Adaptive Methods for Matching Problem

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Abstract

In this paper, we deal with the problem of general matching of two images one of them has experienced geometrical transformations, to find the correspondence between two images. We develop the invariant moments for traditional techniques (moments of inertia) with new approach to enhance the performance for these methods. We test various projections directional moments, to extract the difference between Block Distance Moment (BDM) and evaluate their reliability. Three adaptive strategies are shown for projections directional moments, that are raster (vertical and horizontal) projection, Fan-Bean projection and new projection procedure that is the square projection method. Our paper started with the description of a new algorithm that is low cost ("soft calculation"); the new procedure significantly has improved the Statistical Region Description (SRD). The new method BDM is highly accurate 98% even higher than our previous image matching modified method.

الخلاصة

في بحثنا هذا تطرقنا الى مسألة المطابقة العامة بين صورتين تعاني أحدهما من تحويلات هندسية، وإيجاد التماثل بينهما. طورنا الطرق التقليدية للعزوم الثابتة (عزوم القصور الذاتي) بأسلوب جديد لتحسين أداء هذه الطرق، حيث اختبرنا أنواع متعددة من عزوم المساقط المتجهة، لغرض استخلاص الاختلاف بين BDM بين الصورتين ومقدار الاعتماد عليه. تم تبني ثلاثة استراتيجيات لعزوم المساقط المتجهة وهي المساقط الأفقية والعمودية ومساقط Fan-Beam والأسلوب الجديد للمساقط هو طريقة المساقط المربعة BDM. بحثنا بدأ بوصف الخوارزمية الجديدة ذات الحسابات الميسرة وتحسينها لأداء SRD. حيث ان طريقة BDM هي اكثر دقة وتصل دقتها الى 98% وهي أعلى دقة من الطرق المطورة في بحثنا السابق للمطابقة.

Introduction

Pattern matching is a method of identifying features in an image that match another image has experienced geometrical transformations involving translation, rotation, flip and scaling. Pattern matching involves analyzing the image to find features that can be exploited for efficient matching performance [1]. This block distance moment (BDM) is what gives advanced pattern matching techniques and has dramatically improved performance in comparison to traditional invariant moment's methods. This is very low cost of computation and high stability.

Among the geometrical transformations the rotation may be the most important in affecting the image feature, for this reason we have considered the solution of this type of transformation by finding anew invariant procedure that is the BDM method. The matching algorithm used depends on whether the user has specified projection directional moments to get the desired BDM [2]. There are two types of BDM the first one is the square and the second one is the circular. The projection data has been generated in discrete form, using directional moment sums. However, other methods i.e.

projections in various directions also provide properties that can be useful in the classification and/or recognition of objects (images), particularly the best extracted features are that which can give an invariant geometrical distribution used in recognizing unknown object. Many applications depend on object recognition features. Robotic applications need to recognize mechanical parts in order to perform some automatic actions on them. Other typical astronomical applications and industrial applications for this kind of algorithm are those used to catalogue objects.

Our approach to this problem is to split the matching process into invariant transform for translation, rotation, flip and scale to eliminate the extraneous factors from the image, followed by matching. The essential features of a transform algorithm for the first phase of this process can be summarised as follows:

- It has to maintain shape information. The result must be only shape dependent.
- It has to be robust: additive noise, up to a reasonable level, as a result of digitization errors, must be masked out.
- It has to be flexible: most of the recognition applications today are tailored to specific problems, whereas such an algorithm has to be used for a wide range of recognition problems.

Computation should be performed quickly: speed is a critical factor for some applications. By increasing the number of processors, the computational load must be distributed among the processors very efficiently.

Statistical Region Description (SRD)

The work Can be directly carried out on the image regions, and describe them by various statistical measures. Such measures are usually represented by a single value. These can be calculated as a simple from statistical descriptions, and may be divided into two distinct classes. Examples of each class are given below [3, 4]:

Geometric descriptions: area, length, perimeter, elongation, compactness, moments of inertia and elongation.

Topological descriptions: connectivity and Euler number. Some of the above measures can be define:

Elongation

Sometimes that is called eccentricity. This is the ratio of the maximum length of line or chord that spans the region to the minimum length chord. We can also define this in terms of moments:

$$ecc = \frac{m_{20} + m_{02} + \sqrt{(m_{20} - m_{02})^2 + 4m_{11}^2}}{m_{20} + m_{02} - \sqrt{(m_{20} - m_{02})^2 + 4m_{11}^2}} \text{ --- } (1)$$

Where mpq: moments of order p+q

Compactness

This is the ratio of the square of the perimeter to the area of the region.

$$comp = (pi/2)(m_{00}/(m_{20} + m_{02})) \text{ ---- } (2)$$

Connectivity

This is the number of neighbouring features adjoining the region.

Euler Number

The Euler number for a set of connected regions can be calculated as the number of regions minus the number of holes.

Some of the above measures may be useful in helping to control image reasoning and recognition.

Moment-based Distance Function (Moments of Inertia)

The moment of order (*p*+*q*) for function *f*(*x*,*y*) is defined by Equation (3), and the proposed block distance moment (BDM) is based on this equation. Central moments, which are invariant to translation, are defined by Equation (4) in which *xc* and *yc* is the coordinates of the function's centroid and can be taken as the geometrical center of the mass. Normalized central moments are denoted by μ_{pq} and are defined by Equation (5). In this equation, γ is computed by Equation (6) [5, 6, 3, 7, 8].

$$m_{pq} = \sum_x \sum_y x^p y^q f(x,y) \text{ ----- } (3)$$

$p, q = 0, 1, \ldots.$

$$\mu_{pq} = \sum_x \sum_y (x - xc)^p (y - yc)^q f(x, y) \text{ --- (4)}$$

xc and yc are geometrical center of the mass for object.

$$\mu'_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \quad \text{----- (5)}$$

μ_{00} : moments of order 0, the area of f (number of pixels in f),

$$\gamma = \frac{p+q}{2} + 1 \quad \text{----- (6)}$$

Using moments of order 2 we can define asset of moment invariants. One famous moment invariant is M_1, which is computed by equation (7). This quantity is invariant to translation, rotation, flip and scaling of the original function.

$$M_1 = \mu'_{20} + \mu'_{02} \quad \text{----- (7)}$$

The proposed central moments (CM) as shown in equation (8), are based on this invariant moment.

$$DCM = (abs(M_1 - M_2)/M_1) * 100 \quad \text{---- (8)}$$

Where

DCM : difference central moments.

M_1: central invariant moment for the first image.

M_2: central invariant moment for the second image.

The most important development in the moment theory was performed by Teague [4]. Abu-Mustafa [9], has introduced the notation of complex moments as a simple and straight foreword way to derive moment invariant. Moreover, many authors; e.g. Reddi [10], Sajadi [11], Zkaria [12] added useful extension to the moment theory. The Zernik-moments are largely equivalent to those of Hu. The most important fact in which Zernik-moments out perform ordinary moments is that the Zernik-moments furnish an optimal means to code the essential features of an image pattern and thus can be used in image encoding [13].

Now who we can build the BDM? That is depending on the projection directional moments as shown as in the next section.

Projection Directional Moments

The projection of an image f can be define on any line, suppose a line having raster form, by summing the value of pixels when equal 1 of f along the family of lines straightly. Let f be an m × n digital image. The vector of row sums:

$$\left(\sum_{j=1}^{n} f(1, j), \sum_{j=1}^{n} f(2, j), \ldots, \sum_{j=1}^{n} f(m, j) \right) \text{----- (9)}$$

is called the x-projection of f, while the vector of column sums:

$$\left(\sum_{i=1}^{m} f(i,1), \sum_{i=1}^{m} f(i,2), \ldots, \sum_{i=1}^{m} f(i, n) \right) \text{----- (10)}$$

is called the y-projection of f.

For example consider the set of numerals:

$$\begin{matrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{matrix} \qquad \begin{matrix} 0 & 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 \end{matrix} \qquad \begin{matrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \end{matrix}$$

These have y-projections

(0 , 2 , 0) , (1 , 4 , 2, 5, 1) , (2 , 1 , 3)

And x-projections

(0, 1 , 1 , 0) , (3 , 3 , 2 , 3, 2) , (1 , 1 , 1 , 3)

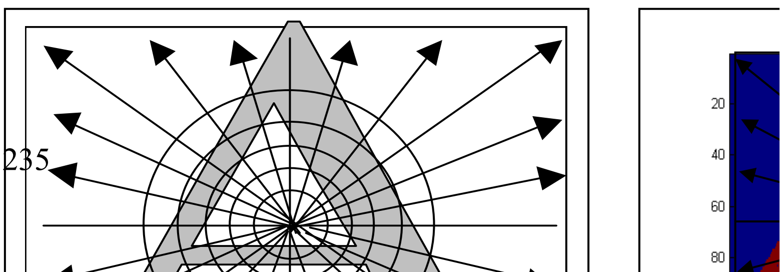
Note that in this case, the sums do not all have the same number of terms. Which are quite distinctive [2], some of the projection systems can be define:

1) Fan-Beam Projection System:

The projection taken along a set of circular emanating from a point source as shown as in figure (1-a). We modified this classical method by transformation the image from Cartesian to polar coordinate [14], as shown as in figure (1-b), and then taken the projection along a set of circles emanating from a point source. For each circle, we complete the summation of the pixels value on this circular projection by the distance from the center (circle radius), which represent circle block distance moments CBDM.

Figure (1-c) shows artificial test images and their polar transform. Although the same object involving transformations, rotation, translation and scale, their transformed images are symmetric and similar, whereas the other object image has different transform.

-a-



-c-

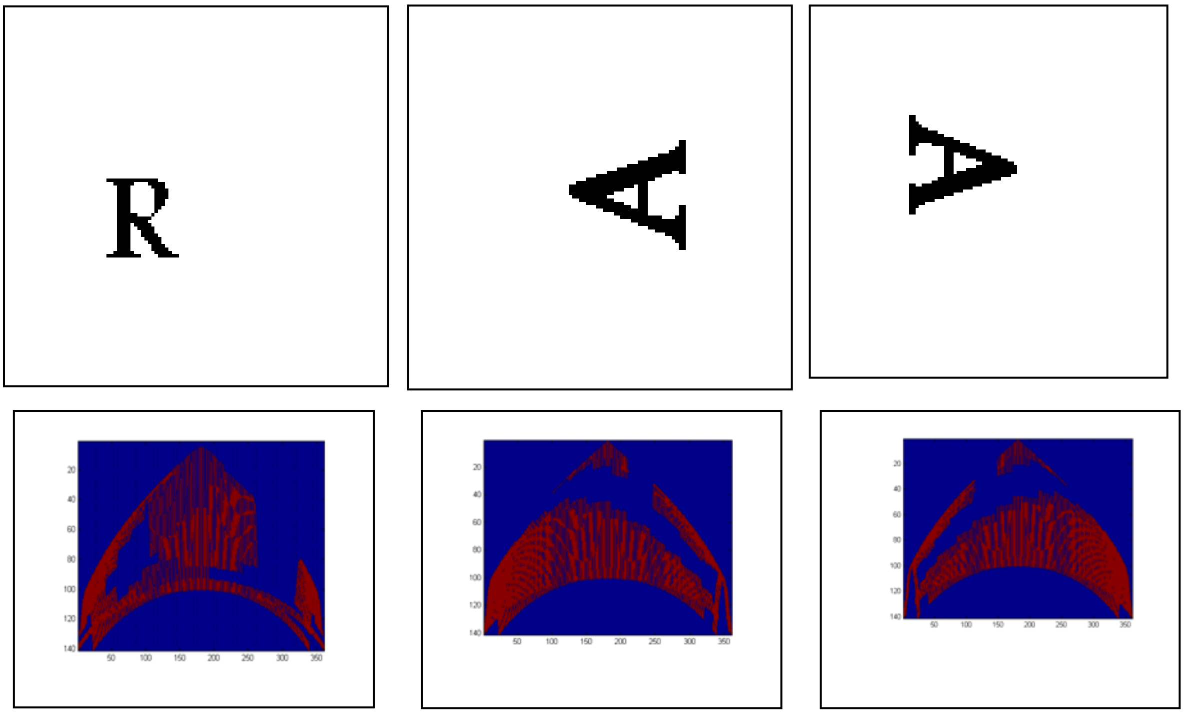


Figure-1: (c) polar transform for different images

2) Raster Projection system:

The projection taken along a set of parallel rays as shown in Figure (2). In this case we can't compute any kind of BDM, therefore can be calculate the CM for each pixel in the image.

3) Square Projection System:

We develop a new projection directional that is Square projection system the projection taken along a set of squares emanating from a point source, as shown as in Figure (3). . For each square, we complete the summation of pixels value on this square projection by the distance from the center, which represent square block distance moments SBDM.

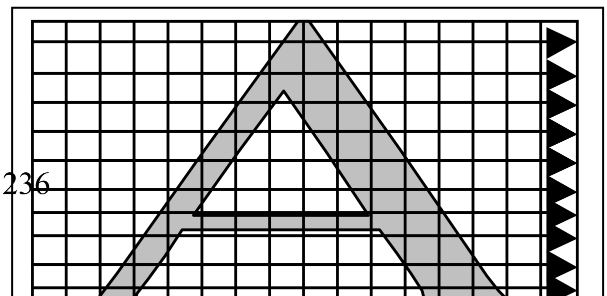


Figure (2) Raster projection

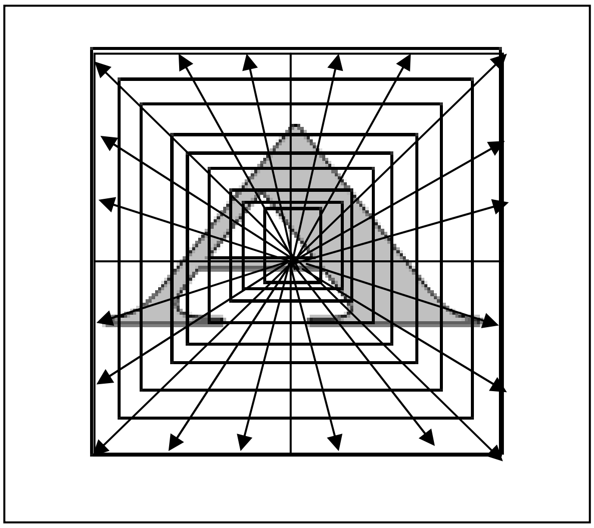


Figure (3) square projection

Problems Companion Invariant Moments Calculations

Moment invariant is considered reliable features in the pattern recognition field, there are, however, some problems associated with their computations. These problems can be summarised by the following:

1- The major problem in the use of moments is the noise; Moments are sensitive to noise. However, to overcome this problem, three methods may be used to reduce the noise effects [15];

a) Segmentation of images; Moments are only calculated for those pixels on the object. In this method, the effect of noise outside an object will be eliminated. This method is adopted in our present work.

b) The image crop is resize to double size of the original image.

c) Avoiding higher orders of moments; higher order moments are more sensitive to noise; thus, to reduce the noise effects higher order moments may be avoided.

Pre-Processing Procedure

The process started by acquisitioning the known object, transformed it into an image shape that can be processed by further steps in order to extract the characteristic features of the image. We depend on the pre-processing that adopted in paper [16].The preprocessing contains four steps:

1. Transformation the input image to binary image, by one of the known method (threshold method for example).
2. The edge detection is taken for the binary image to reduce the consuming time of calculations.
3. Extract the object (crop) from the input image.
4. The crop image is resizes to double size of the input image using interpolation method (bicubic method).

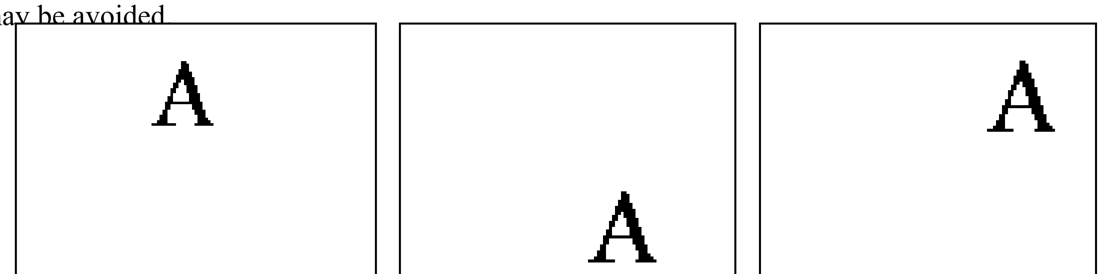
After this process we applied the adopted methods, In this paper, three methods were used, the first method is central moments (CM) method and the second one is block distance moment (BDM) method, and third one is statistical region descriptions (SRD) like area and compactness.

Experimental Results

In this section, we presented the results of applying the CBDM, SBDM and CM algorithms. Figures 4 to 9 below shows nine artificial test images contain three object in random position, three object in random rotation and flip and three object in different sizes, and their CBDM and SBDM respectively, we can seen their transformed images are very similar.

BDM (Block Distance Moment) and SRD (Statistical region description Analysis

In the previous sections we have introduce theoretical concept about central moments (CM), block distance moment (BDM) and statistical region description (SRD), In this section figures 10 to 15 describe our initial work and we focus on accuracy for adopted algorithms were used in matching process.



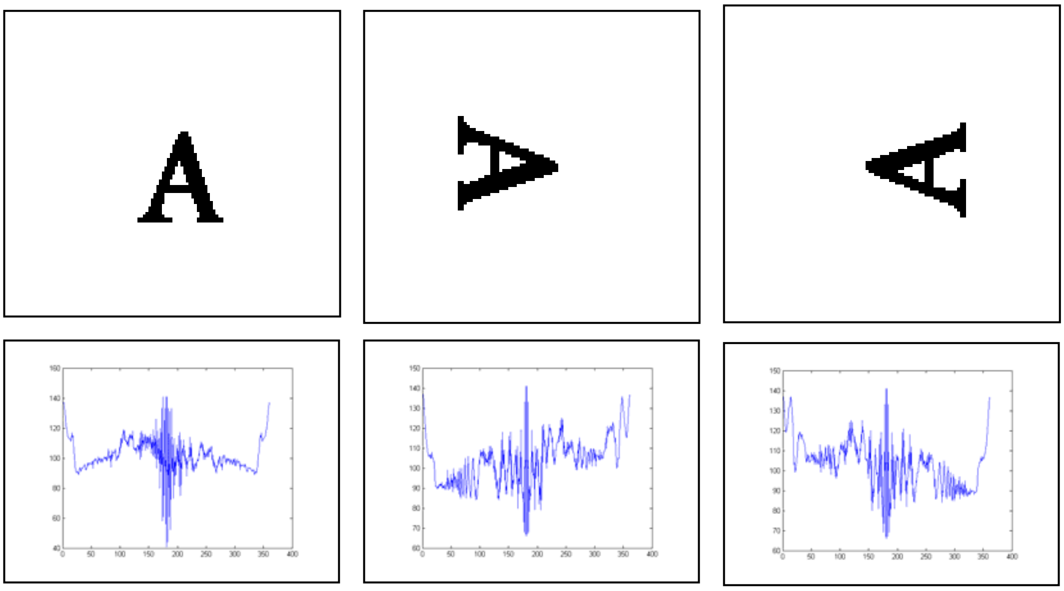
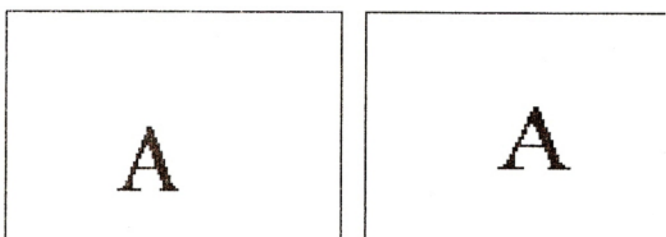
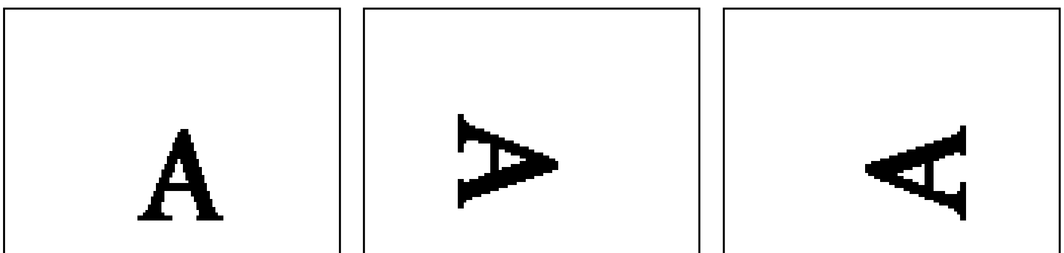


Figure (5) CBDM for rotation object

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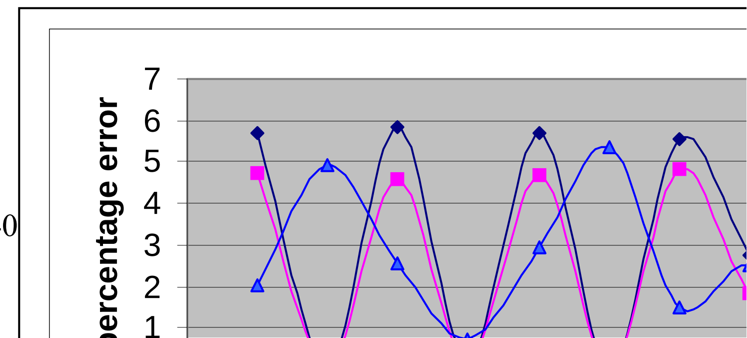
percentage error
7
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1

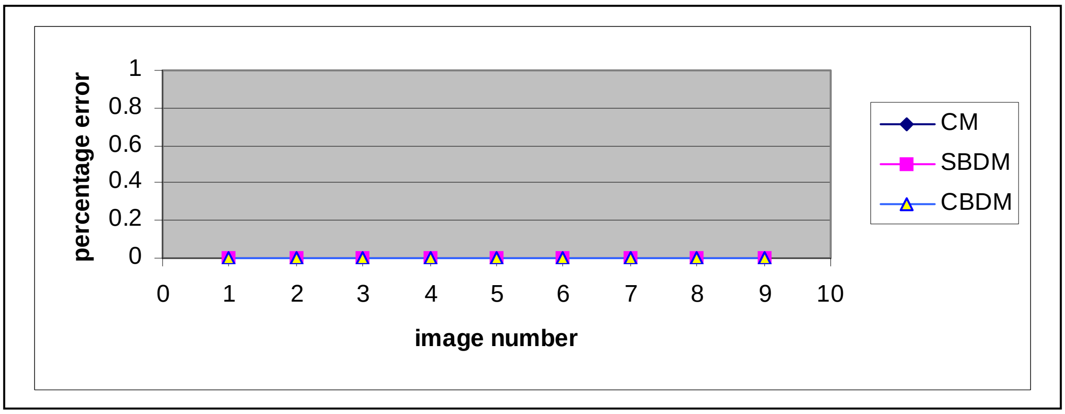
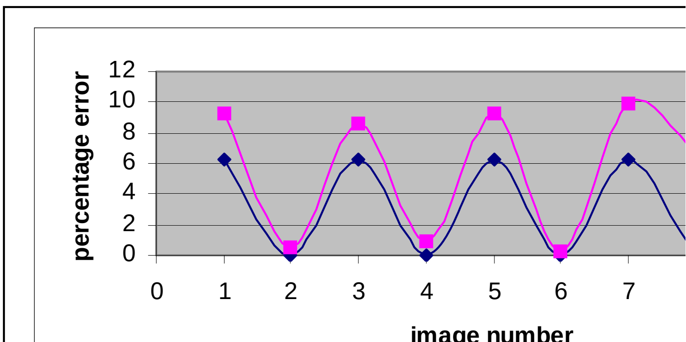


Figure (12) shows the accuracy for central moments (CM) and square block distance moments (BDM) and circle block distance moment (CBDM) for matching translation object



Conclusion

In this paper, we presented block distance moment (BDM) based invariant matching algorithm. The SBDM and CBDM methods were found to be high accurate than the CM method. Also for SRD that area method is better than compactness method, its mean that the new hyper algorithm (BDM) is simple and efficient, its execution time being a fraction of the other matching methods. In contrast the BDM method is highly accurate 98% even higher than our previous image matching modified CM method [16]. Experimental evidence suggests that optimal values for SRD can be established and used in image recognition and the accurate well and stable. We can note the complete identical between our adopted methods for all image translation and the accurate almost 100%. Applying the filters to the image in parallel can decrease the methods execution time. A large-range projection algorithm can then be formed by a combination of that three projection algorithms.

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