Content-based Image Recognition Technique Using Area Moments

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***Abstract* - We propose an automatic moment-based image recognition technique in this paper. The problem to be solved consists of classifying the images from a set, using the content similarity. In the feature extraction stage, we compute a set of feature vectors using area moments. An automatic unsupervised feature vector classification approach is proposed next. It uses a hierarchical agglomerative clustering algorithm, the optimal number of clusters being determined using validation indexes.**

***Keywords* - image recognition, feature vector, area moments, automatic classification, region-growing, validation index.**

I. Introduction

In this article we approach the image analysis domain, providing an automatic content-based image recognition technique [1]. We consider the following recognition problem to be solved: dividing a set of digital images in a proper number of clusters, based on the image content similarity.

This kind of image classification task could be applied easily in the image indexing domain. Using our image clustering result one may develop cluster-based image indexing structures for large databases.

A moment-based image feature extraction method is described in the next section. For each image from the set, one computes the corresponding feature vector, as sequence of area moments [2,3].

An automatic feature vector clustering method is proposed in the third section. Thus, a hierarchical agglomerative clustering algorithm is described. Some validation indexes are used with this unsupervised region-growing approach to provide an automatic classification technique.

We have performed many experiments using the proposed approach, which are mentioned in the fourth section. Our paper ends with a conclusions section and with a list of references.

2. Moment-based Image Feature Extraction

Therefore, we consider the set of images to be recognized: $S=\{I_1,...,I_n\}$. If a certain amount of noise is still present in these images, several image filtering operations should be applied to them, before performing the featuring process.

There are many image feature extraction techniques that could be used in this case. In our previous works, we computed image feature vectors based on image histograms, *DCT* Transforms [4], Gabor filters [5,6] and Wavelet features [6]. We propose a moment-based featuring approach in this section [2].

Thus, for each $i \in [1,n]$, a feature vector $V(I_i)$ is computed using discrete area moments. As one knows, the discrete moment of a 2D image function I_i is defined as $m_{pq}(I_i)=\sum_{x=1}^{X_i}\sum_{y=1}^{Y_i} I_i(x,y)\cdot x^p y^q$, where $p,q \geq 0$ and X_i, Y_i represent the image dimensions. The *central moment* of the image is obtained by computing the discrete moment with regard to its center of gravity, as in:

$$\mu_{pq}(I_i)=\sum_{x=1}^{X_i}\sum_{y=1}^{Y_i} I_i(x,y)(x-\bar{x})^p(y-\bar{y})^q \qquad (1)$$

where $\bar{x}=\frac{m_{10}}{m_{00}},\ \bar{y}=\frac{m_{01}}{m_{00}}$.

By introducing the standard deviations in directions *X* and *Y* in formula (1), we get the following new moment:

$$\hat{\mu}_{pq}(I_i)=\sum_{x=1}^{X_i}\sum_{y=1}^{Y_i} I_i(x,y)\left(\frac{x-\bar{x}}{\sigma_x}\right)^p\left(\frac{y-\bar{y}}{\sigma_y}\right)^q \qquad (2)$$

where $\sigma_x=\sqrt{\frac{\mu_{20}}{m_{00}}},\ \ \sigma_y=\sqrt{\frac{\mu_{02}}{m_{00}}}$.

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Then, another normalized discrete moment is computed as $\eta_{pq}(I_i) = \dfrac{\hat{\mu}_{pq}(I_i)}{\mu_{00}{}^{\gamma}(I_i)}$, where we choose $\gamma = \dfrac{p+q}{2} + 1$.

This moment is a translation, scaling and smooth deformation measure. We obtain the following moment-based feature vector, composed of 16 coefficients:

$$V(I_i) = (\eta_{00}, \eta_{01}, \eta_{02}, \eta_{03}, \eta_{10}, \eta_{11}, \eta_{12}, \eta_{13}, \eta_{20}, \eta_{21}, \eta_{22}, \eta_{23}) \quad (3)$$

The computed feature vector provides a satisfactory description for the image content.

The result of the image feature extraction process is the feature vector set, $\{V(I_1),...,V(I_n)\}$, with each component computed as in (3).

3. Automatic feature vector clustering

Image classification, the next step of recognition, represents an equivalent process to the feature vector classification [1]. Thus, a classification operation has to be performed within the feature set, $\{V(I_1),...,V(I_n)\}$.

Thus, we propose an automatic classification approach using an unsupervised agglomerative hierarchical algorithm [7]. Our region-growing technique uses the Euclidean distance and it is characterized by the following steps:

1. We set a number of clusters $K \le n$

2. Initially, we have n clusters, which are $C_1 := \{V(I_1)\},..., C_n := \{V(I_n)\}$

3. At each iteration the algorithm computes the overall minimum distance between clusters and merges those being at that distance from each other. For $i < j$, we have:

$$d(C_i, C_j) = d_{\min} \Rightarrow C_i = C_i \cup C_j, C_j = \phi \qquad (4)$$

where

$$d_{\min} = \min_{i \ne j \in [1,n]} d(C_i, C_j);$$

$$d(C_i, C_j) = \frac{\sum_{x \in C_i} \sum_{y \in C_j} dist(x, y)}{card(C_i) \cdot card(C_j)} \qquad (5)$$

where $dist$ is the Euclidean distance and $card(C_i)$ represents the cardinal of a cluster.

4. The region-growing clustering process goes on until the stopping condition is reached: the number of clusters becomes K.

Obviously, our classification technique uses the average linkage clustering and produces K feature vector classes [7]. Then we have to determine the optimal number of clusters, from 1 to T, where T represents a given threshold.

We use some cluster validity indexes for this purpose [8,9].

We compute a parameter based on a combination of Dunn and Davies-Bouldin validity indexes, that must be minimized for an optimal clustering. The Dunn measure aims to maximize the intercluster distances and minimize the intracluster distances [8].

The number of clusters that maximize the Dunn index is taken as the optimal number of clusters.

The index proposed by Davies and Bouldin is a function of the ratio of the sum of within-cluster scatter to between-cluster separation [9]. Its lowest value indicates an optimal clustering operation. We set as a good value for the threshold: $T = n/2$.

If the obtained feature vector classes, for a given K, are $C_1,..., C_K$, the optimal number of classes is computed as follows:

$$K_{optim} = \arg \min_{K \in [1,T]} \left(DB(K) + \frac{1}{D(K)} \right) \qquad (6)$$

where the Davies-Bouldin index is computed as

$$Db(K) = \frac{1}{K} \sum_{i=1}^{K} \max_{i \ne j} \frac{d(C_i) + d(C_j)}{d(Cen_i, Cen_j)} \qquad (7)$$

and the Dunn index is obtained as

$$D(K) = \min_{i \in [1,K]} \left\{ \min_{j \ne i} \left\{ \frac{d(Cen_i, Cen_j)}{\max_{t \in [1,K]} d(C_t)} \right\} \right\} \qquad (8)$$

where Cen_i is the centroid of C_i and $d(C_i)$ represents the intra-cluster distance of C_i.

Therefore, the optimal feature vector clustering process is that which corresponds to the identified K_{optim} value.

4. Experiments

We have performed many numerical experiments, testing the proposed recognition technique on various image data sets.

We have obtained quite satisfactory image recognition results.

This image recognition approach has been tested on hundreds images and a high recognition rate, approximately 85%, has been obtained. A small image recognition example is depicted in the next figure.

Then, we compute the distances between feature vectors and obtain the following values:

$d(V(I_1),V(I_2)) =$ 7.1418/10000,

$d(V(I_1),V(I_3)) =$ 2.2615/10000,

$d(V(I_1),V(I_4)) =$ 6.4562/10000,

$d(V(I_1),V(I_5)) =$ 2.7760/100000,

$d(V(I_2),V(I_3)) =$ 7.9141/10000,

$d(V(I_2),V(I_4)) =$ 7.5178/100000,

$d(V(I_2),V(I_5)) =$ 7.0172/10000,

$d(V(I_3),V(I_4)) =$ 7.1781/10000,

$d(V(I_3),V(I_5)) =$ 2.1480/10000,

$d(V(I_4),V(I_5)) =$ 6.2933/10000.

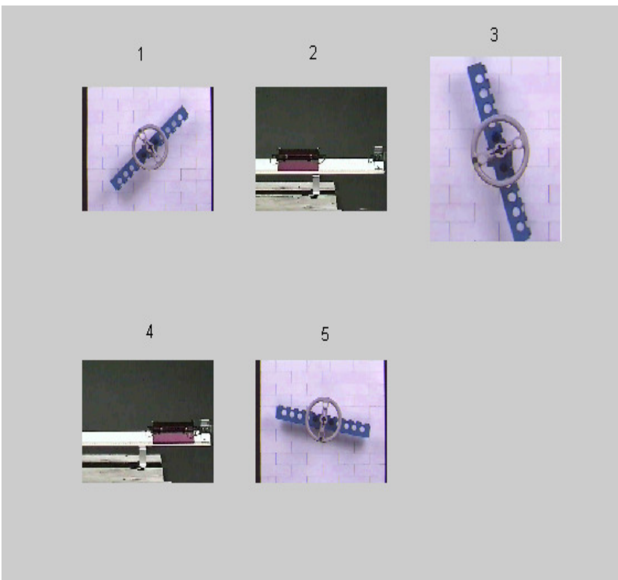

Fig. 1. Digital image set to be clustered

We get K = 2, the image clusters being $\{I_1, I_3, I_5\}$ and $\{I_2, I_4\}$.

VII. Conclusion

An automatic unsupervised image recognition method has been provided in this paper. The main contributions of this article are the feature extraction approach using discrete area moments and the automatic classification procedure.

Our recognition technique can be successfully applied in various image and video analysis areas. One of them is the temporal video segmentation task which requires the featuring and classification of the video frames [5]. Another video analysis problem using the unsupervised image classification is the video key frame extraction. Image indexing, mentioned in the introduction, is another important application area.

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