region.

$$-\beta \sum V(y_i, y_j) \tag{10}$$

Where

$$V(y_i, y_j) = \begin{cases} 1 & y_i = y_j \\ -1 & y_i \neq y_j \end{cases} \tag{11}$$

β is the connection parameter which represents the uniformity of region. Segmentation result is directly influenced by the selection of MRF parameter β. If the value of selected parameter is large, long edge is easily formed. If small, short edge is easily formed. The fixed parameter makes the edge of the object fuzzy which influences the segmentation result[16]. Since most of images are non-stationary such as uneven illumination, drastically changing scene and so on, the fixed MRF parameter is limited for application. The accurate segmentation is badly influenced by the fixed parameter which can lead to aliasing of local attribute and feature attribute.

The algorithm of adaptive weight β is provided in this paper. Watershed and fuzzy c-means are combined to produce the pre-segmentation result. Then the connection parameter β of MRF is evaluated. The parameter β is adaptively updated in this paper. After pre-segmentation, each regional block has one or several regional blocks connected which are called regional neighborhood. For two adjacently regional blocks, the connection degree is represented by the connection parameter β shown as in the formula (12).

$$\beta = \frac{N_n^m}{\sum_i N_i^m} \tag{12}$$

Where N_n^m --- the number of connected pixels between regional block m and regional block n;

$\sum_i N_i^m$ ---the total number of pixels connected with regional block m.

The connection parameter can reflect the close degree between the current regional block and its connected regional blocks. Because different image produces different pre-segmentation results, the connection parameter β of MRF which is calculated by the formula (12) is different too. Then potential function of a regional block and potential function of neighborhood regional blocks are balanced. The larger value of a parameter β represents the closer degree and the smaller value of a parameter β represents the less degree between the regional block and neighborhood regional blocks.

According to the above discuss, the formula (8) is represented by the formula (13).

$$\begin{aligned} p(y/x) &\propto \ln p(X = x / Y = y) + \ln p(Y = y) \\ &\propto -\sum \varphi(x_i / y_i) - \beta \sum V(y_i, y_j) \end{aligned} \tag{13}$$

Image segmentation's procedure of improved adaptive MRF based on region is as follows:

step 1: The RGB image is transformed into gray image.

step 2: The image is processed with open morphology filter.

step 3: The median filter and the bilateral filter are implemented in order to reduce shot noise and Gaussian noise.

step 4:The image is implemented with morphological gradient.

step 5:The image is segmented with watershed algorithm.

step 6:Gray mean and variance are extracted from each region after segmentation. Gray mean and variance are as the feature value.

step7:According to the extracted feature value, the initial segmentation is implemented with fuzzy c-means algorithm.

step8:The conditional probability of MRF is represented with the membership function of each region block to the center. Then the conditional potential function is obtained.

step 9: The potential function of priori probability is computed according to the formula (10).

step 10: The total potential function is obtained on the above basis. The minimum of potential function is searched by ICM(Iterated Conditional Modes). Then the maximum of posteriori probability is evaluated and then the segmented image is obtained.

step 11:The image is processed with the open and close operation of binary mathematical morphology. The operation can remove tiny burrs and fill holes and then the image segmentation is finally completed.

5 ICM

The optimization algorithms of MRF have ICM(Iterated Conditional Modes) algorithm, EM(Expectation-Maximization) algorithm, simulated annealing algorithm, maximum belief propagation algorithm and relaxation labeling algorithm and so on. ICM algorithm is a kind of local optimization algorithm. Initial state value is assigned firstly which is a significant step. The image is over-segmented with the watershed algorithm in this paper. Then gray mean and variance are extracted from each segmented region. Gray mean and variance are as the feature value for the initial segmentation of the image with fuzzy c-means algorithm. Then the initial state value is determined and is fairly accurate based on the above algorithm. Thus the maximum of a posteriori probability is evaluated with the local optimization algorithm such as ICM while not with the global optimization algorithm such as simulated annealing algorithm. The ICM algorithm has the advantages of fast convergence speed, small number of iterations and good real-time. With better initial state value, ICM algorithm has an obvious advantage. Thus this paper adopts ICM algorithm.

ICM algorithm is based on the criterion of maximum a posteriori probability. Each regional block of observed image X is classified to one kind of L. ICM is a kind of iterative algorithm. During the iteration, the criterion of MAP is utilized to classify each regional block. Each classified regional block needs to utilize obtained category to revaluate the parameters of probability density function for each kind. The iteration is completed until the category number of transformation is small enough when each iteration process.

$Y = \{y_i, i \in (1,2,\cdots L)\}$ is category label. $X = \{x_c\}$ is observed image. According to MAP and Bayesian formula, the value of y_i makes the formula (14) maximize.

$$p(y_i / x_c) = \frac{p(x_c / y_i)p(y_i)}{p(x_c)} \tag{14}$$

y_i satisfies the formula (15).

$$\begin{aligned} \hat{y}_i &= \arg\max_{y_i \in \{1,2,\cdots L\}} \{p(y_i / x_c)\} \\ &= \arg\max_{y_i \in \{1,2,\cdots L\}} \left\{ \frac{p(x_c / y_i)p(y_i)}{p(x_c)} \right\} \end{aligned} \tag{15}$$

Because $p(x_c)$ is constant, the formula (15) is transformed into the formula (16).

$$\hat{y}_i = \arg\max_{y_i \in \{1,2,\cdots L\}} \{p(x_c / y_i)p(y_i)\} \tag{16}$$

According to Hammers-Clifford theorem, the maximum of posterior probability is equivalent to the minimum of potential function. The formula (16) is equivalent to the formula (13).Then the minimum of potential function is evaluated in ICM optimization algorithm.

With better initial state value, ICM algorithm is the best optimization algorithm. Thus ICM algorithm is adopted in this paper.

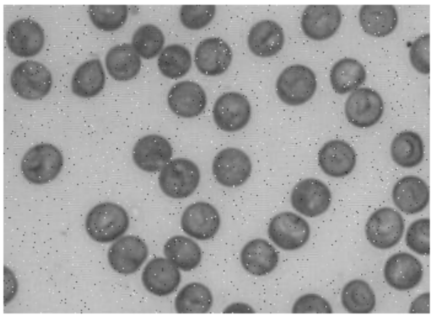
6 Experimental results and analysis

The microscopic cell image and microscopic tool image are implemented with improved adaptive MRF based on region in experiments. This method is compared with OTSU(Prof.otsu's) method, traditional MRF segmentation method, MRF method with fixed connection parameter based on region.

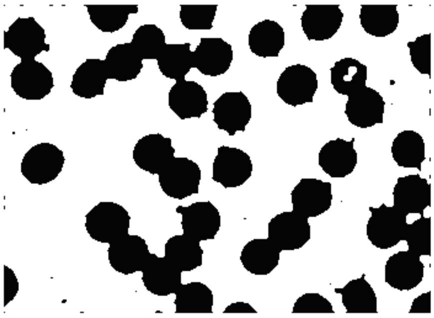
The cell image with noise is processed in experiment 1 as shown in Fig.2. Microscopic tool image is implemented in experiment 2 as shown in Fig.3. The source images with noise are as shown in Fig.2(a) and Fig.3(a). The segmentation results of OTSU are as shown in Fig.2(b) and Fig.3(b). The segmentation results of classical MRF are as shown in Fig.2(c) and Fig.3(c). The segmentation results of MRF method with fixed connection parameter based on region are as shown in Fig.2(d) and Fig.3(d). The segmentation results of MRF method with adaptive connection parameter based on region are as shown in Fig.2(e) and Fig.3(e). This paper adopts improved adaptive MRF based on region. The difference of Fig.2(d)(or Fig.3(d)) and Fig.2(e)(or Fig.3(e)) is that a fixed connection parameter is used or an adaptive connection parameter is used. Other process is exactly the same.

and Fig.3. More pixels are segmented falsely. The pre-process and post-process are exactly the same between the Fig.2(d)(or Fig. 3(d)) and Fig.2(e) (or Fig.3(e)). The only difference is a priori potential

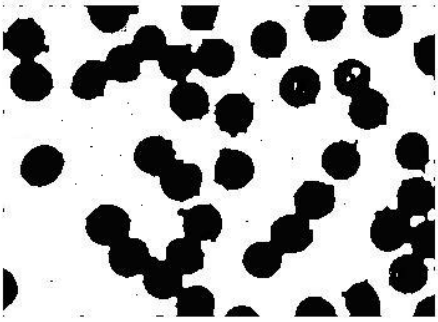
OTSU method and the traditional MRF method are influenced much with noise as shown in Fig.2 function with a fixed connection parameter in Fig.2(d)(or Fig.3(d)) and an adaptive connection parameter in Fig.2(e)(or Fig. 3(e)).



(a) source image

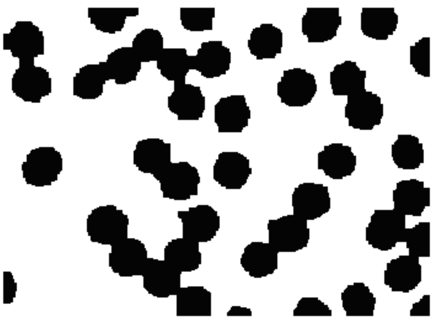


(b) OTSU segmentation result



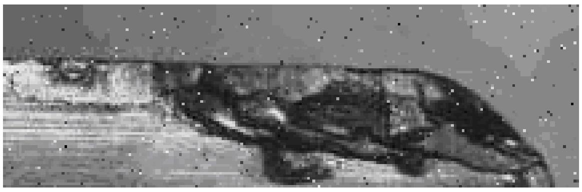
(c) Traditional MRF segmentation result

(d) MRF segmentation result with fixed connection parameter based on region



(e)MRF segmentation result with adaptive connection parameter based on region

Fig.2 the segmentation result of cell image



(a) source image

(b) OTSU segmentation result

(c)Traditional MRF segmentation result

(d) MRF segmentation result with fixed connection parameter based on region

(e)MRF segmentation result with adaptive connection parameter based on region

Fig.3 the segmentation result of microscopic tool image

The edge result of image segmentation is better with an adaptive connection parameter than with a fixed connection parameter as shown in Fig.2 and Fig. 3.

7 Conclusion

This paper provides a new adaptive image segmentation method which combines watershed algorithm, fuzzy c-means algorithm, morphological operation, MRF model and ICM together. On the basis of median filter and bilateral filter, image is processed with morphological gradient. Watershed algorithm is adopted to over-segment the image. The gray values of each segmented regional pixels are substituted by gray mean of each region which can restrain the noise influence. Gray mean and variance of regions are as feature values. Feature values are utilized for initial segmentation with fuzzy c-means algorithm. Then MRF segmentation based on region is implemented. The condition potential function is computed with Gaussian membership function. When computing the priori potential function, the connection parameter is adaptively determined according to the close degree between regional block and surrounding regional blocks. Then the minimum of total potential function is obtained which is equivalent to the maximum of posterior probability. When computing the maximum of posterior probability, ICM algorithm is adopted. Fuzzy c-means algorithm provides the better initial state value for ICM algorithm, so ICM has the advantages of fast convergence speed, small number of iterations and good real-time.

Compared with OTSU algorithm, the traditional MRF and MRF based on region with fixed connection parameter, the experimental results show that this paper's algorithm can better reduce the noise's influence and can obtain better edge segmentation results.

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