IMAGE REPRESENTATION USING EPANECHNIKOV DENSITY FEATURE POINTS ESTIMATOR

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ABSTRACT

In image retrieval most of the existing visual content based representation methods are usually application dependent or non robust, making them not suitable for generic applications. These representation methods use visual contents such as colour, texture, shape, size etc. Human image recognition is largely based on shape, thus making it very appealing for image representation algorithms in computer vision.

In this paper we propose a generic image representation algorithm using Epanechnikov Density Feature Points Estimator (EDFPE). It is invariant to rotation, scale and translation. The image density feature points within defined rectangular rings around the gravitational centre of the image are obtained in the form of a vector. The EDFPE is applied to the vector representation of the image. The Cosine Angle Distance (CAD) algorithm is used to measure similarity of the images in the database. Quantitative evaluation of the performance of the system and comparison with other algorithms was done.

KEYWORDS

Image representation, Segmentation, Visual content, Image retrieval

1. INTRODUCTION

With vast collection of digital images on personal computers, institutional computers and the Internet, the need to find a particular image or a collection of images of interest has increased tremendously. This has motivated the researchers to find efficient, effective and accurate algorithms that are domain independent for representation, description and retrieval of images of interest. There have been many algorithms that have been developed to represent, describe and retrieve images using their visual features such as shape, colour and texture [1], [2], [3], [4], [5]. Visual feature representation and/or description play an important role in image classification, recognition and retrieval. A successful image representation and description is dependent on the selection of suitable image features to encode and quantification of these features [4].

Shape representation and description have been dominant in research area of image processing because shape is considered to be the basis of human visual recognition [4]. The shape representation can be classified as Region based or Contour based.

The contour based techniques use the boundary of shape to describe an object. It is commonly believed that human beings can differentiate objects by their boundaries or contours [2]. Usually

DOI : 10.5121/sipij.2013.4107

most objects form shapes with defined contours, making the use of these techniques most appealing. The techniques can generally be applied to different application areas with a considerable success. The techniques have a low computation complexity as compared to region based techniques and they are sensitive to noise. Some of the techniques in this group are Compactness, Eccentricity, Shape signature, Hausdoff Distance, Fourier Descriptors, Wavelet Descriptor, etc [5].

The region based shape representation uses the boundary pixels and the interior pixels of the shape. This group of shape representation algorithms are robust to noise, shape distortion and they are applicable to generic shapes [6]. Some of the techniques in this group are Geometric moments, Legendre moments, Zernike moments, Generic Fourier Descriptor, Object representation by the Density Histogram of Feature Points, etc [5].

In this paper we propose an Epanechnikov Density Feature Points Estimator (EDFPE) representation of an image object. This method imitates human visualization of image object shape and matching similar object shapes. A comparison of retrieval of similar image object shapes is done between EDFPE and DHFP representation [7] of image object shapes.

2. SHAPE REPRESENTATION BY EPANECHNIKOV DENSITY FEATURE POINTS ESTIMATOR (EDFPE)

This method describes the feature points within the rectangle boundary in an image grid. Assume we have a silhouette object shape segmented by some means such as active contour without edges [8] and let the feature points set $P(x, y)$ (intensity function) of the object shape be defined as

$$\begin{aligned} &P(x, y) = p_i(x_i, y_i) \\ &where \\ &i = 1, 2, \ldots.n, n \varepsilon \mathrm{N} \end{aligned} \tag{1}$$

We find the centroid of the object shape. The following formulae will be used to calculate the centroid [9],[10]:

$$x_c = \frac{m_{1,0}}{m_{0,0}} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

$$y_c = \frac{m_{0,1}}{m_{0,0}} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{3}$$

where (x_i, y_i) are coordinates of image shape and $m_{1,0}, m_{0,1}, m_{0,0}$ are derived from the silhouette moments given by

$$m_{i,j} = \sum_x \sum_y x^i y^j P(x, y). \tag{4}$$

The theorems that guarantee the uniqueness and existence of silhouette moments can be found in [9]

Thus for silhouette image $P(x, y)$, $m_{0,0}$ the moment of zero order represents the geometrical area of the image region and $m_{1,0}, m_{0,1}$ moment of first order represents the intensity moment about the y-axis and x-axis of the image respectively. The centroid (x_c, y_c) gives the geometrical centre of the image region.

Suppose the size of the grid occupied by the object shape is N x N. The vector dimension to represent the density of object shape will be N-1. From the centroid we count the number of image pixels in the rings with defined equal width around the centroid. The total number of pixels in each image is given as

$$X_i = (n_1, n_2, ...n_m) \tag{5}$$

where m is the number of rings in each image from the centroid.

The EDFPE is then applied. The Second-order Epanechnikov Kernel Density Estimator (SEKDE) is used. The SEKDE is given in [11] as

$$f(x) = \frac{1}{mh} \sum_{i=1}^{m} k\left(\frac{X_i - x}{h}\right) \tag{6}$$

where

$$k(u) = \begin{cases} \frac{3}{4}\left(1 - \left(\frac{X_i - x}{h}\right)^2\right) & if \ |\frac{X_i - x}{h}| < 1 \\ 0 & otherwise \end{cases} \tag{7}$$

where $$u = \frac{X_i - x}{h}$$

The second order Epanechnikov plug-in formula for optimal bandwidth will be as given in (8):

$$h_o = 2.345\left(\frac{s}{m^{\frac{1}{5}}}\right) \tag{8}$$

where m is the number of rings from the centroid, s is the sample standard deviation and x_i is the vector elements of the image. The vector elements of the image are recalculated to make $f(x_i)$ becomes the image representation vector. Thus,

$$f(x_i) = \begin{cases} \frac{3}{4}\left(1 - \left(\frac{X_i - \bar{x}}{h_o}\right)^2\right) & \text{if} \quad \left|\frac{X_i - \bar{x}}{h_o}\right| < 1 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

2.1. To make the ideas more clearer

Suppose we have the following object shape features on a grid given in fig 1.

0,0	1,0	**2,0**	**3,0**	**4,0**
0,1	**1,1**	**2,1**	**3,1**	**4,1**
0,2	**1,2**	**2,2**	**3,2**	**4,2**
0,3	1,3	2,3	**3,3**	**4,3**
0,4	1,4	2,4	**3,4**	**4,4**

Figure 1 Segmented object shape

The red-bold indicate the image pixels. The size of the grid occupied by the object shape is 5X5. It means the vector dimension to represent the density of object shape in grid will be 4. The centroid calculated equations (8) and (9) is (3, 2), the centroid pixel is in blue. The first rectangle ring in fig. 1 is made up of the following pixels

(2,1), (3,1), (4,1), (4,2), (4,3), (3,3), (2,3), (2,2)

and there are seven image pixels that constitute our first element of the vector. The vector that represents object shape in fig.1 is

(7, 7, 1, 0, 0), using DHFP

Rectangle ring 4 and 5 are outside the grids so there are represented by zeros in the vector.

The second-order Epanechnikov KDE is given as generally:

$$f(x) = \begin{cases} \frac{1}{3h}\sum_{i=1}^{3}\frac{3}{4}\left(1 - \left(\frac{X_i - x}{h}\right)^2\right) & \text{if} \quad \left|\frac{X_i - x}{h}\right| < 1 \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

$$= \begin{cases} \frac{1}{4h}\sum_{i=1}^{3}\left(1 - \left(\frac{X_i - x}{h}\right)^2\right) & \text{where} \quad \left|\frac{X_i - x}{h}\right| < 1 \\ 0 & \text{otherwise} \end{cases}$$

The optimal bandwidth h_o for each image shape is calculated using (8). Then we recalculate the vector elements of the image to represent the image using the following

$$f(x_i) = \begin{cases} \frac{3}{4}\left(1 - \left(\frac{X_i - \bar{x}}{h_o}\right)^2\right) & where \quad \left|\frac{X_i - \bar{x}}{h_o}\right| < 1 \\ 0 & otherwise \end{cases} \tag{11}$$

The vector elements of the image in Figure 1 in the example will be given as:

(0.679449058, 0.679449058, 0.467796232, 0, 0) using EDFPE

3. Similarity Measurement

In order to measure the similarity of the images we used the Cosine Angle Distance (CAD) given in [12] as

$$s_{\cos} = \frac{\sum_{i=1}^{m} X_i Y_i}{\sqrt{\sum_{i=1}^{m} X_i^2}\sqrt{\sum_{i=1}^{m} Y_i^2}} \tag{12}$$

The CAD, which is angular metric is also called cosine coefficient, is the normalized inner product of two vectors because it measures the angle between those vectors. The cosine coefficient has lower and upper bounds of 0 and 1 respectively. This makes it more suitable than Euclidean metric to establish comparison of results produced by two different image retrieval methods such as DHFP and EDFPE.

4. Accuracy Measurement

The most frequently and important basic measures for information retrieval effectiveness are precision and recall [13, 14]. Precision can be defined as the fraction of retrieved items that are relevant to all retrieved items or the probability given that an item is retrieved it will be relevant and recall as the fraction of relevant items that are retrieved to relevant items in the database or the probability given that an item is relevant it will retrieved [13]. These notions can be made clear by examining the following set diagram (Figure 2). Figure 2 indicates the most important components of these measurements and formulas can be derived from the diagram.

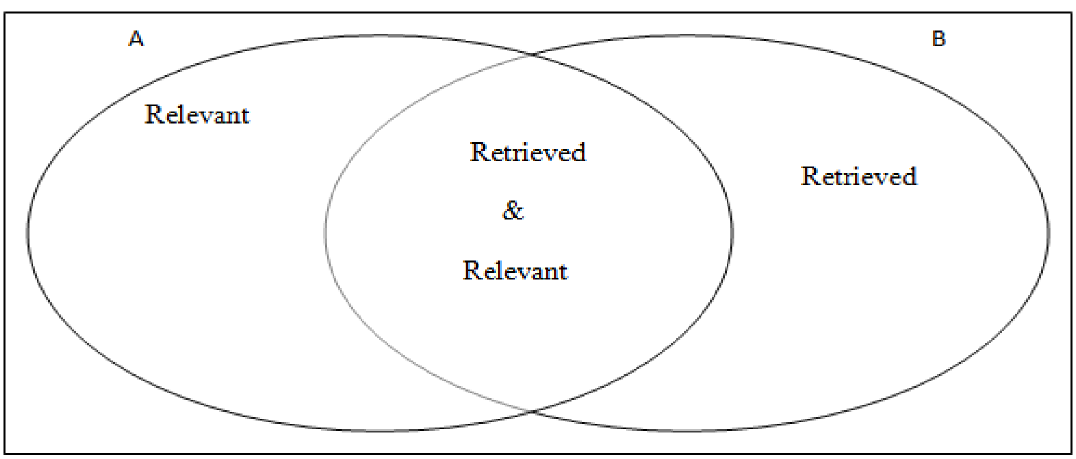

Figure 2: Set Diagram showing elements of Precision and Recall

The formulas for Precision (P) and recall (R) using set notation are below in 13 and 14:

$$P = \frac{n(A \cap B)}{n(B)} \tag{13}$$

$$R = \frac{n(A \cap B)}{n(A)} \tag{14}$$

To the user the scalar value of recall indicates the ability of the system to find relevant items as per query from the collection of different items and precision ability to output top ranked relevant items as per query. In general the user is interested in the relevant retrieved items thus the measures of precision and recall concentrate the evaluation on the relevant output of the system. The lower the values indicates bad performance of the system and the higher the values the more the user is encouraged to use the system due to the anticipation of getting more of the relevant search items. These evaluation measures are inter-dependent measures in that as the number of retrieved items increases the precision usually decreases while recall increases.

We also used the bull's eye score to measure the retrieval rate. The bull's eye score in percentage is measured by the number of correct retrievals divided by the number of relevant items in the dataset.

$$B = \frac{D}{P} * 100 \tag{15}$$

where B is a Bull's eye score in percentage, D is the total sum of correct retrieval and P is the total possible outcome.

These evaluation techniques were used in this paper.

5. EXPERIMENTATION

Our main objective is to make a comparison of the representation algorithms DHFP and EDHFP in representation and retrieval of image objects. We used the cosine coefficient Similarity in retrieving similar image objects. We created image database of shopping item image shapes. The image objects were not rotated lossless at 90, 180 and 270 degrees that mean degradation of the image object occurred during rotation. The query images were captured using different camera enabled devices. The images objects were of different dimensions MXN or NXN where M and N belong to natural numbers.

The images that we used were only having one image object with a homogeneous background. We then segmented using Chan & Vese algorithm [8] the image object shape by a 45X45 grid. All images were converted to gray scale images. After segmentation the output was a binary image object (silhouette). They were then represented using EDHFPE and DHFP. Each image was used as a query and the retrieval rate was measured using the Bull's Eye Performance (BEP), recall and precision performance. Matlab 7.6 was used to implement the system. Example of classes of shapes experimented with are given in Figure 3. In each class there are ten elements with some items rotated and scaled.

Figure 3: Classes of shapes experimented with inn this paper

6. RESULTS

Figure 4: Ten retrieval results of EDFPE on left and DHFP on the right (query at the top left of the figure)

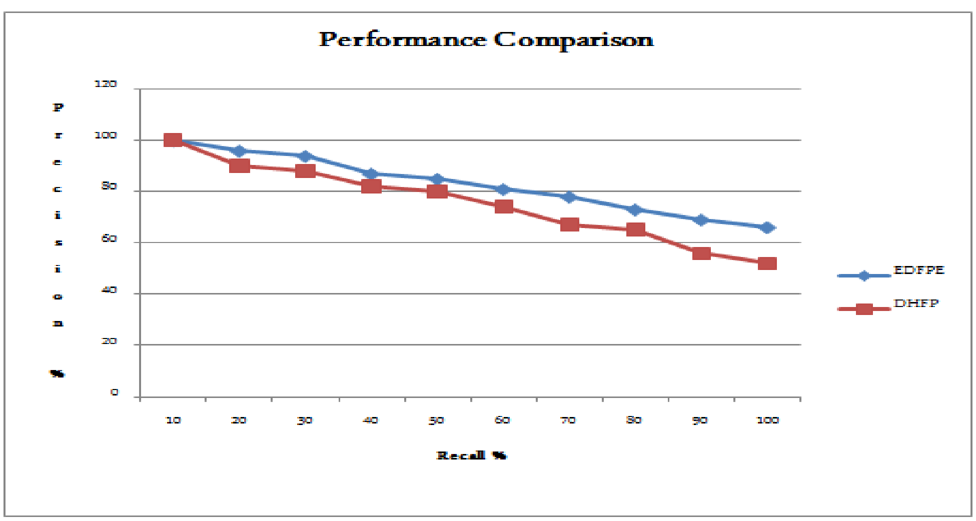

Figure 5: Average precision-recall chart on Image Retrieval

Figure 4 shows the normal retrieval results of the retrieval system that the users experience. It shows EDFPE and DHFP have a precision of 70% as a whole. If we look at different recall levels it can be seen that EDFPE performs better than DHFP. Figure 5 shows the performance measure of the retrieval system using the recall-precision graph. The results in figure 4 and in figure 5 show that EDFPE performs better as compared with DHFP method. The BEP score of 93.86 for EDFPE and 92.18% for DHFP confirming the superiority of EDFPE method.

7. Summary and Conclusion

From our results we can conclude that EDFPE method of image object representation was able to differentiate similar object shapes from dissimilar object shapes just as human beings perceive image objects shapes. The recall-precision graph shows the performance of the methods at different recall levels. This enables the users to select the best method for different situations. Recall and precision separately does not give the overall picture of performance of a method. The BEP score does not also give the overall picture of performance but summarises the overall performance of the methods. We can conclude that the EDFPE performs better at almost every recall level and as a whole without looking at the ordered performance. We assume that that EDFPE is better due to the fact that it estimates the feature points of the image instead of taking absolute values.

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