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A Sequential Matching Algorithm Using Moment–Preserving Pattern Features

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RÉSUMÉ

Résumé– L'harmonisation des jauges pour l'enregistrement d'images translationelles est fondamentale dans les disciplines de la reconnaisance des structures et du traitement des images. Comme le procédé de calcul est intensif, il est fort desirable dans le cas de l'application au traitement d'images de disposer d'un algorithme harmonié précis et rapide. Nous présentons ici un algorithme séquentiel d'une seule passe et de deux phases qui accélère le procédé d'harmonisation. L'ordre de vérification des pixels de jauge est déterminé par les structures particulières obtenues par la conservation des statistiques locales de la jauge.

ABSTRACT

Abstract– Template matching for the registration of translational images is fundamental to the disciplines of pattern recognition and image processing. It is, however, a computationally intensive process. An accurate and fast matching algorithm of low computational complexity is thus highly desired by many image–processing applications. In this paper, a single–pass, two–stage sequential algorithm is presented to speed up the matching process, in which the testing order of template pixels is determined by the pattern features obtained from preserving local statistics of the template.

1. INTRODUCTION

Image template matching is a computationally intensive process. To alleviate the computational burden of similarity measure at the test positions that are mismatched. The sequential approach was proposed to be an effective method to save the computation time. The basic idea of sequential matching algorithm is to reduce the number of template pixels that must be taken into the similarity measure by accumulating the errors between template pixels and the windowed search–area pixels [1]. By employing a properly designed order in which template pixels are examined, the testing threshold is expected to be exceeded much sooner than if they are examined row by row, and thus resulting in computational savings. In the method proposed by Nagel and Rosenfeld [2], the template pixels are tested in order of their expected absolute differences from a randomly selected pixel in the search area, or in order of the joint probability of occurrences in the template and search area. Barnea and Silverman [3] have developed a class of algorithms, called sequential similarity detection algorithms (SSDA). In their approach, two ordering algorithms are employed, respectively, to select the test positions and to select the template pixels for accumulating measure errors. In some applications, the random selection of template pixels is considered to be inefficient and time–consuming, since the prominent features contained in the template are not fully exploited. Reed *et al.* [4] have therefore proposed a feature–based method for registering retinal images, where the prominent patterns of retina vessels are employed to accelerate the matching process. The selection of vessel points is performed through a procedure that thresholds the template pixels with the median of gray levels if the standard deviation of template pixels exceeds a given test level. In this paper, a single–pass two–stage sequential matching algorithm is proposed to generalize the method of Reed *et al.* through the utilization of moment–preserving pattern features

2. MOMENT–PRESERVING PATTERN FEATURES

Moment–preserving quantization was originally proposed in an image coding technique known as block truncation coding (BTC) [5]. The essence of this coding method is the employment of a one–bit nonparametric quantizer that preserves brightness (sample mean) and contrast (sample standard deviation) of an image block in the quantized output. The output of the quantizer is described by one bit plane and two output quantization levels. The pixels of the image block are then classified into two groups. The bit plane is used to indicate which group a certain pixel in the image block belongs to. Let $t_1, t_2, \ldots, t_\lambda$ be the intensity values of $\lambda = m \cdot n$ pixels in an image block (or template). Then the sample mean and sample standard deviation of this image block to be preserved are

$$\eta = \frac{1}{\lambda} \sum_{i=1}^{\lambda} t_i \;, \tag{1}$$

$$\sigma = \left[\left(\frac{1}{\lambda} \sum_{i=1}^{\lambda} t_i^2 \right) - \eta^2 \right]^{\frac{1}{2}} . \tag{2}$$

The one–bit quantizer is designed by setting the threshold value, t_{th} , equal to η such that the resulting bit plane contains 1's in those places where $t_i \geq \eta$ and 0's otherwise. Two output levels $\boldsymbol{a}$ and $\boldsymbol{b}$, that are used to reconstruct the image block in accordance with the resulting bit plane, are obtained as follows

$$\boldsymbol{b} = \eta + \sigma \cdot (\frac{\lambda - q}{q})^{\frac{1}{2}} \qquad \text{for } t_i \geq \eta \tag{3}$$

$$\boldsymbol{a} = \eta - \sigma \cdot (\frac{q}{\lambda - q})^{\frac{1}{2}} \qquad \text{for } t_i < \eta \tag{4}$$

where q is the number of pixels with their gray levels greater than or equal to η.

It is noted that, in addition to the preserving of the first two moments, the resulting bit plane also preserves the spatial distribution of those pixels of the same group by the positions of 1–bits and 0–bits. Attempt is thus made to utilize these bit–pattern features inherent in the output of moment–preserving quantization to detect the template location. In order to obtain a sharp match, the distinctive bit–pattern features must be extracted from the template. Two feature bit–planes are thus considered, by assuming that the histogram of the template has a bimodal distribution (if the standard deviation of the template is beyond a predefined threshold) with the upper centroid equal to $\boldsymbol{b}$ and the lower centroid $\boldsymbol{a}$. One of these two bit planes is obtained as the output of a one–bit quantizer that features the location patterns of template pixels of higher values around $\boldsymbol{b}$ and bounded by the deviation of $\mathrm{F} \cdot \sigma \cdot (\frac{\lambda - q}{q})^{\frac{1}{2}}$, where F is a fraction parameter used to adjust the decision levels of the quantizer. The function of this one–bit quantizer, Q_u , can be defined as

$$Q_u(x) = \begin{cases} 1 & \text{if } U_l \leq x \leq U_u \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where

$$U_l = \boldsymbol{b} - \mathrm{F} \cdot \sigma \cdot (\frac{\lambda - q}{q})^{\frac{1}{2}} , \tag{6}$$

$$U_u = \boldsymbol{b} + \mathrm{F} \cdot \sigma \cdot (\frac{\lambda - q}{q})^{\frac{1}{2}} , \tag{7}$$

and the resulting template bit–plane is denoted as

$$T_u = \{ t_u(i,j) = Q_u(t\,(i,j)) : 0 \leq i \leq m-1,\ 0 \leq j \leq n-1 \}.$$

Similarly, the function of the other one–bit quantizer, Q_l , that results in the bit plane featuring the location patterns of those template pixels of lower values around $\boldsymbol{a}$ and bounded by the deviation of $\mathrm{F} \cdot \sigma \cdot (\frac{q}{\lambda - q})^{\frac{1}{2}}$ can be defined as

$$Q_l(x) = \begin{cases} 1 & \text{if } L_l \leq x \leq L_u \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where

$$L_l = \boldsymbol{a} - \mathrm{F} \cdot \sigma \cdot (\frac{q}{\lambda - q})^{\frac{1}{2}} , \tag{9}$$

$$L_u = \boldsymbol{a} + \mathrm{F} \cdot \sigma \cdot (\frac{q}{\lambda - q})^{\frac{1}{2}} , \tag{10}$$

and the resulting template bit plane is denoted as

$$T_l = \{ t_l(i,j) = Q_l(t\,(i,j)) : 0 \leq i \leq m-1,\ 0 \leq j \leq n-1 \}.$$

3. SEQUENTIAL TEMPLATE MATCHING

In the method of SSDA, a constant threshold Υ is intro–duced, against which the accumulated error of randomly selected windowing pairs is tested. When the accumulated error exceeds Υ at the rth step, the measure operation ceases for this test position and the value r is recorded. The SSDA similarity measure surface $\mathcal{I}(f,g)$ is defined as

$$\mathcal{I}\,(f,g) = \left\{ c \mid \min_{1 \leq c \leq m \cdot n} \left\{ \sum_{v=1}^{c} \epsilon\,(\, f, g, k_v\,, l_v\,) \geq \Upsilon \,\right\} \right\} \tag{11}$$

where

$$\epsilon\,(\, f, g, k_v\,, l_v\,) = \mid p\,(f{+}k_v\,, g{+}l_v\,) - t\,(\, k_v\,, l_v\,) \mid , \tag{12}$$

with $0 \leq k_v \leq m-1$ and $0 \leq l_v \leq n-1$, and $\{ p(f{+}k_v , g{+}l_v) \}$ the pixels of the underlying search area. The larger the value of $\mathcal{I}(f,g)$ is, the more likely the test point is a candidate for a match. The average value of a point in the surface $\mathcal{I}(f,g)$ and the maximum value of $\mathcal{I}(f,g)$ grows linearly with threshold. It has been found in [3] that, for the case of constant threshold, the ratio of the maximum value to the average value of $\mathcal{I}(f,g)$, an indicator of the accuracy of the method, is relatively constant. This implies that accuracy grows linearly with the threshold value, and is achieved by an associated increase in computation. Since the error increasing rate at the candidate template positions is low, the search process can be simply performed by evaluating the count at various thresholds. In the experiments made in [4], It is found that the correct matching is included in the 10 most likely points for almost all threshold levels. Therefore, a two–stage two–threshold scheme is a promising method to accelerate the matching process. In the following description, a single–pass two–stage matching algorithm that uses moment–preserving pattern features is described.

4. THE PROPOSED ALGORITHM

In the first–stage search, an ordering algorithm by which the template pixel is taken to accumulate the measure error is determined. Through the employment of the two–level quantization described in Sec. 2, the selection of template pixels is determined by adjusting the parameter F of the one–bit quantizers to a value F_1, such that 1~2% of all template pixels, or at least 10 template pixels, are selected and have intensity values ranged from U_{l1} to U_{u1} or from L_{l1} to L_{u1}. This results in a set of template coordinates $\{ (x,y) : U_{l1} \leq t(x,y) \leq U_{u1}\,,\ L_{l1} \leq t\,(x,y) \leq L_{u1}\,,\ 0 \leq x \leq m-1,\ 0 \leq y \leq n-1 \}$, which are selected in an unrepeated random order to accumulate the measure error. Then, supposing ψ template pixels are selected, the similarity counting surface $\mathcal{I}_1(f,g)$ of the first–stage search is defined as

$$\mathcal{I}_1(f,g) = \left\{ c \mid \min_{1 \le c \le \psi} \left\{ \sum_{v=1}^{c} \epsilon(f, g, k_v, l_v) \ge \Upsilon_1 \right\} \right\} \tag{13}$$

where

$$\epsilon(f, g, k_v, l_v) = \mid p(f+k_v, g+l_v) - t(k_v, l_v) \mid ,$$

$$(k_v, l_v) \in \{ (x,y) : U_{l1} \le t(x,y) \le U_{u1}, L_{l1} \le t(x,y) \le L_{u1}, \\ 0 \le x \le m-1, 0 \le y \le n-1 \} \tag{14}$$

The associated threshold value of the first stage, Υ_1, is set equal to the sum of the maximum possible intensity deviations at the match position, where the pairs of pixels to be compared are considered to have intensities of the same range. That is

$$\Upsilon_1 = \kappa \cdot (U_{u1} - U_{l1}) + \iota \cdot (L_{u1} - L_{l1}) , \tag{15}$$

where κ out of ψ selected template pixels have intensity values ranged from U_{l1} to U_{u1}, and the intensity values of the remaining ι template pixels ranges from L_{l1} to L_{u1}. When this threshold is reached at a test position, the count is tested. If it exceeds 85% of ψ points, this template position is taken as a candidate for a match, and the process proceeds to perform the second–stage search. Otherwise, this test position is considered as a mismatch and the process proceeds to perform the first–stage search at the next test position. In the second stage, the threshold level is increased to a value as

$$\Upsilon_2 = K \cdot (U_{u2} - U_{l2}) + \Gamma \cdot (L_{u2} - L_{l2}) , \tag{16}$$

where the decision levels, U_{u2}, U_{l2}, L_{u2} and L_{l2}, are obtained by adjusting F to a larger value F_2 ($> F_1$). K is the number of template pixels with intensity values ranged from U_{l2} to U_{u2}, and Γ the number of template pixels with intensity values ranged from L_{l2} to L_{u2}. The similarity counting surface $\mathcal{I}_2(f,g)$ of the second–stage search is thus

$$\mathcal{I}_2(f,g) = \left\{ c \mid \min_{1 \le c \le K+\Gamma} \left\{ \sum_{v=1}^{c} \epsilon(f, g, k_v, l_v) \ge \Upsilon_2 \right\} \right\} \tag{17}$$

where

$$\epsilon(f, g, k_v, l_v) = \mid p(f+k_v, g+l_v) - t(k_v, l_v) \mid ,$$

$$(k_v, l_v) \in \{ (x,y) : U_{l2} \le t(x,y) \le U_{u2}, L_{l2} \le t(x,y) \le L_{u2}, \\ 0 \le x \le m-1, 0 \le y \le n-1 \} \tag{18}$$

The template coordinates in (18) are also selected in an unrepeated random order to accumulate the measure error in the second stage. As this higher threshold value is reached at a template location, the count is tested and recorded. The testing threshold is then reset to the lower one and the process proceeds to perform the first–stage search at the next template position. When all of the template positions are tested, the candidate position at which the count has the highest value is selected as the best match position.

5. SIMULATION RESULTS

In order to evaluate the performance of the proposed algorithm, two templates, **u** and **v**, of size 32×32 and their corresponding search areas, **U** and **V**, of size 128×128 are selected from an aerial image (Fig. 1) for simulation. The simulation is performed on a PC–386 with proper programming. The simulation results show that, for the template **u** and search area **U**, the proposed algorithm is 156 times faster than the matching process using the sum of absolute differences (SAD), and 572 times faster than the matching process using correlation coefficients. For the template **v** and search area **V**, the speedup is found to be 204 and 647, respectively.

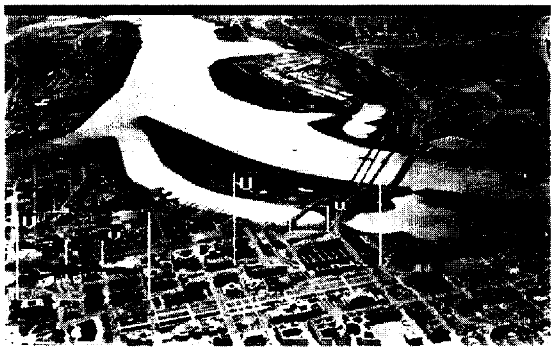

Fig. 1 An aerial image used for simulation

6. CONCLUSION

In this paper, a feature–extraction method based on moment–preserving quantization is proposed, and is verified to be effective in reducing computational overhead, while increasing the reliability, of the sequential matching algorithm. This feature–based algorithm can be used effectively in many applications for fast image registration.

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