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A ROBUST AND REAL-TIME TEXTURE ANALYSIS SYSTEM USING A DISTRIBUTED WORKSTATION CLUSTER

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ABSTRACT

This paper presents a parallel approach to the development of a real-time system for recognition of textured objects. In order to find an efficient and effective approach to identify and localize objects in textured images invariant of translation, rotation and scale changes and occlusion, we propose a new method which involves dynamic texture feature extraction and hierarchical image matching. Based on our previous work, we extend the concept of interesting points and develop a dynamic detection procedure on texture energy image which is in conjunction with Laws' texture energy concept and our mask tuning scheme. The search for the best fit between two objects in terms of Hausdorff distance is guided through an interesting point pyramid from coarse level to fine level. In addition, unlike current approaches which mostly rely on specialized multiprocessor architectures for fast processing, we use a distributed workstation cluster to support parallelism, which provides a different approach to real-time computing and applicable to many classes of tasks.

Key words and phrases: Object recognition, image matching, texture feature extraction, interesting points, parallel implementation, real-time computing, distributed system.

1. INTRODUCTION

Many important object recognition applications involve textured objects. Real-time and relatively low-cost systems for recognizing textured objects will be crucial to the practice of medicine, photo-interpretation and other industrial and defense applications. The central problem concerned is to find an efficient and effective approach to image matching which can identify and localize objects in textured images. In the past, many of the matching methods were based on the detection of edge points as image features. Examples include Barrow *et al*'s Chamfer matching[1], Borgefors' multi-resolution Chamfer matching[2] and Huttenlocher *et al*'s Hausdorff distance[3], however, they are not suitable for a general matching task and are limited for applications. Our previous research has investigated how to extract image feature points more reliably for matching and concluded that interesting points can preserve image features more effectively with less points[4]. However, such a claim will not be suitable for textured images because texture is characterized by its local features over some neighbourhood rather than in pixel gray scale. Consequently, an immediate and important question is how to extract reliable interesting points from textured images so that the related matching method is still applicable. In our brief, such a problem can be tackled by utilising and extending the results of our previous work[8].

In this paper we describe a simple but reliable approach to recognize and localize objects in textured images. Section 2 introduces our extension of the concept of texture interesting points while Section 3 summarizes a dynamic procedure to detect such points for textured image matching. Section 4 outlines a hierarchical structure to perform guided search for the best matching in terms of Hausdorff distance, and Section 5 highlights the main steps of parallel implementation using a distributed workstation cluster. Finally, Section 6 presents some experimental results and our conclusions.

2. DYNAMIC DETECTION OF TEXTURE FEATURE POINTS

Texture is a vital element in segmenting images and interpreting scenes. We aim to detect texture interesting points invariant of scale and rotation changes as the basis for textured image matching. In contrast to the conventional approaches, the interesting points are dynamically detected on texture energy image which is based on Laws' texture energy concept in conjunction with the 'tuned' mask. The key points regarding such an extension are summarized as below.

2.1. Adaptive Texture Feature Extraction

Structural and statistical approaches can be both applied to extract texture features[5]. The statistical approach to texture classification and segmentation pioneered by Laws is notable for its computational simplicity[6]. However, the application of his scheme was limited by its classification accuracy due to the used of fixed masks.

The objective of the mask tuning scheme is to increase the classification accuracy by replacing the constants of Laws' masks with variables. The mask coefficients are therefore adjusted on the training samples by optimising a given performance index. Our extension is based on Laws' texture energy concept[6] and Benke *et al*'s initial mask tuning scheme[7]. The mask is assumed 5*5 size with zero sum in each row. Thus there are 20 mask coefficients to be determined during the training session. In our approach the local variance after convolution is well-approximated the

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sum of squared values of convolved image within the test window, which is expressed as below:

$$TE(i,j) = \frac{\sum_{W_x} \sum_{W_y} {(I * A)^2}_{rs}}{P^2 W_x W_y}$$

where the rs sum is over all pixels within a square window W of size $W_x * W_y$ centered on the pixel at i, j, A is a zero sum 'tuned' $5 * 5$ convolution mask and P is the parameter normalizer $P^2 = \sum_{i,j} (A_{i,j})^2$.

2.2. Texture Interesting Points

The detection of interesting points is based on the measure of how interesting a point is. *Interesting* here has its own special meanings depending on different applications. Unlike the traditional methods in which interesting point detector is directly applied to the original gray scale image, the detection procedure in our test is performed on the texture energy image associated with the 'tuned' mask. From the simplicity point of view, Moravec operator is used for testing.

It should also be drawn attention that the traditional selection of interesting points on the basis of Moravec operator depends on the pre-defined threshold value. We further introduce a dynamic thresholding procedure based on the histogram. Figure 1 shows the comparison of textural image feature pixels represented by edge points, texture energy, interesting points and texture interesting points respectively. Figure 1(a) is a template image and Figure 1(b) is a two-texture composite image to be processed, where the background is featured by Brodatz texture raffiad84 and the object in the shape of the coast line of Australia is filled with Brodatz texture pigskind92. Figure 1(c) demonstrates edge points detected by Prewitt operator, Figure 1(d) represents texture energy image using Laws' R5R5 mask, Figure 1(e) shows interesting points detected by Moravec operator on the original image shown in Figure 1(b) and Figure 1(f) presents texture interesting points detected by Moravec operator on the texture energy image shown in Figure 1(d). It is clear that texture interesting points best represent the original image with less points.

3. HIERARCHICAL TEXTURED IMAGE MATCHING

Our goal is to develop a general hierarchical textured image matching method using texture interesting points. The Hausdorff distance is used as the matching measurement to determine the similarity between two objects that are superimposed on one another. In contrast to other methods reported in the literature, we are concerned to perform matching on an interest image pyramid which is used to guide the search for the optimal position for matching. A dynamic thresholding scheme is developed to construct the required pyramid for the guided matching from the low level with less interesting points for coarse matching to the fine level with more interesting points for precise matching.

3.1. The Hausdorff Distance

The Hausdorff distance is a non-linear operator which measures the mismatch of the two sets. It can be used for object recognition by comparing two images which are superimposed on one another. Such an operation is summarised below:

Given two finite point sets $A = \{a_1, ..., a_m\}$ and $B = \{b_1, ..., b_n\}$, the Hausdorff distance D_H between these two sets is defined as

$$D_H = \max(d_{AB}, d_{BA})$$

where d_{AB} is the distance from set A to set B expressed as

$$d_{AB} = \max_{a_i \in A}(d_{a_i B})$$

while $d_{a_i B}$ is the distance from point a_i to set B given by

$$d_{a_i B} = \min_{b_j \in B}(d_{a_i b_j})$$

Obviously the Hausdorff distance D_H is the maximum of d_{AB} and d_{BA} which measures the degree of mismatch between two sets A and B. In our test, the calculation is performed on the texture feature image characterized by texture interesting points.

3.2. Interesting Point Pyramid

An image pyramid is a structure that stores not only the original image, but also a collection of related images derived from the origin. The image pyramid applied in our test is built up based on the number of interesting points used for matching. The selection of interesting points is through a dynamic thresholding scheme guided by the histogram. For a given original image, a so-called interest image is obtained by applying interesting point detector to the image. Each pixel value of this image actually represents the interest degree of the corresponding pixel in the original image. If a certain threshold value is determined, those pixels whose values are below the selected threshold value will be considered as interesting points and set to 1 in the image feature map while those above threshold value will be ruled out and assigned to 0 in the feature map. Consequently a distance image will be created by applying distance transform using 3-4 DT mask. As the more interesting points involved, the better the image feature is represented and the more precise the matching will be. Figure 2 shows an example of such an interesting points pyramid.

3.3. Guided Matching

We are concerned to search for the best fit between the template and the target image. In general, the operation of any hierarchical approach is performed from low level to high level where the results at the low level will guide the operation at the higher level. The hierarchical matching presented in this paper is performed on the interesting points pyramid from coarse level to fine level by minimizing the Hausdorff distance. The matching starts from the coarse level in the pyramid with less interesting points. A limited number of areas corresponding to relatively low value of the Hausdorff distance detailed in Section 3.1 are marked as possible candidates for further precise matching. Then the matching process is moved to the upper level with more interesting points considered and the searching for the best matching is focused on those areas which are marked in the previous level and the same marking process will be repeated in search for the global minimum Hausdorff distance.

4. PARALLEL IMPLEMENTATION

As emphasized before, the execution time of a matching task can be reduced by utilizing distributed workstations to execute multiple sub-tasks simultaneously. While most

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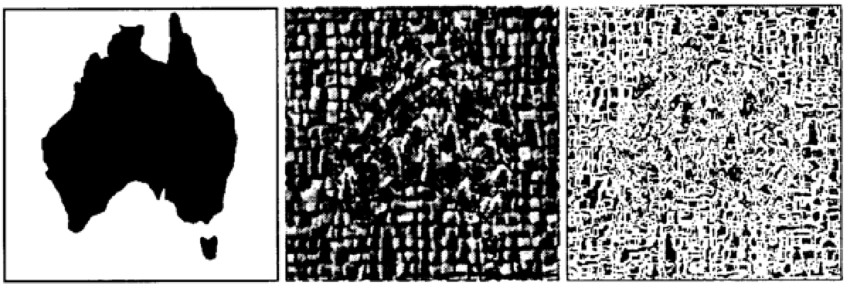
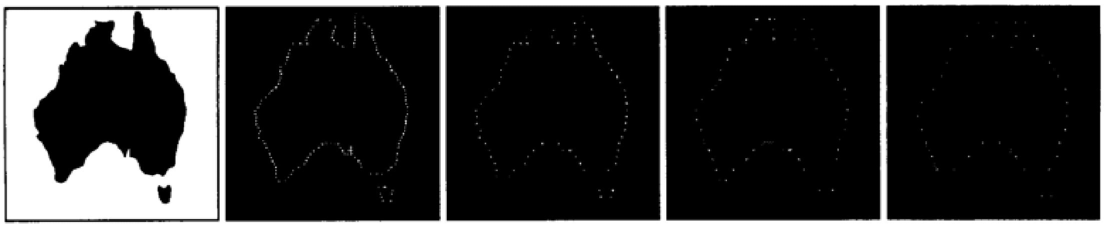


(a) image template (256*256) (b) texture image (two-texture composite) (c) edge image (Prewitt operator)

(d) texture energy image (Laws' R5R5 mask) (e) interesting points image (Moravec operator) (f) texture interesting points (Moravec operator)

Figure 1. Comparison of feature piexls for texture image matching



(a) Original image (b) Level 1 points (c) Level 2 points (d) Level 3 points (e) Level 4 points

Figure 2. An example of interesting points pyramid

Table 1: The comparison of execution time in parallel and sequential

image size	execution time (in sequential)	execution time (in parallel)
128*128	3.3 sec.	1.79 sec.
256*256	15.7 sec.	7.07 sec.
512*512	140.7 sec.	46.62 sec.

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of the sequential execution time is spent on distance transform and matching measurement due to cache miss on a single processor, our investigation shows that the distributed workstations can meet the high computational and memory access demands in image processing.

The utilization of workstation clusters can yield many potential benefits, such as performance and reliability. Some researchers even predict that workstation clusters in practice can replace supercomputers in the future. Although we are not sure about this argument, we do believe that workstation cluster can take over some tasks which were done by supercomputers, especially those computation intensive tasks such as vision-related tasks. Another obvious advantage that workstation clusters are superior to supercomputers is the availability. Currently, there are a variety of systems which provide message-passing services for parallelism such as PVM, Express, Linda and P4. Although distributed shared memory seems more attractive and effective for the vision tasks which require iterative operations on the same areas, we use PVM at the first stage to implement our proposed matching scheme. The version using distributed shared memory will be reported elsewhere. The following lists the main steps involved:

- parallel image convolution with texture 'tuned' mask
- parallel texture feature extraction – texture energy image
- parallel detection of texture interesting points
- parallel creation of interesting points pyramid
- parallel distance transform
- parallel matching measurement

5. EXPERIMENTAL RESULTS

The textures used in this study were selected from Brodatz's well-known compilation. It is noted that convolution operation plays a key role during mask tuning, the speed-up of the calculation will benefit the overall performance. On the average the sequential execution time for each convolution with 5*5 mask on 256*256 image implemented on Classic SPARC workstation is about 5.8 sec. while the parallel computation with 4 processes increases the processing speed by 15% to 4.96 sec. for each convolution. The processes involved are invoked on four different SPARC workstations which are connected by an Ethernet. The higher speed is expected when high speed network, such as ATM , is used and more processes are invoked for parallel implementation.

The advantages and potentials of a general distributed system for parallel image processing is further demonstrated by the parallel detection of interesting points for image matching. The parallel performance improvement is measured by the following ratio:

$$\gamma = \frac{T_s - T_p}{T_s}$$

where T_s refers to the sequential execution time and T_p refers to the parallel execution time. Table 1 lists the average execution time for the detection of interesting points on different images with various sizes. It should be pointed out that the distribution of workload plays an important role in achieving a desirable performance in parallel implementation of many computational tasks. During the parallel experiment of our hierarchical matching system, the workload of each processor heavily depends on the complexity of each subtasks and the related algorithms. In order to speed up the processing and reduce the delay spent on synchronization, a task scheduling procedure is required which can map a series of subtasks to a workstation cluster and dynamically relocate those tasks when it is necessary in order to attain high performance. In our future work, we aim to develop a workload allocator for dynamic resource allocation so as to reduce execution time.

6. CONCLUSION

We propose a guided matching scheme by developing a hierarchical matching algorithm based on the detection of texture interesting points by means of a mask tuning scheme. We conclude that texture interesting points reduce the number of pixels essential for distance transformation in image matching and the detection of texture interesting points following texture feature extraction provides an efficient method for object recognition in textured images. The algorithm is easy to implement and provides satisfactory results. Such a hierarchical scheme is further extended by parallelism on a low cost heterogeneous PVM (Parallel Virtual Machine) network on the basis of a divide-and-conquer policy. Our investigation confirms that a distributed memory multicomputer can meet the high computational and memory access demands in image processing and the parallel implementation on a general distributed system can be widely applied in practice for better performance without specific hardware requirements.

REFERENCES

[1] H.G. Barrow, J.M. Tenenbaum, R.C. Bolles and H.C. Wolf, "Parametric correspondence and chamfer matching: Two new techniques for image matching", *Proc. 5th Int. Joint Conf. Artificial Intelligence*, Cambridge, MA, pp. 659-663, 1977.

[2] G. Borgefors, "Hierarchical chamfer matching: a parametric edge matching algorithm", *IEEE Trans. Patt. Anal. Machine Intell.*, Vol. PAMI-10, pp. 849-865, 1988.

[3] D.P. Huttenlocher, G.A. Klanderman and W.J. Rucklidge, "Comparing images using the Hausdorff distance", *IEEE Trans. Patt. Anal. Machine Intell.*, Vol. PAMI-15, pp. 850-863, 1993.

[4] J. You, E. Pissaloux, J.L. Hellec and P. Bonnin, "A guided image matching approach using Hausdorff distance with interesting points detection" *Proc. of 1st IEEE international conference on image processing*, Austin, USA, November 13-16, 1994, pp. 968-972.

[5] R.M. Haralick, "Statistical and structural approaches to texture", *Proc. IEEE*, Vol. 67, pp. 786-804, 1979.

[6] K.I. Laws, "Textured image segmentation", *Ph.D thesis*, University of Southern California, January, 1980.

[7] K.K. Benke, D.R. Skinner and C.J. Woodruff, "Convolution operators as a basis for objective correllates for texture perception", *IEEE Trans. Syst., Man, Cybern.*, Vol. SMC-18, pp. 158-163, 1988.

[8] J. You and H.A. Cohen, "Classification and Segmentation of Rotated and Scaled Textured Images Using Texture 'Tuned' Masks", *Pattern Recognition*, Vol. 26, No. 2, Feb., pp. 245 - 258, 1993.