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Fast matching algorithm based on moment feature of image

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Abstract: To deal with the large amount of computation of moments during matching, we propose a novel fast matching algorithm based on moment invariants. This algorithm utilizes the computational characteristic of moments and sets ten sum-tables to reduce the computational complexity of moments during matching. With the proposed algorithm, lower order moments of each sub-image can be determined by using only a few additive and multiplicative operations, which shortens the matching time greatly. Meanwhile, the proposed algorithm computes moment features directly from the gray value of image and the result is accurate and independent from the matching precision. Simulation results illustrate the effectiveness of the proposed algorithm.

Key words: scene matching; consuming time; moment invariants; sum-table; wavelet decomposition

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图像矩特征匹配的快速算法

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摘要: 针对图像匹配过程中矩特征计算量大的问题, 从矩特征求解特点出发, 提出了一种快速的矩特征匹配算法. 该算法利用匹配过程中相邻待匹配子图间的相关性, 通过设置十个和表, 使得每个待匹配子图低阶矩的计算只需很少的几次加乘运算, 大大降低了矩特征的计算复杂度, 缩短了匹配耗时. 同时, 由于所提算法矩特征的计算是基于图像灰度值的精确计算, 且匹配过程采用遍历搜索策略, 因此其匹配精度与传统遍历搜索的匹配精度相当. 仿真结果验证了所提算法的有效性.

关键词: 景象匹配; 耗时; 矩不变量; 和表; 小波分解

1 Introduction

Image matching refers to the ability to locate or match a region of an image representing a view of a scene with a corresponding region of another view of the same scene often taken under different sensor pose geometry, or different type of sensor. Generally, there may exist geometric distortion such as translation, rotation and scaling between reference and actual image. In such applications, invariant moment-based methods provided by Hu[1] can be used. Since the evaluation of the moment is computationally expensive, there has been a need for low-cost moment algorithms for real-time processing. Many fast computation methods of single image moment have been proposed[2∼4], however, in the matching process, it needs to compute the moment invariants of each sub-image to find the final location, and it is still hardly practical for real-time matching even the methods mentioned above[2∼4] are applied to each sub-image. Then, aiming at moment-based matching process, various methods have been brought forward to speed up this process. The papers[5,6] took histogram-based moment invariants as matching features to reduce the computational complexity from two dimension into one dimension. The papers[7,8] applied wavelet transform to images first to decrease the searching space of moment-based matching process. Tong[9] performed the moment-based matching by using the genetic algorithm to avoid point by point searching. The methods described above[5∼9] speeded up matching process ef-

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fectively, however, those methods may lose some image information during matching and will affect the match precision. In this paper, we propose a fast novel matching algorithm by means of calculation characteristic of moment features, which adopts point by point searching in the original gray image and could not miss the optimum points or lose any image information. The remainder of the paper is organized as follows. Section 2 gives a brief overview of Hu's seven famous moment invariants. Section 3 presents the proposed algorithm for fast matching. Section 4 analyses the computational complexity of various algorithms. In Section 5, various simulation results from the use of the proposed algorithm are showed and compared with results from the conventional methods in terms of the speed and precision of the algorithm. Finally, we give concluding remarks in Section 6.

2 Moment invariants of digital image

The two-dimensional $(p+q)\mathrm{th}$ order geometric moment (or just moment for short) of a digital image f is defined by:

$$m_{pq}=\sum_{i=1}^{M}\sum_{j=1}^{N}i^pj^qf(i,j), \tag{1}$$

where $f(i,j)$ is the pixel value of image f at location (i,j).

The central moment μ_{pq} and its normalized central moment are defined by:

$$\mu_{pq}=\sum_{i=1}^{M}\sum_{j=1}^{N}(i-\bar{i})^p(j-\bar{j})^qf(i,j), \tag{2}$$

where $\bar{i}=m_{10}/m_{00},\ \bar{j}=m_{01}/m_{00},\ i\in M, j\in N$,

$$\eta_{pq}=\frac{\mu_{pq}}{\mu_{00}^r},\ r=(p+q)/2,\ p+q=2,3,\cdots, \tag{3}$$

η_{pq} varies with respect to the rotation of image f . The moments which are invariant with respect to rotation and translation of image are as follows[1]:

$$\phi_1=\eta_{20}+\eta_{02}, \tag{4}$$

$$\phi_2=(\eta_{20}-\eta_{02})^2+4\mu_{11}^2, \tag{5}$$

$$\phi_3=(\eta_{30}-3\eta_{12})^2+(3\eta_{21}-\eta_{03})^2, \tag{6}$$

$$\phi_4=(\eta_{30}+\eta_{12})^2+(\eta_{21}+\eta_{03})^2, \tag{7}$$

$$\begin{aligned}\phi_5=&(\eta_{30}-3\eta_{21})(\eta_{12}+\eta_{03})[(\eta_{30}+\eta_{12})^2-\\&3(\eta_{21}+\eta_{03})^2]+(3\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})\cdot\\&[3(\eta_{12}+\eta_{30})^2-(\eta_{21}+\eta_{03})^2],\end{aligned} \tag{8}$$

$$\begin{aligned}\phi_6=&(\eta_{20}-\eta_{02})[(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2]+\\&4\eta_{11}(\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03}),\end{aligned} \tag{9}$$

$$\begin{aligned}\phi_7=&(3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2-\\&3(\eta_{21}+\eta_{03})^2]-(\eta_{30}-3\eta_{12})(\eta_{21}+\eta_{03})\cdot\\&[3(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2].\end{aligned} \tag{10}$$

3 Fast moment matching algorithm basedon sum-tables

In the moment-based scene matching process, the operation of feature extraction in actual image only needs one time, but this operation is executed in each sub-image of reference image, so, it is very significant to simplify the moments computation of sub-images.

3.1 Hu's moment invariants of reference sub-image

Let $M\times N$ be the size of the reference image f and $m\times n$ the actual image, as illustrated in Fig.1, then the geometric moment $m_{pq}(u,v)$ and central moment $\mu_{pq}(u,v)$ of this sub-image can be expressed as:

$$\begin{aligned}&m_{pq}(u,v)=\\&\sum_{i=u-m+1}^{u}\sum_{j=v-n+1}^{v}\{[i-(u-m)]^p[j-(v-n)]^qf(i,j)\},\end{aligned} \tag{11}$$

$$\begin{aligned}&\mu_{pq}(u,v)=\\&\sum_{i=u-m+1}^{u}\sum_{j=v-n+1}^{v}\{[i-(u-m)-\bar{i}]^p\cdot\\&[j-(v-n)-\bar{j}]^qf(i,j)\}.\end{aligned} \tag{12}$$

Let

$$sm_{pq}(u,v)=\sum_{i=u-m+1}^{u}\sum_{j=v-n+1}^{v}i^pj^qf(i,j). \tag{13}$$

Then, the ten lower-order geometric moments of sub-image determined by expansion (11) can be written as:

$$m_{00}(u,v)=\sum_{i=u-m+1}^{u}\sum_{j=v-n+1}^{v}f(i,j)=sm_{00}(u,v), \tag{14}$$

$$\begin{aligned}&m_{01}(u,v)=\sum_{i=u-m+1}^{u}\sum_{j=v-n+1}^{v}[j-(v-n)]f(i,j)=\\&sm_{01}(u,v)-(v-n)sm_{00}(u,v),\end{aligned} \tag{15}$$

$$\begin{aligned}&m_{10}(u,v)=\sum_{i=u-m+1}^{u}\sum_{j=v-n+1}^{v}[i-(u-m)]f(i,j)=\\&sm_{10}(u,v)-(u-m)sm_{00}(u,v),\end{aligned} \tag{16}$$

$$\begin{aligned}&m_{11}(u,v)=\\&\sum_{i=u-m+1}^{u}\sum_{j=v-n+1}^{v}[i-(u-m)][j-(v-n)]f(i,j)=\\&sm_{11}(u,v)-(u-m)sm_{01}(u,v)-\\&(v-n)sm_{10}(u,v)+(u-m)(v-n)sm_{00}(u,v),\end{aligned} \tag{17}$$

$$m_{02}(u,v)=\sum_{i=u-m+1}^{u}\sum_{j=v-n+1}^{v}[j-(v-n)]^2f(i,j)=$$

$$sm_{02}(u,v) - 2(v-n)sm_{01}(u,v) + (v-n)^2 sm_{00}(u,v), \tag{18}$$

$$m_{20}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [i-(u-m)]^2 f(i,j) = sm_{20}(u,v) - 2(u-m)sm_{10}(u,v) + (u-m)^2 sm_{00}(u,v), \tag{19}$$

$$m_{12}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [i-(u-m)][j-(v-n)]^2 f(i,j) = sm_{12}(u,v) - 2(v-n)sm_{11}(u,v) + (v-n)^2 sm_{10}(u,v) - (u-m)sm_{02}(u,v) + 2(u-m)(v-n)sm_{01}(u,v) - (u-m)(v-n)^2 sm_{00}(u,v), \tag{20}$$

$$m_{21}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [i-(u-m)]^2 [j-(v-n)] f(i,j) = sm_{21}(u,v) - 2(u-m)sm_{11}(u,v) + (u-m)^2 sm_{01}(u,v) - (v-n)sm_{20}(u,v) + 2(u-m)(v-n)sm_{10}(u,v) - (u-m)^2(v-n)sm_{00}(u,v), \tag{21}$$

$$m_{30}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [i-(u-m)]^3 f(i,j) = sm_{30}(u,v) - 3(u-m)sm_{20}(u,v) + 3(u-m)^2 sm_{10}(u,v) - (u-m)^3 sm_{00}(u,v), \tag{22}$$

$$m_{03}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [j-(v-n)]^3 f(i,j) = sm_{03}(u,v) - 3(v-n)sm_{02}(u,v) + 3(v-n)^2 sm_{01}(u,v) - (v-n)^3 sm_{00}(u,v). \tag{23}$$

By substitution of (11) into the expansion (12), various lower-order central moments can be expressed as:

$$\mu_{00}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} f(i,j) = m_{00}(u,v), \tag{24}$$

$$\mu_{10}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [i-(u-m)-\bar{i}] f(i,j) = m_{10}(u,v) - m_{00}(u,v)\bar{i} = 0, \tag{25}$$

$$\mu_{01}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [j-(v-n)-\bar{j}] f(i,j) = m_{10}(u,v) - m_{00}(u,v)\bar{i} = 0, \tag{26}$$

$$\mu_{11}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} \{[i-(u-m)-\bar{i}] [j-(v-n)-\bar{j}] f(i,j)\} = m_{11}(u,v) - m_{01}(u,v)\bar{i}, \tag{27}$$

$$\mu_{02}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [j-(v-n)-\bar{j}]^2 f(i,j) = m_{02}(u,v) - m_{01}(u,v)\bar{j}, \tag{28}$$

$$\mu_{20}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [i-(u-m)-\bar{i}]^2 f(i,j) = m_{20}(u,v) - m_{10}(u,v)\bar{i}, \tag{29}$$

$$\mu_{12}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} \{[i-(u-m)-\bar{i})] [j-(v-n)-\bar{j}]^2 f(i,j)\} = m_{12}(u,v) - 2m_{11}(u,v)\bar{j} - m_{02}(u,v)\bar{i} + 2m_{10}(u,v)\bar{j}^2, \tag{30}$$

$$\mu_{21}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} \{[i-(u-m)-\bar{i})]^2 [j-(v-n)-\bar{j}] f(i,j)\} = m_{21}(u,v) - 2m_{11}(u,v)\bar{i} - m_{20}(u,v)\bar{j} + 2m_{01}(u,v)\bar{i}^2, \tag{31}$$

$$\mu_{03}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [j-(v-n)-\bar{j}]^3 f(i,j) = m_{03}(u,v) - 3m_{02}(u,v)\bar{j} + 2m_{01}(u,v)\bar{j}^2, \tag{32}$$

$$\mu_{30}(u,v) = \sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} [i-(u-m)-\bar{i}]^3 f(i,j) = m_{30}(u,v) - 3m_{20}(u,v)\bar{i} + 2m_{10}(u,v)\bar{i}^2. \tag{33}$$

It follows from the definition of Hu's moment invariants[1] that the computational complexity of seven moment invariants $\phi_{pq}(u,v)$ mainly focuses on the computation of lower-order central moments $\mu_{pq}(u,v)$, and we can see from (24)∼(33) that the computation of $\mu_{pq}(u,v)$ is centralized at the computation of $m_{pq}(u,v)$. If the ten lower-order central moments had been worked out, the computation of lower-order central moments $\mu_{pq}(u,v)$ will be easy. In the other hand,we can see from (13)∼(23) that the computation of $sm_{pq}(u,v)$ costs most of the time during the computation of $m_{pq}(u,v)$. From the aforesaid derivation process we can see that the key problem of speeding up matching is to find a method to simplify the computational complexity of the local-sum $sm_{pq}(u, v)$ defined by (13). In the following section, we will give the derivation process of fast computation of $sm_{pq}(u, v)$.

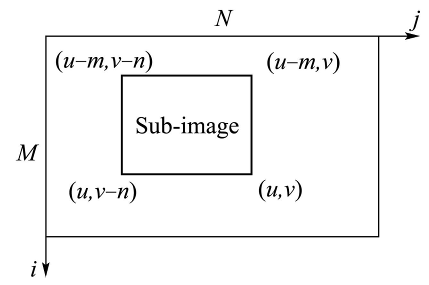


Fig. 1 Reference image and sub-image

3.2 Deriving fast computation of local-sum $\boldsymbol{sm_{pq}(u, v)}$

In Fig.1, we define

$$g_{pq}(u, v) = u^p v^q f(u, v), \tag{34}$$

$$S_{pq}(u, v) = \sum_{i=1}^{u} \sum_{j=1}^{v} i^p j^q f(i, j) \tag{35}$$

where $u = 1, 2, \cdots, M; v = 1, 2, \cdots, N$, then, it follows from (34) and (35)that[10]

$$S_{pq}(u, v) = g_{pq}(u, v) + S_{pq}(u-1, v) + S_{pq}(u, v-1) - S_{pq}(u-1, v-1), \tag{36}$$

where $S_{pq}(0, 0) = 0, S_{pq}(0, v) = 0, S_{pq}(u, 0) = 0$, We first set up ten sum-table matrixes $(M \times N)$ of S_{00}, S_{01}, S_{10}, S_{11}, S_{02}, S_{20}, S_{03}, S_{30}, S_{12}, S_{21} and in terms of (34)$\sim$(36) respectively. According to (36), all elements of each sum-table matrix can be worked out only one time traversal over the whole reference image. With ten sum-table matrixes S_{pq}, the computing of $g(u, v)$ sum within $(m \times n)$ range can be simplified as

$$\sum_{i=u-m+1}^{u} \sum_{j=v-n+1}^{v} g_{pq}(i, j) = sm_{pq}(u, v) = S_{pq}(u, v) - S_{pq}(u-m, v) - S_{pq}(u, v-n) + S_{pq}(u-m, v-n). \tag{37}$$

It follows in terms of (37) that the computing of each local-sum $sm_{pq}(u, v)$ at any location (u, v) can be worked out with 3 additive operations.

3.3 Similarity measure

Considering the difference among the magnitude order of Hu's seven moment invariants, we take Camberra distance[11] as the similarity measure, and the point corresponding to the minimum distance will be the matching location.

Let $X = (x_1, x_2, \cdots, x_n)^{\mathrm{T}}$, $Y = (y_1, y_2, \cdots, y_n)^{\mathrm{T}}$. Camberra distance is defined by:

$$d(X, Y) = \sum_{i=1}^{n} \frac{|x_i - y_i|}{|x_i + y_i|}, \tag{38}$$

where $x_i, y_i \geqslant 0, x_i + y_i \neq 0$.

3.4 Main steps of the fast matching algorithm

Let $M \times N$ be the size of the reference image f_{R} and $m \times n$ the actual image f_{A}. The main steps of matching based on moment invariants are as follows:

1) Calculate $S_{pq}(M \times N)$ with respect to (34)$\sim$(36);

2) Calculate m_{pq} of f_{A} with respect to (1);

3) In terms of (2)$\sim$(10), calculate ϕ_{A} of f_{A};

4) For any sub-image at location (u, v) in reference image f_{R}, where $u \geqslant m, v \geqslant n$, calculate $\phi_{\mathrm{R}}(u, v)$ according to the following procedures:

Calculate $sm_{pq}(u, v)$ with respect to (37) ;

Calculate $m_{pq}(u, v)$ with respect to (14)$\sim$(23);

Calculate $\mu_{pq}(u, v)$ with respect to (24)$\sim$(33);

Calculate $\phi_{\mathrm{R}}(u, v)$ with respect to (3)$\sim$(10);

5) Calculate Camberra distance $d(u, v)$ between ϕ_{A} and $\phi_{\mathrm{R}}(u, v)$ with respect to (38);

6) Repeat 4) to 5) until all locations in reference image have been searched;

7) Take the location corresponding to the minimum distance d as the match point.

4 Analysis of computational complexity

The traditional moment-based matching algorithms[7~9] calculate moments of each sub-image independently, and the computational complexity of each sub-image is the same as that of the actual image. Compared with the proposed algorithm, it can be seen that their computational disparity mainly centralizes on the computation of m_{pq} during matching process. For the reason that the global searching efficiency of genetic algorithm is related to the control parameters adopted and much lower than that of the hierarchical matching methods[12], what's more, the success match rate based on wavelet decomposition is highest among the hierarchical matching methods[13], so, in this paper, we only compare computational complexity of m_{pq} between the proposed and the wavelet-based methods.

4.1 Complexity of the proposed algorithm

Ten lower-order geometric moments of actual image and each sub-image can be worked out by 1) 2) and the first two procedures of 4) described in Section 3.4.

Accomplishing 1) of Section 3.4 needs $30MN$ additions and $9MN$ multiplications;

Accomplishing 2) of Section 3.4 needs $10mn$ additions and $9mn$ multiplications[14];

Accomplishing the first procedure of 4) in Section 3.4 needs only 30 additions;

Accomplishing the second procedure of 4) in Section 3.4 needs only 55 additions and 52 multiplications;

The proposed algorithm adopts point by point searching and the number of the participant match points is $(M-m)(N-n)$. So, to calculate the geometric moments m_{pq} of actual image and all sub-images needs additive operations:

$$30MN + 85(M-m)(N-n) + 10mn \quad (39)$$

and multiplicative operations:

$$9MN + 52(M-m)(N-n) + 9mn. \quad (40)$$

4.2 Complexity of the wavelet-based method

Note that, with the wavelet-based methods[7,8], the computational complexity of each sub-image's geometric moments is the same as that of the actual image. Suppose a j-level wavelet transform is applied to the actual and reference images ($j=0$ corresponding to the traditional point by point matching), and we now only consider the coarse matching complexity in the lowest resolution image.

Computing ten lower geometric moments of actual image needs $10mn/4^j$ additions and $9mn/4^j$ multiplications, and the number of the participant match points is $(M-m)(N-n)/4^j$. So, to calculate the geometric moments m_{pq} of actual image and all sub-images needs additive operations:

$$10mn(M-m)(N-n)/16^j + 10mn/4^j \quad (41)$$

and multiplicative operations:

$$9mn(M-m)(N-n)/16^j + 9mn/4^j. \quad (42)$$

With respect to the aforesaid analysis, it can follow that, on condition that $j<4$, the computational complexity of the proposed algorithm is lower than that of the wavelet-based method, however, that condition is also required by the match precision[15].

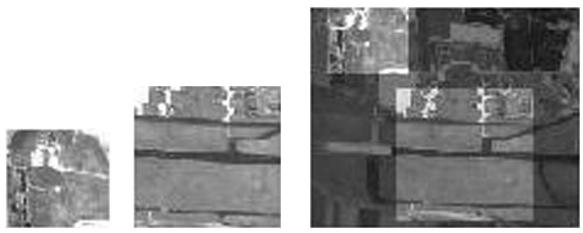
5 Simulation results and discussions

To measure the performance of the proposed algorithm in terms of match speed and precision, experiments with different types of images have been performed on a 2.6GHz Pentium-IV PC and MATLAB7.5 platform. Considering that this paper emphasizes on the speed of moment-based matching method, and that the robustness of moment invariants had been proved by Hu[1], the actual images in our tests are directly taken from the corresponding reference image without any geometric distortion. For simplicity, we only provide two sample test results in this paper.

Sample1 is conducted with SAR image. The size of the reference image is 200×200, and the actual image size varies from 60×60 to 90×90. Fig.2 shows part of the results, where (a) and (b) are actual images and (c) shows the simulation result of their location in reference image. Sample 2 is conducted with IKONOS image. The size of the reference image is 300×300, and the actual image size varies from 90×90 to 150×150. Fig.3 shows part of the results, where (d) and (e) are actual images and (f) shows the simulation result of their location in reference image. It is easy to see from (c) and (f) that the proposed algorithm has located the position of each actual image precisely. To emphasize the rapidity of the proposed approach, we do the simulation experiments with the same images using the traditional point-by-point method and the wavelet-based method respectively. Table1 shows their comparison results. It is easy to see from table1 that the precision of the proposed approach is the same as the traditional one, but costs much less time. At the same time, the proposed method is also faster than the wavelet-based method provided that the match precision is assured.

(a) (b) (c)

Fig. 2 Simulation result using SAR image



(d) (e) (f)

Fig. 3 Simulation result using IKONOS image

Table 1 Comparison of matching algorithms

reference image size	actual image size	actual match point	the proposed algorithm simulated match point	the proposed algorithm consuming times/s	traditional point by point searching method simulated match point	traditional point by point searching method consuming times/s	wavelet-based method simulated match point	wavelet-based method consuming times/s
200∗200 SAR	60∗60	30,30	30,30	2.402	30,30	242.6	28,32	6.74
	70∗70	100,120	100,120	2.019	100,120	261.4	100,120	6.14
	90∗90	15,70	14,70	1.925	14,70	263.9	40,60	4.01
300∗300 IKONOS	90∗90	20,20	20,20	8.575	20,20	1782.2	128,184	14.07
	100∗100	50,180	50,180	8.894	50,180	1870.9	56,184	14.14
	150∗150	130,100	130,100	8.184	130,130	1616.065	130,102	12.402

6 Conclusions

In this paper, we proposed a new fast moment-based matching algorithm. The traditional moment-based methods speed up matching often by reducing the searching space, which may make a bad influence on matching precision, and furthermore yields mismatch. The proposed algorithm, however, utilizes the computational correlativity of neighborhood sub-images in terms of moment features to reduce the computational cost, which could not influence the matching precision. Experimental results show that the proposed algorithm has a good performance both in speed and precise.

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