

**ANALOGY OF DIFFERENT MATCHING METHODS  
USING SATELLITE IMAGERY**

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ABSTRACT

The problem of scene matching is a challenging problem in the field of image processing and pattern recognition. Given a pictorial description of a region of a scene, it is desired to determine which region in another scene is similar. The simplest method to solve this problem is called "template matching" and suffers from the great amount of computations required.

The most efficient algorithms for scene matching are discussed. Those are the sequential hierarchical scene matching algorithms for gray-scale and binary images and the two-stage template matching algorithm.

Experimental results are presented for matching satellite images of Al-Minea (EGYPT) and Montana (USA) using those approaches. The experimental work is done using the Remote Image Processing System, Military Technical College. The results prove efficiency and success in reaching the best match location with minimum required computations. A comment on the results is presented as well as a comparison between the applied methods.

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## I- Introduction :

The target of this paper is to reach the best match location with minimum computations required and this leads us to deal with the most efficient scene matching algorithms. Those are the basic sequential hierarchical scene matching , the sequential hierarchical scene matching using edge features, and the two-stage template matching for binary images. An overview of the techniques is provided as well as an analogy between the different algorithms applied .

## II- The Sequential Hierarchical Scene Matching Algorithms :

These approaches incorporate a hierarchical search for a possible match location starting at a low resolution level. During the search at each resolution level, sequential testing and detecting rules are applied to further minimize the amount of computations.

### A- The Basic Sequential Hierarchical Scene Matching Algorithm :

The simple rule by which the level-K scene is reduced to a level K-1 scene is simple four-point averaging [1], i.e.

$$f_{K-1}(i,j) = (1/4)[f_K(2i,2j) + f_K(2i,2j+1) + f_K(2i+1,2j) + f_K(2i+1,2j+1)] \quad (1)$$

By this rule, it is possible to create a set of images which are of lower resolution and smaller size. Hierarchical search analysis is created in [2]. Two sets of these images are created, one for the window and the other for the search region. For a search region of size  $N \times N$  and a window of size  $M \times M$  in the highest resolution level, the number of possible match locations is  $(N-M+1)^2$ . This number reduces to

$[(N/2^L) - (M/2^L) + 1]^2$  when dealing with lower resolution levels, where L is the search level.

### Sequential Decision Rules :

Dealing with the lowest resolution level, each window pair (the window W and the the subimage of the search region of the same size S ) are compared and the error measurement is calculated as :

$$E_n^K(u,v) = \sum_{i=1}^n e_{u,v}^K(s_i, w_i) \quad (2)$$

where,

$e_{u,v}^K(s_i, w_i) = |s_i - w_i|$  is the error measure of the ith window pair of test location  $(u,v)$ ,  $n = M \times M$ , and K is the resolution level.

This is done for all possible test locations in the lowest resolution level, then this error measure is compared against a threshold  $T$ .

#### Threshold Sequence Categories :

The threshold  $T_n$  is determined as the average of the cumulative error, i.e.,

$$T_n = \bar{E}_n. \quad (3)$$

As the search resolution increases, the threshold sequence previously introduced must be modified. [3,4,5] suggested a method of determining the threshold for every resolution level  $K$  :

$$T_n^K = (\sqrt{2})^{m-K} r_m (n + g_K \sqrt{n}) \quad (4)$$

where,

$r_m$  = the amplitude of the average error measure at the matched location of the lowest resolution level  $m$ .

$g_K$  = amount of deviation from the mean.

As the value of  $g_K$  increases, the threshold increases, and so is the probability of match. However, the computational efficiency decreases.

Let this method be denoted as method A1 for  $g_K=0$ .

The most reasonable method of determining the threshold is to consider the accumulated error measurement for the number of successful test locations. Then the new threshold will be the average error calculated. In general, the threshold at any resolution level will be [6],

$$E_n^K = (1/n) \sum_{j=1}^n E_j \quad (5)$$

where,

$E_j$  ≡ The total error at each successful test location

$n$  ≡ The number of successful test location which is determined by the previous level.

Let this method be denoted as method A2.

Also, one may think of these error measurements as if they were the spectrum of computations. So, the effective number of results may be considered as the 3dB bandwidth of the last measured one of equation (5), so

$$T_n^K = (1/n \sqrt{2}) \cdot \sum_{j=1}^n E_j \quad (6)$$

Let this method be denoted as method A3.

The sequential decision rules can be formulated as follows, [4]: Let  $N_K$  be a set of test locations  $(u,v)$  at search level  $K$

such that :

$$N_K \equiv \{ (u,v) \mid E_n^K(u,v) < T_n^K, \quad 1 \leq n \leq M^2 \} \quad (7)$$

where

$T_n^K$  is the threshold computed at search level K.

To deal with the resolution level K-1 a location matrix  $G_{K-1}$  is generated whose dimension depends on the way the resolution decreases. This location matrix here is of dimension  $(2N-2M+1)^2$ . So,  $G_{K-1}$  is generated such that [6] :

$$G_{K-1}(2i-1, 2j-1) = \begin{cases} 1 & , (i,j) \in N_K \\ 0 & , (i,j) \notin N_K \end{cases} \quad (8)$$

for the level K-1, tests are to be performed only at the location (u,v) for  $G_{K-1}=1$ . The search continues until one of two cases is encountered :

- a)  $G_{K-1}(u,v)=1$  for only one value of (u,v)
- b) At K=0, there exist several locations (u,v) such that  $G_0(u,v)=1$ . Select the location with the smallest accumulated error as the most likely match location.

#### (b) Sequential Hierarchical Scene Matching Using Edge Features:

For this method, it is the similarity between the two images that is important, it is more appropriate to use edge features and introduce a measure of similarity.

##### (1) Edge Extractions :

Edge images created for scene matching must be capable of meeting some basic requirements [7]. Letting the gray-scale image to be  $S(x,y)$ , we can generate a binary image  $S^*(x,y)$  such that :

$$S^*(x,y) = \begin{cases} I_{\max} & \text{if } S(x,y) \geq T \\ I_{\min} & \text{if } S(x,y) < T \end{cases} \quad (9)$$

where  $I_{\max}$  and  $I_{\min}$  are the maximum and minimum gray values reflecting the brightness of the image.

##### (2) Pairing Functions:

In a matching process two image arrays are produced. With two level quantization (0 and 1), there will be four types of pairs : 0-0, 0-1, 1-0, and 1-1. The pairing functions matrix would be given by [8],

$$\begin{bmatrix} N_{00} & N_{01} \\ N_{10} & N_{11} \end{bmatrix} \quad (10)$$

where  $N_{ij}$  = The number of  $i$  in  $W$  that pair with  $j$  in  $S$ .  
 A similarity correlation  $R(u,v)$  can be constructed as :

$$R(u,v) = \prod_{i=0}^{n-1} [N_{ii}(u,v) / \sum_{j=0}^{n-1} N_{ij}(u,v)] \quad (11)$$

where  $n \equiv$  The number of quantization levels.

$R(u,v)$  is the product of the ratios of the number of matched window pairs to the number of possible matches of each type. For binary case

$$R(u,v) = \left( \frac{N_{00}}{N_{00} + N_{01}} \right) \left( \frac{N_{11}}{N_{10} + N_{11}} \right) \quad (12)$$

For each resolution level, given a probability of match, one can determine the threshold required as in [7]:

$$R_T^K = \max [R_K(u,v)] - y R_b^K \quad (13)$$

where,

$R_b^K \equiv$  The background level at resolution level  $K$ .

$y \equiv$  A parameter determines the probability of match.

The test location which has a similarity measure less than this threshold is eliminated from discussion in higher resolution levels.

### III-The binary Two Stage Template Matching :

This approach towards increasing the efficiency of template matching is to divide the matching process into two stages. The first stage applies the optimum subtemplate of the given template (window) at each location of the picture (the search region). The second stage applies the entire template, but only at locations where there is a sufficient match between the subtemplate and the picture. This match is determined for every test location by applying a mismatch measure which counts the number of mismatch points for each kind (0 and 1) normalized to the total number of points in the template, [9], i.e.

$$(1/n)[N_U(0) + N_Z(1)] \quad (14)$$

where,

$U \equiv$  The set of template points which are 1.

$Z \equiv$  The set of template points which are 0.

$N_U(0) \equiv$  The number of picture points in  $U$  which are 0.

$N_Z(1) \equiv$  The number of picture points in  $Z$  which are 1.

Each mismatch measure is examined against a threshold  $t$ . The successful match locations are those which have mismatch measures less than this threshold which is determined for each

optimum subtemplate size. This optimum size is determined for minimum computational cost which is determined as follows [9],

$$E(p,q,t,m,n) = m + \phi (c m^{1/2}) [n - m] \quad (15)$$

where,  
m≡Subtemplate size  
n≡Template size

$\phi(c m^{1/2})$ ≡False alarm probability  
q≡Fraction of template points which are 1.  
p≡Probability of occurrence of 1 in the background.

**IV-Experimental Work And Conclusion :**

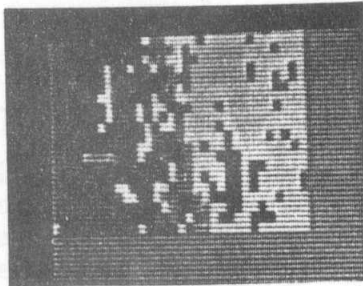
Applying the previous algorithms on satellite imagery of parts of Al-Minea (Egypt) and Montana (USA) of size 64x64 and different window sizes. The window is selected from the search region to be at the top left corner (position (1,1)). This work is done using the Remote Image Processing System (RIPS). Figures 1, 2 and 3 show the search regions under test. Samples of the results are listed in tables I, II, and III for a search region of Al-Minea and a window size of 24x24 at the highest resolution level.

Table I  
Performance of the basic sequential hierarchical technique

Resolu- tion level,K	SR Size	Window Size	Threshold			No. of successful test locations		
			A1	A2	A3	A1	A2	A3
2	16x16	6x6				122		
1	32x32	12x12		1453		60		
1	64x64	24x24	8219	3010	2129	60	39	15
						Minimum error at position (1,1)		

Table II  
Performance of the sequential hierarchical scene matching  
using edge features .

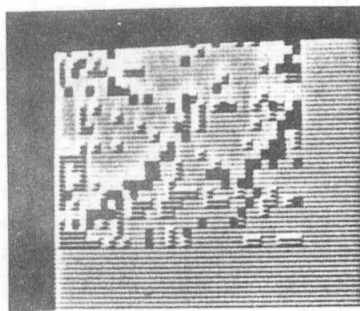
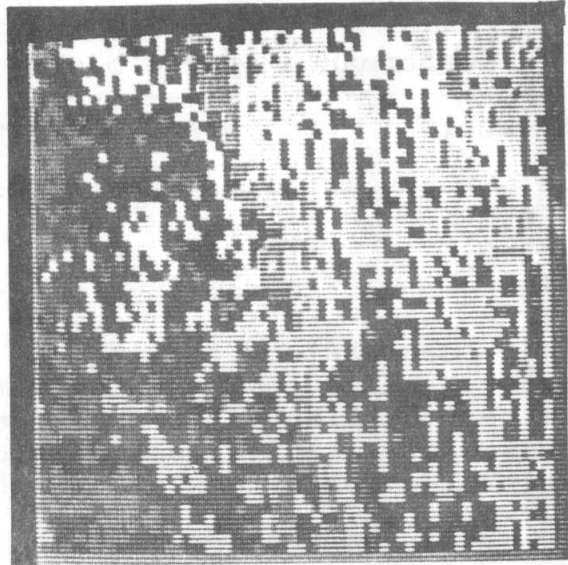
Resolution level,K	R <sub>b</sub>	Max[R]	Y	R <sub>T</sub>	P <sub>K</sub>	No. of successful test locations
2						121
1	0.241	1.0	3	0.276	0.998	49
			2	0.519	0.977	31
0	0.240	1.0	1	0.760	0.841	8
			0.5	0.860	0.691	1
						at position (1,1)



(a) Image of Size 32x32.

Fig. (1) Image of Al-Minea.

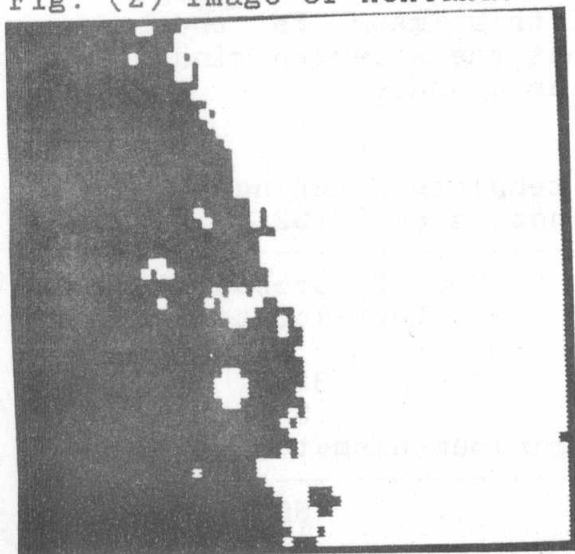
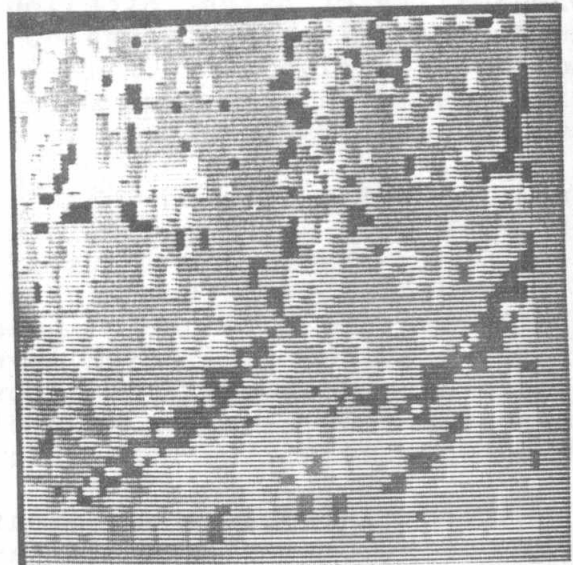
(b)  
Image of  
Size  
64x64.



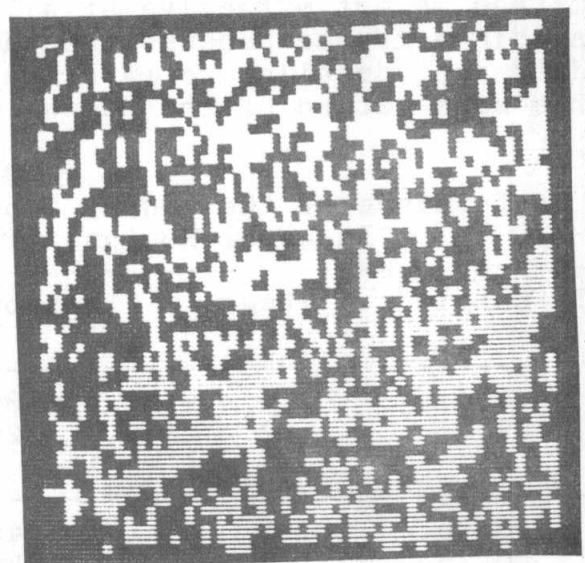
(a) Image of Size 32x32.

Fig. (2) Image of Montana.

(b)  
Image of  
Size  
64x64.



(a) Image of Al-Minea.



(b) Image of Montana.

Fig. (3) Binary Images of Al-Minea and Montana.

Table III  
 Performance of the binary two stage template matching

Threshold	Stage	window Size	No. of successful test locations
0.3	1	3×3	809
0.3	2	24×24	569

It is seen that on the three matching methods, sequential hierarchical scene matching with edge features appeared to be the best candidate for scene matching. The second candidate is the basic sequential scene matching algorithm then finally the binary two-stage template matching.

The first candidate has an advantage of having a high probability of match. Excellent performance was obtained in the matching of images of regions that have a variety of contents to have a variability of gray values. The results show that the final decision (the true match location) is reached at greatly reduced computations than the other two methods.

Scene matching with the basic sequential hierarchical method provides good performance in matching of scenes that contain relatively man-made objects of varying background. A final direct decision of the true match is rarely reached from the first step and this needs investigations of the error measure of the previous resolution level. It is noted that as the window size decreases the number of successful test location increases. As a matter of fact, the efficiency of this method will increase as the resolution levels increase.

The third candidate shows great efficiency in dealing with the image of Montana as seen in table IV. On the other hand, this method is not effective at all in dealing with the image of Al-Minea may be because the nature of this image is that the different details are rare besides that the selected window has the same nature of the search region as a whole.

Table IV  
 Performance of the binary two-stage template matching for the Image of Montana with a window size 32×32

Threshold	Stage	Window Size	No. of successful test test locations
0.4	1	3×3	333
0.4	2	32×32	3
minimum mismatch at (1,1)			
0.25	1	4×4	69
0.25	2	32×32	2
minimum mismatch at (1,1)			



The disadvantages of the methods dealing with edge features, in general, lie in the problem of edge extractions which may result in a loss of the desired object with respect to the background.

The problem of deciding which matching method is more effective for a certain image than the others depends on many factors such as : the kind of objects to be investigated, the dynamic range of the scene and the relation between the objects and the background. As a matter of fact the choice is restricted to the sequential hierarchical scene matching algorithms only for their superior performance which could be guaranteed for almost all images. Edge feature methods is the best for scenes which have objects that have gray scale values that vary considerably with respect to the background.

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#### References:

- 1) Tanimoto, S. and Pavlidis, T., "A Hierarchical Data Structure for Picture Processing." Comp. Graphics Image Processing 4, 104-119, (1975).
- 2) Hall, E.L., "Computer Image Processing and Recognition," Academic Press, New York, (1979).
- 3) R.Y. Wong and E.L. Hall, "Sequential Hierarchical Scene Matching," IEEE Trans. Comp. C-27, 359-366, (1978).
- 4) Hall E. L., Wong, R.Y., and Rouge, J., "Sequential Scene Matching with Hierarchical Search," Proc. IEEE Southeast Conf., Williamsburg, Va., April, pp.402-405, (1977).
- 5) Wong, R.Y., Hall, E.L. and Rouge, J., "Hierarchical Search for Image Matching," Proc. IEEE Conf. Decision and Control, Clearwater, Va., December (1976).
- 6) E.M. Abdel-Raheem, "Microcomputer Applications in Scene Matching," M.Sc. Thesis, Faculty of Eng., Ain Shams Univ., Cairo, December (1988).
- 7) Wong, R.Y., " Sequential Scene Matching Using Edge Features," IEEE Aerosp. Electr. Syst., Vol. Aes-14, Jan. (1978).
- 8) Green, G.S., Reagh, F.L. and Hibbs, E.B., "Detection of Threshold Estimation for Digital Area Correlation," IEEE Trans. Syst. Man Cybern. SMC-6, No.1, 65-70, (1976).
- 9) G.J. VanderBrug and A. Rosenfeld, " Two-Stage Template Matching," IEEE Trans. Comput., Vol. C-26, No.4, April (1977).