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An automatic image recognition approach

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Abstract

Our paper focuses on the graphical analysis domain. We propose an automatic image recognition technique. This approach consists of two main pattern recognition steps. First, it performs an image feature extraction operation on an input image set, using statistical dispersion features. Then, an unsupervised classification process is performed on the previously obtained graphical feature vectors. An automatic region-growing based clustering procedure is proposed and utilized in the classification stage.

Keywords: image recognition, feature extraction, feature vector, standard deviation, statistical dispersion, unsupervised classification, automatic clustering, region-growing.

1 Introduction

Image recognition represents an important pattern recognition domain [1,2]. This work provides a novel automatic image recognition approach.

We consider the following image analysis task: having a set of images, we have to perform a proper recognition within that set. The given images have to be grouped, using their features, in several classes of similarity.

In the next section, a standard deviation based image feature extraction technique is proposed by us. The graphical feature vectors are obtained as the dispersion matrices of those images.

The resulted image feature vectors are then classified using the region-growing based automatic unsupervised classification procedure provided in the third section. The obtained image classes represent the recognition result.

Several results of our practical experiments are presented in the fourth section. The work ends with a conclusion section. The main contributions of this paper are the proposed image featuring approach and the automatic image feature vector clustering technique, respectively.

2 Dispersion-based feature extraction

We consider the following recognition task. Let $S = \{I_1, ..., I_n\}$ represent a set of input images to be recognized. A feature extraction process has to be performed on the set S, first. 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 procedure.

There are many image feature extraction technologies, the most used being based on image histograms [1,6], *DCT Transforms* [1,2], *Gabor filtering* [3,5], *Wavelet features* [3,5] and discrete moments [4]. In this section we propose a featuring method which uses image statistical features.

Thus, we provide a more powerful feature vector, based on the standard deviation values. A grayscale conversion can be operated on these images to facilitate the computation of these features. Then, each image I_i is decomposed into $[a$ x $b]$ blocks, usually considering $a = b$. If a perfect division is not possible, the transformed grayscale image could be padded with zero values.

The statistical dispersion (standard deviation) of each rectangular graphical region is then computed, as the square root of its variance, a *dispersion matrix* thus being obtained for each image. This matrix, containing the dispersions of the blocks of I_i, is utilized as the image feature vector $V(I_i)$.

The graphical feature vector obtained as a dispersion matrix offers a satisfactory characterization of the image content. Also, its sizes are proportional to the sizes of the corresponding image. The images from the set S could often have different dimensions, so the matrices from the feature vector set could differ in size too.

This means that a special metric should be used to measure the distance between these feature vectors. In our previous works we provided a Hausdorff derived metric which works properly for the classification of different-sized matriceal feature vectors [5-8].

If the images I_i have identical or quite close dimensions, the Euclidean distance can be applied. Some smooth transformation operations, consisting in resizing or padding with zeros, could be performed first on the images from the set S, for bringing them to the same dimension. The vectors of the feature set will have identical sizes too, so the Euclidean metric can be used successfully in their classification.

3 Image feature vector classification

The next step of image recognition is the classification process over S. Obviously, image classification is an equivalent process to the feature vector classification, the content of each image from the given set being described by the feature vector of that image.

Therefore, a grouping operation must be performed on the feature vector set, $\{V(I_1), ..., V(I_n)\}$. First, we propose a semiautomatic unsupervised classification procedure based on a region-growing technique [1,6,7]. Then, we extend it and use this method to develop an automatic classification approach. The region-growing clustering algorithm is characterized by the following main processing steps:

The desired number of clusters, $K \leq n$, is set interactively.

Initially, there are considered n clusters: $C_1 := \{V(I_1)\}, ..., C_n := \{V(I_n)\}$, where ":=" represents the assignment operator.

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

$$d(C_i, C_j) = d_{\min} \Rightarrow C_i := C_i \cup C_j, C_j := \phi \qquad (1)$$

where

$$d_{\min} = \min_{i \neq j \in [1,n]} d(C_i, C_j), \tag{2}$$

where distance between clusters is computed with *single linkage clustering* as in

$$d(C_i, C_j) = \min_{x \in C_i, y \in C_j} dist(x, y) \tag{3}$$

where *dist* represents the proper distance for these vectors (the Euclidean metric, for example). Also, *average linkage clustering* could be applied for distance computation [8], as in the formula

$$d(C_i, C_j) = \frac{\sum\limits_{x \in C_i} \sum\limits_{y \in C_j} dist(x, y)}{card(C_i) \cdot card(C_j)}, \tag{4}$$

where $card(C_i)$ is the cluster's cardinal.

The algorithm ends when the *stopping condition* is achieved, which requires that the number of clusters becomes K.

The provided clustering algorithm produces K feature vector classes, corresponding to the K image classes. Let us extend now the described semiautomatic classification method to obtain an automatic variant of it which does not require any previous knowledge about number of clusters [8]. This means it does not imply any interactivity also.

The new clustering algorithm we propose consists of two main parts. The first one operates on the feature vectors, while the second one focuses on the distances between them. Thus, the first part resembles the presented region-growing algorithm. It starts, like the previous one, with all the feature vectors as clusters. Then, it unifies these clusters using the same method, but removing the stopping condition.

The second part of the procedure analyzes the previously computed minimum distances between clusters. The described region-growing algorithm is then applied to them, these distance values being clustered in two categories: *large* distances and *small* distances, the latest being those which determine the feature vector classes. Therefore, the automatic clustering (unsupervised classification) procedure is described by the following steps:

1. Initialize the distance set: $D := \phi$.

2. Starts the classification process with the n initial clusters, one for each graphical feature vector: $C_1 := \{V(I_1)\}, ..., C_n := \{V(I_n)\}$.

3. At each iteration computes the overall minimum distance between clusters, using formula (2), and merges those being at that distance from each other, using (1). The distance between clusters d is computed from (3) only. Minimum distance is then registered: $D := D \cup \{d_{\min}\}$.

4. When a single cluster remains, a new clustering process is performed on the distance set D, using the previous region-growing algorithm with parameter $K = 2$. Two classes containing distance values are thus obtained.

5. One element from each class is randomly selected and the two distance values are then compared. The class corresponding to the greater value represents the set of large distances, D_l. The smaller value belongs to the set of small distances, D_s. Obviously, $D = D_l \cup D_s$.

6. Each image receives its order number as an initial class label: $\forall i \in [1, n], C(I_i) := i$.

7. For any *small* distance, it searches for all pairs of vectors corresponding to it and the images related to the feature vectors from each pair must be inserted in the same class:

$$\forall dis \in D_s, \forall i < j \in [1, n],\ \text{if } d(V(I_i), V(I_j)) = dis \Rightarrow C(I_j) := i. \quad (5)$$

This clustering algorithm assigns a class label to each member of the set S, the final image classes representing the recognition result. The classification performed this way is totally automatic, no interactivity being present. Although the previously described region-growing algorithm is used here for distance classification, the process has an automatic character, because the number of classes, K, is already known. The provided automatic unsupervised classification (recognition) approach works successfully on large sets of images, which means great n values.

4 Experiments

The described graphical recognition technology provides satisfactory results when applied to particular sets of images. We have performed many image recognition experiments. For space reasons, let us present a quite simple example in this paper.

So, let $S = \{I_1, I_2, I_3, I_4, I_5\}$, where the RGB color images from S converted in grayscale form are displayed in Fig. 1. A recognition process has to be performed on them. Each image I_i is marked by its number, i.

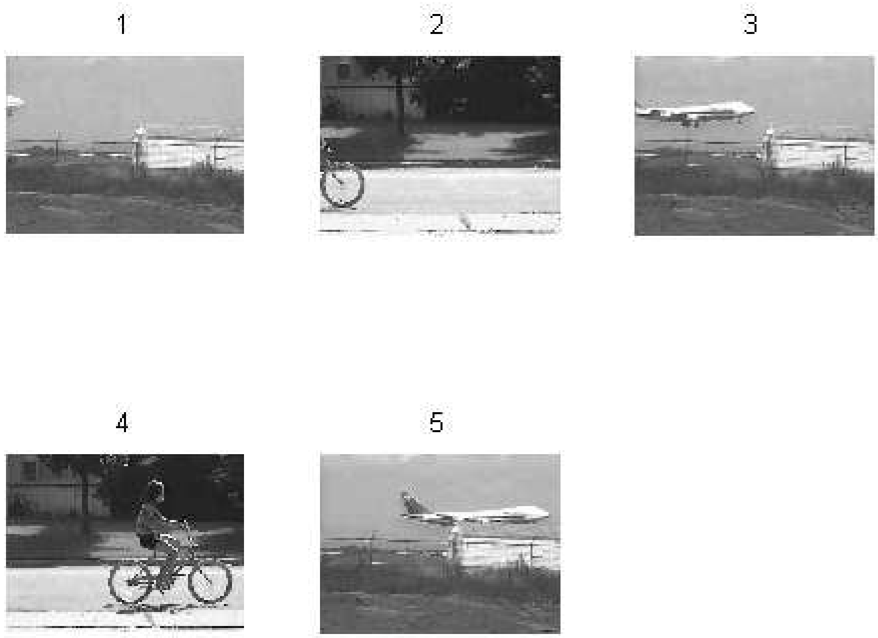

Figure 1. Set of RGB images converted in grayscale form

All the images are converted to a grayscale form and a filtering procedure is applied to them for noise removal. Initially, they have different dimensions, therefore a resizing operation is needed. Thus, a [240 x 320] size is obtained for all of them.

Next, the feature extraction procedure described in section 2 is performed on the five images. For each image we consider square blocks of size $a = 8$ and compute their standard deviation. The resulted dispersion-based graphical feature set, $\{V(I_1), ..., V(I_5)\}$ is represented in Fig. 2. Each image feature vector $V(I_i)$ constitutes a [31x41] matrix. It is displayed as a $3D$ surface plot in Fig. 2, being indicated by its number, i.

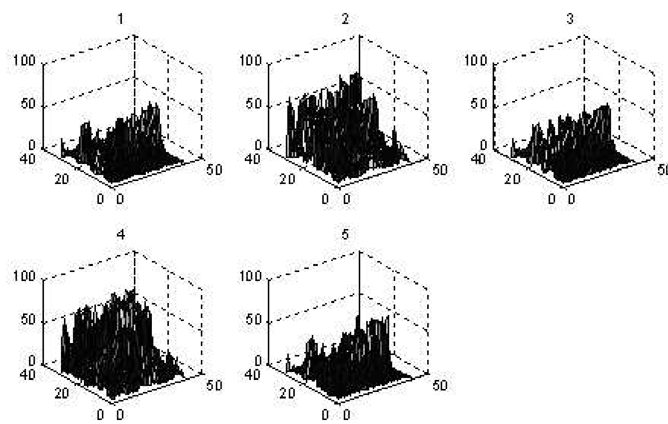

Figure 2. The feature vector set

The automatic classification provided in section 3 is applied to this feature set. The Euclidean distance is used in the classification process, because the image feature vectors have identical sizes. In the next table there are registered the computed distance values between all the pairs of feature vectors.

Table 1. Distances between image feature vectors

	$V(I_1)$	$V(I_2)$	$V(I_3)$	$V(I_4)$	$V(I_5)$
$V(I_1)$	0	571.3183	293.0381	675.6527	319.3169
$V(I_2)$	571.3183	0	599.5098	359.3718	618.9163
$V(I_3)$	293.0381	599.5098	0	686.5573	361.6215
$V(I_4)$	675.6527	359.3718	686.5573	0	712.8829
$V(I_5)$	319.3169	618.9163	361.6215	712.8829	0

Let us apply now our clustering algorithm, using the values from Table 1. It begins with five initial clusters, $\{V(I_1)\}, \{V(I_2)\}, \{V(I_3)\}$, $\{V(I_4)\}$ and $\{V(I_5)\}$. Also, we use the notation $d_{i,j} = d(V(I_i), V(I_j))$.

From the table, it results that the minimum distance between two different clusters is $d(\{V(I_1)\}, \{V(I_3)\}) = d(V(I_1), V(I_3)) = 293.0381$, therefore the new cluster $\{V(I_1), V(I_3)\}$ is obtained and $D = \{d_{1,3}\}$. The next minimum distance between two clusters is $d(\{V(I_1), V(I_3)\}, \{V(I_5)\}) = d(V(I_1), V(I_5)) = 319.3169$, so the new cluster $\{V(I_1), V(I_3), V(I_5)\}$ results and $D = \{d_{1,3}, d_{1,5}\}$. The next overall minimum distance value is $d(\{V(I_2)\}, \{V(I_4)\}) = d(V(I_2), V(I_4)) = 359.3718$, so cluster $\{V(I_2), V(I_4)\}$ is obtained and $D = \{d_{1,3}, d_{1,5}, d_{2,4}\}$. The next minimum distance is $d(\{V(I_1), V(I_3), V(I_5)\}, \{V(I_2), V(I_4)\} = d(V(I_1), V(I_2)) = 571.3183$, thus the final cluster containing all the feature vectors is obtained and $D = \{d_{1,3}, d_{1,5}, d_{2,4}, d_{1,2}\}$.

A region-growing clustering is then performed on distance set D. The closest values are $d_{1,3} = 293.0381$ and $d_{1,5} = 319.3169$, so they must be inserted in the same cluster. The next pair of closest distance values contains $d_{1,5} = 319.3169$ and $d_{2,4} = 359.3718$, therefore the two distance clusters are $D_s = \{d_{1,3}, d_{1,5}, d_{2,4}\}$ and $D_l = \{d_{1,2}\}$ respectively.

Using the values from the set D_s, we obtain from the relation (5) the image classes $\{I_1, I_3, I_5\}$ and $\{I_2, I_4\}$. These final graphical classes provide the following similarity relations between images: $I_1 \approx I_3 \approx I_5$ and $I_2 \approx I_4$.

5 Conclusion

We have provided an automatic unsupervised image recognition approach in this paper. First, a feature extraction approach using statistical features is described, then a semiautomatic image clustering technology being proposed. That semiautomatic procedure is further extended, resulting in an automatic classification technique [8].

In the described experiments, the Euclidean distance have been used for vector classification and we have obtained satisfactory results. An image recognition system using other special nonlinear metrics in the different-sized feature vector classification process will be one of our future directions.

Our recognition method 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 [7]. Another video analysis problem using the unsupervised image classification is the video key frame extraction [7].

Some image analysis fields used in *biometric authentication* require this kind of graphical recognition. Thus, this image recognition technology could be applied in various biometrics related domains, like *fingerprint recognition* [5], *facial recognition*, *eye retinas recognition* or *iris recognition*.

Other important application areas of our automatic recognition approach are *image indexing* and *image retrieval* [3], respectively. Indexing of large image databases and information retrieval from these databases are made possible by the proposed classification method, because it works properly for very large graphical data sets.

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