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Comparison Between Zernike Moment and Central Moments for Matching Problem

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Abstract

Moment invariants have wide applications in image recognition since they were proposed. The recognition problem is very often connected with image reconstruction technique to determine a desired set of invariants for use feature extractor in the recognition system. The low order moments are found to be related to the global properties of the image, while high order moments contains information about details. It was found that the low order moments are not efficient for image recognition because the general shape of different objects can be similar and do not allow distinguishing one object from another. For this reason, some preprocessing have to be done to enhance this weakness, and use low order moments to overcome the weakness and test it for image recognition, image transformation (rotation, flip, translation and scaling). The main difficulty in the application of the invariant moments is an absence of the theoretical methods of estimation their efficiency in recognition tasks. In this paper, the goal is to analyze the significance of Zernike moments and central moments of different orders and compare them to determine who the best for matching in cases of is image transformation. The accuracy for matching is almost (90%) for Zernike moments and (95%) for central moments.

الخلاصة

للعزوم الثابتة تطبيقات واسعة لأغراض تمييز الصور. ان مشكلة التمييز ذات ارتباط كبير بتقنيات إعادة تركيب الصورة لتحديد مجموعة من الثوابت المستخدمه لاستخلاص المعلم او السمة في منظومات التمييز. وجد ان الرتب المنخفضة مرتبطة بالصفات العامة للصورة، بينما الرتب العالية تحتوي على تفاصيل المعلومات. كما وجد ان الرتب المنخفضة غير كفوءة لتمييز الصور لكون الشكل العام لمختلف الأجسام ممكن ان يكون متشابه ومن ثم لا يسمح بالتمييز بين جسم وأخر. لهذا السبب يتوجب إجراء بعض المعالجات الأولية لتحسين ضعف الرتب المنخفضة واختبارها في تمييز الصور والتحولات في الصور(التدوير والقلب والانتقال والتكبير والتصغير). الصعوبة الرئيسة في تطبيق العزوم الثابتة هي غياب الطرق النظرية في تخمين الأكفأ في مهام التمييز. الهدف في هذا البحث هو تحليل الصفات المهمة لعزوم Zernike, Central لرتب مختلفة والمقارنة بينهما لتحديد الأفضل في المطابقة في حالات تحولات الصورة. حيث كانت الدقة في المطابقة تقريبا" 90% لعزوم Zernike وتقريبا" 95% لعزوم Central.

1. Introduction

Image shape descriptors which are invariants to the basic image transformation (translation, scaling, flip and rotation) have a great importance in computer vision. They are widely used in character recognition, medical imaging ...etc.

The main field of using moments and invariants is pattern recognition. From that point, the difference between invariants for the different images must be as greater as possible, and the difference between invariants for the same images but contains transformations image must be as smallest as possible, at the same time these invariants must have a good stability [1].

As we know the low order invariants moment are stable but they describe only general shape of the image, which can be assumed to similar class for different images [2]. High order invariants moment are the descriptors of the image details, but their stability is worse. The most popular technique to determine an appropriate set of invariants is image recognition [3] [4].

In this technique many authors used all image moments form lowest order up to some high order and decided how moment order is significant for recognition basing on image reconstruction errors. Then they usually use all moments up to some order including low order moments which do not help to find the difference between images. Thus, recognition and reconstruction problems are mixed. However, really they are sufficiently different ones. In this paper, our goal is to enhance the low order invariant moments for image recognition and analyzes a significance of Zernike moments and central moment of different low orders from a viewpoint of pattern recognition theory. We want to introduce simple ideas about feature selection in invariant domain which can be improved and lead to building a robust technique in invariant domain.

2. ZERNIKE Moments Descriptor (ZMD)

ZMD is one of the most desirable shape descriptors among the existing shape descriptors. Many researchers report promising results of ZMD. Basically, it is derived by applying Zernike moment transform on shape image in polar space. The following describes the definition of Zernike moments. The complex Zernike moments are derived from Zernike polynomials[5][6]:

$$V_{nm}(x,y)=V_{nm}(r\cos\theta, r\sin\theta)=R_{nm}(r).\exp(jm\theta) \quad ---(1)$$

And

$$R_{nm}(r)=\sum_{s=0}^{(n-|m|)/2}(-1)^s\frac{(n-s)!}{s!\times(\frac{n+|m|}{2}-s)!\times s!\times(\frac{n-|m|}{2}-s)!}r^{n-2s} \quad -------(2)$$

Where r is the radius from (x, y) to the shape centroid, θ is the angle between r and x axis, n and m are integers and subject to $n|m|$ = *even*, $|m|\leq n$. Zernike polynomials are a complete set of complex-valued function orthogonal over the unit disk, i.e., $x^2+y^2\leq 1$.

The complex Zernike moments of order n with repetition m are defined as [6]:

$$Z_{nm}=\frac{n+1}{\pi}\sum_x\sum_y f(x,y).V^*_{nm}(x,y)$$

$$=\frac{n+1}{\pi}\sum_r\sum_\theta f(r\cos\theta, r\sin\theta).R_{nm}(r).\exp(jm\theta) \quad ---(3) \qquad r<=1$$

3. Central Moments Descriptor

The central moment of order p,q for object (image) f is defined as [8]:

$$\mu_{pq}=\frac{1}{S}\sum_{x,y\in f}(x-x_c)^p.(y-y_c)^q \quad -----(4)$$

Where $S=m_{00}$ is area of f (number of pixels in image).

x_c, y_c centroid of f calculated by:

$$x_c=\frac{1}{S}\sum_{x,y\in f}x=\frac{1}{m_{00}}\sum m_{10}$$

$$y_c=\frac{1}{S}\sum_{x,y\in f}y=\frac{1}{m_{00}}\sum m_{01} \quad --------(5)$$

m_{10},m_{01} are the first order moment for object

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

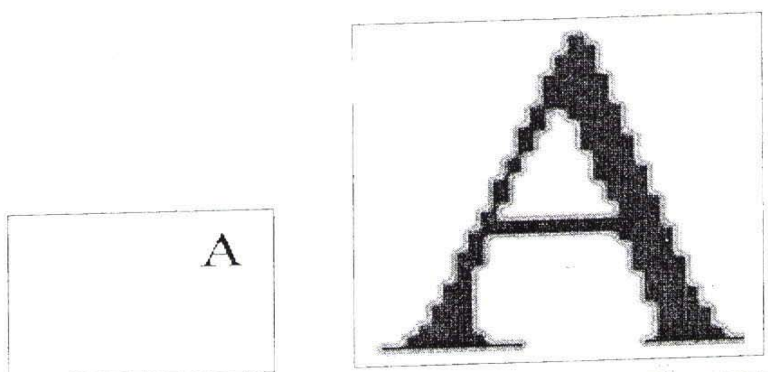
μ_{pq} are called central because they are defined relative to centre of mass.

4. Pre-Processing Procedure for Image Recognition

To solve the problems companion invariant moments calculations, 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. In this paper, two methods were used. After the proposed preprocessing is being applied, the first method is Zernike moments method and the second one is the central moments method are applied.

The preprocessing contains five steps:

1. Transform the input image to binary image, by one of the known methods (threshold method for example).
2. The edge detection is taken for the binary image to reduce the consuming time of calculation. Canny algorithm used to find the edges of the object, this method as edge detector was adopted according to its powerful results. Canny method where finds edges by looking for local maxima of the gradient of image. The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. This method is more likely to detect true weak edges.
3. The object dimension is determined in both vertical and horizontal axes by searching for the start and end points of each axes to the object in the image (cropping image).
4. The object is extract (crop) from the input image.
5. Knowing μ_{pq} is called central because they are defined relative to centre of mass, to enhance the performance we taking μ_{pq} equal to the geometrical center.
6. Resizes the crop is resizes image to double size of the input image using interpolation method (bicubic method) as shown as in figure (1).



Figur (1) a) original image b) resize object (crop image)

After this process we applied the adopted methods (Zernike moments method and central moments method).

5. Moments Calculation Analysis

In the present research work, to make comparison between zernike and central moments for different cases that shown in figures (2-4), the comparison is done between the same object of different geometrical transformation (rotation, flip, scaling and translation).

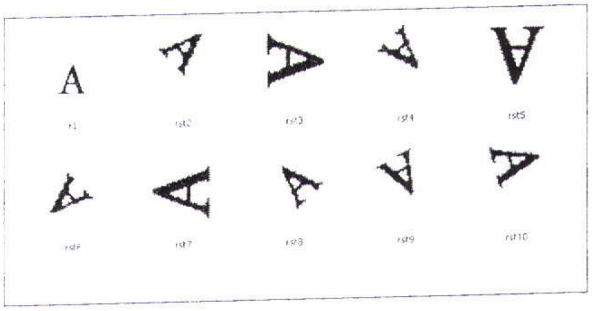


Figure (2) scaling and rotation object

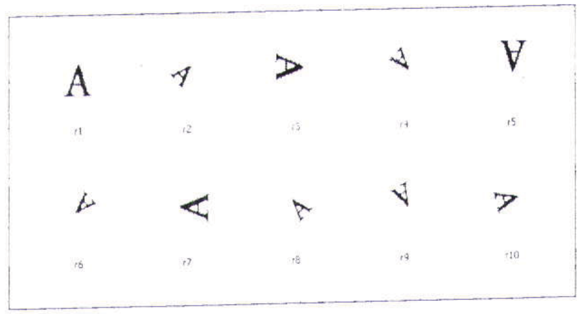


Figure (3) rotation and flip object

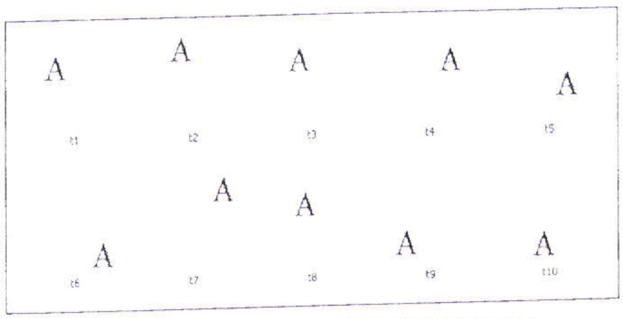


Figure (4) translation object

If we plot the percentage error as a function for geometrical transformation images, was found that the Zernike and central moments without preprocessing reflect a very bad result of matching as shown in figure (5).

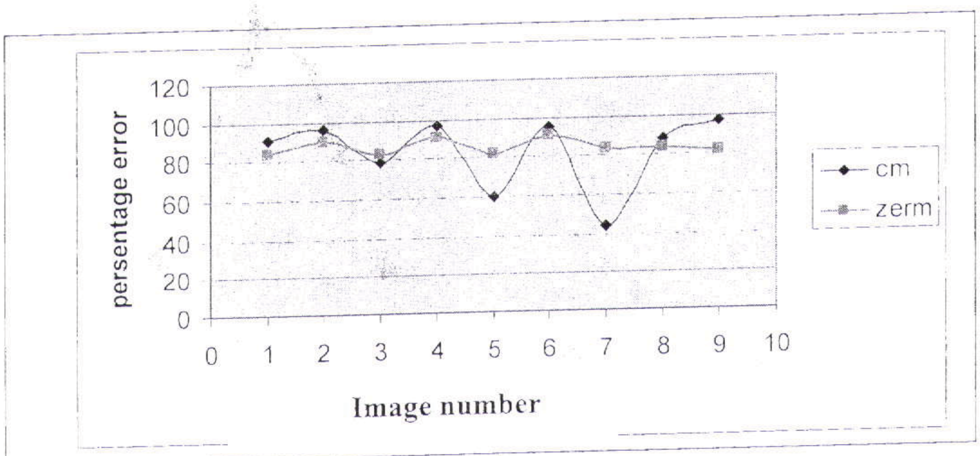


Figure (5) shows a bad accuracy for central moments (cm) and Zernike moments (zerm) for translation, rotation, flip and scaling object without preprocessing

Down figures (6-10) be very different from the initial case (the accuracy was improved strongly) were multiple geometrical transformations (rotation, flip, scaling and translation) take into account.

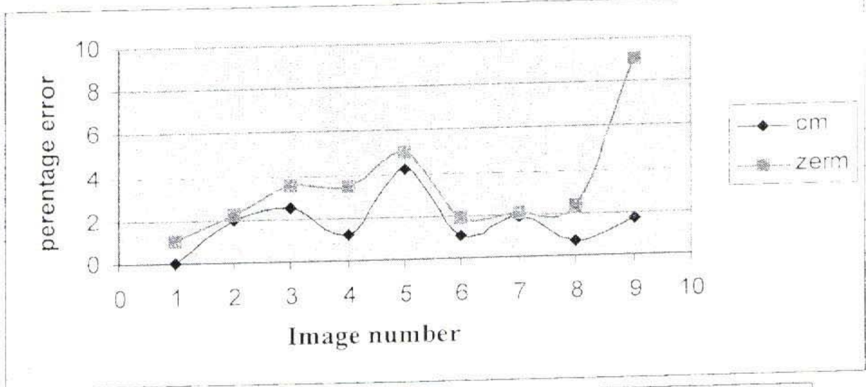


Figure (6) shows the accuracy for central moments (cm) and Zernike moments (zerm) for scaling object

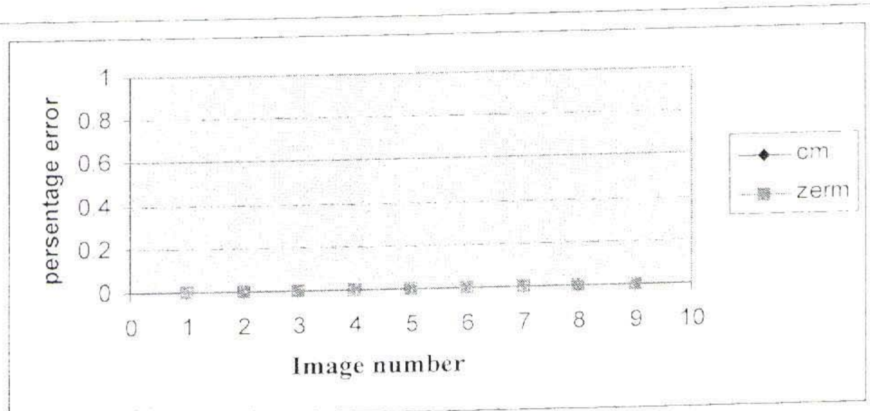


Figure (7) shows the accuracy for central moments (cm) and Zernike moments (zerm) for translation object

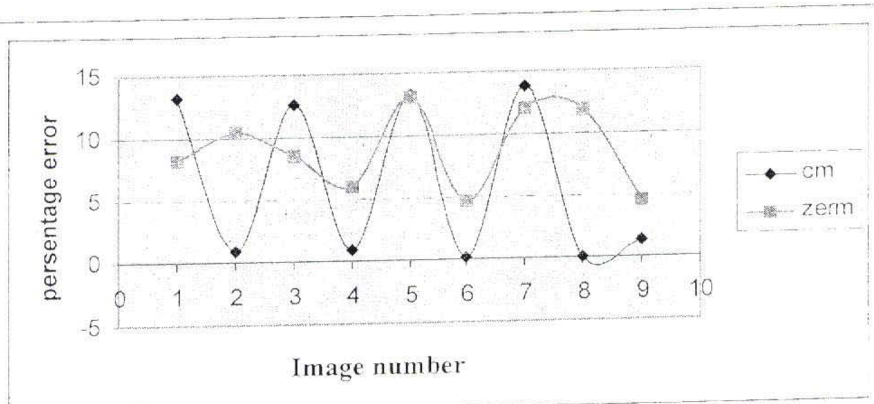


Figure (8) shows the accuracy for central moments (cm) and Zernike moments (zerm) for rotation and flip object