[11] Near-duplicate image recognition based on the rank distribution of the brightness clusters cardinality

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Abstract

In this paper the usage of multi-step segmentation for near-duplicate image recognition is investigated. The clustering of image pixels brightness is used for segmentation. The clustering is implemented by means of a recurrent neural network.

The search pattern based on the rank distributions of the brightness clusters cardinality is suggested. Experimental results on the near-duplicate image recognition based on the application of the suggested search pattern are given. It is shown that the use of multi-step segmentation and rank distributions of the brightness clusters cardinality allows successfully recognize the duplicates obtained by the considerable visual distortion of the original image or by scale change of image.

Keywords: *image, pixel, point mapping, recurrent neural network, clustering, segmentation, recognition of images, ranking distribution.*

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Introduction

The problem of near-duplicate image recognition is relevant to search image patterns through the Internet, in digital archives and libraries; to analyze satellite and aerial imagery, as well as for computer vision systems, etc. [1].

We use the near-duplicate images to mean the images which can be changed by such transformations as rotation, shift, change of vision angle, change of resolution, scaling, change of light [2]. These images may be obtained by changing their mapping conditions or upon their editing [3-8].

The problem of near-duplicate image recognition refers to image recognition problems. Modern image recognition techniques are based on the comparison of their visual primitives and quantitative estimation of the image proximity using these primitive values. Image visual primitives are considered to be those image characteristics which are calculated by the original image, and can be used for recognition and search. A search image generated from such primitives reflects its content, is small in size and easy to search. The usage of visual primitives is so far quite an effective and universal mean of image recognition and search in digitized image collections [9].

Histograms are very often used as the search patterns in image recognition tasks [10]. These can be light intensity, color or filter output histograms etc. The application of histograms seems to be attractive since the proximity between them can be easily determined and quickly calculated using the known proximity measures. In spite of the infinite simplicity of the approach, it may show rather stable results [9]. However, when comparing images by means of histograms many erroneous outcomes may occur.

A histogram is a concise description of the analogue image quantized in brightness, which is particularly used as the search pattern. Another way to concisely describe the image based on the use of brightness is segmentation. By the segmentation we mean the process of partitioning the image into areas close in their brightness. The use of special segmentation methods based on the clustering enables to give more detailed information about image objects. It is a fair assumption to say that the pixels of allocated image areas got into the same cluster shall belong to the same image object.

Thus, we can assume that a segmented image shall allow us to solve the problem of image recognition more accurately thereby not requiring the same computational costs as, for example, when using correlation techniques.

The purpose of this paper is to investigate the possibility of the usage of multi-step segmentation based on a recurrent neural network to recognize near-duplicate images.

1. Multi-step image segmentation

The multi-step segmentation for images in greyscale has been proposed and discussed in [11-13]. It is based on the clustering of brightness values of image pixels using the recurrent neural network shown in Fig. 1.

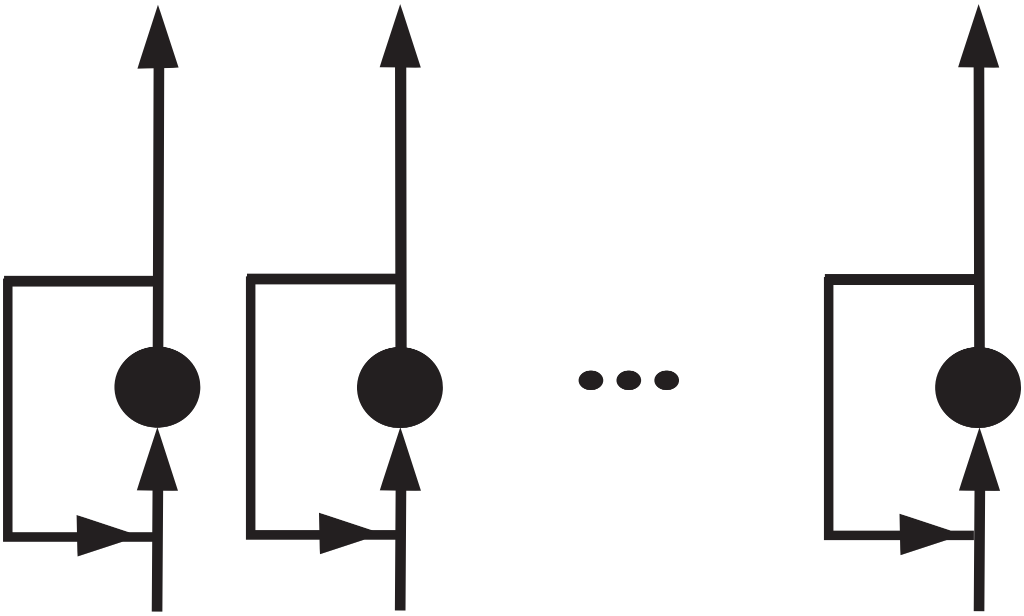

Fig.1. Structure of the simulated neural network

In [13] it is shown that the neural network with a local feedback of input layer neurons can be used for data clustering. The feedback leads to one-dimensional mapping of input values on the activation function of the neural network. The segmentation is performed in several steps, each of which uses results of a previous step as the input data. The segmentation is completed when the image entropy obtained at the next step ceases to change. This procedure has been called the multi-step segmentation.

The multi-step segmentation ensures the rank distribution of homogeneous image pixel regions maximally arranged by their brightness. It helps suppose that the transformed image is free from excessive details and at the same time it can best produce the semantics of the scene presented thereon.

2. Recognition of segmented images

In order to clear up the features of the image recognition segmented by the aforementioned multi-step segmentation procedure, we should refer to the Lamerey diagram (Fig. 2).

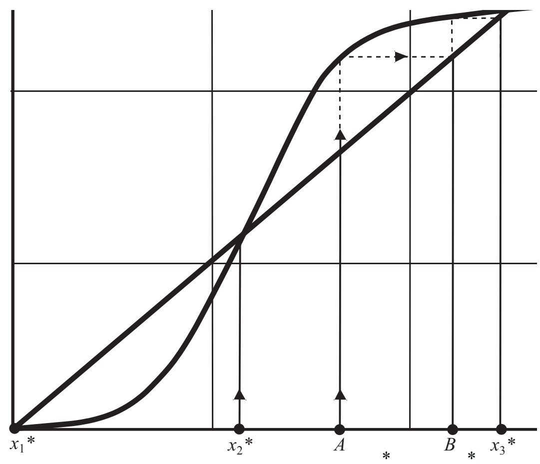

Fig. 2. The Lamerey diagram for one-dimensional brightness mapping, x_1^* and x_3^* – are stable points; x_2^* – is an unstable mapping point

It clearly visualizes the process of one-dimensional brightness mapping on the neuron activation function $f(x)$ being the basis of the clustering. A sigmoid function can be considered as this activation function. In the process of mapping $x_{n+1} = f(x_n)$, where n – is a current iteration number, any value of x within the interval between A and B points shall reach the stable point x_3^* for the same number of iterations. This particular feature provides the effect of the brightness clustering and, consequently, the image segmentation [11].

We will show that this feature of one-dimensional mapping enables to identify a segmented original image and its near-duplicate images even at pixel brightness distortions.

Suppose the interval AB involves the value x which corresponds to the brightness of a certain pixel of the original image. Let us assume that as a result of some image transformations the brightness of this pixel on the obtained duplicate image has changed its value. Two options are possible thereby.

Option 1: after transformation the changed brightness value shall stay within the interval AB. Then in the process of mapping this value shall reach the stable point x_3^* for the same number of iterations as in the case with the original image (i.e. the value enters into the same cluster).

Option 2: as the result of transformation, the pixel brightness value of the original image will go beyond the interval AB. In this case after transformation the value shall enter in another cluster.

Thus, for a certain part of clusters the brightness distribution per clusters of the segmented duplicate images will remain unchanged with respect to the original image. For the other part of clusters this distribution may change.

Let us denote the brightness clusters cardinality to be the number of elements entering thereinto. It is obvious that the distribution of the segmented brightness cluster cardinality per clusters (the cluster distribution of the brightness clusters cardinalities) may feature any image, i.e. be its search pattern, which can be used to compare the images. It is thereby convenient to set the brightness clusters cardinality in relative terms (to calculate a proportion of elements entered in the cluster of the total number thereof).

3. Image proximity estimation

Proximity estimation of the image to be recognized compared to the original image is the most important part of the recognition technique. For this purpose different images are reduced to the form of feature vectors in a certain n-dimensional space. Each image has a peculiar vector in this space.

Let us conceive the brightness clusters cardinality of the segmented image as a vector in the space whose dimension is equal to the number of clusters allocated in the image brightness clusters. Then the proximity of the images to be compared may be measured by the proximity of vectors corresponding to the received distributions of the brightness clusters cardinalities.

The proximity measure between two vectors (i.e. the images) in n-dimensional vector space may be defined in the form of an angle. Given the entering image vector is $S = (s_1, s_2, ..., s_n)$ and the original image vector is $X = (x_1, x_2, ..., x_n)$. Then the vectors proximity d_{sx} shall be determined as follows:

$$d_{sx} = \arccos\left(\frac{\sum_i s_i \cdot x_i}{|X|\cdot|S|}\right) \qquad (1)$$

where $|S|$ and $|X|$ in denominator mean the vector lengths S and X, respectively, and in numerator we have their scalar product. This measure is called a cosine distance and all needed metric space postulates shall be obeyed thereto. The identity of the entering image S to the original image X shall be determined by the decision rule: $S \in X$ if $d_{sx} \le \varepsilon$, where $\varepsilon << 1$ – is a prescribed positive value.

When calculating in (1) the scalar product of the vectors representing the images, the problem of vectors arrangement comes up. We offer to use, as the search pattern, the rank distribution of the brightness clusters cardinality on the segmented image.

The rank distribution is the dependence of a certain value from the rank, i.e. a serial number in series of its values arranged in descending order. This distribution is widely used in the analysis of texts, technical and physical systems, and is the basis for the system rank analysis [14].

The use of this distribution allows us to compare the vectors of the brightness clusters cardinality even when the clusters have different brightness boundaries.

4. Experimental results by recognition of grayscale duplicate images

The aforementioned principles of the multi-step segmentation for the near-duplicate image recognition have been analyzed in a number of experiments with grayscale images [15].

In these experiments a brightness clustering module included a software model of the recurrent neural network shown in Fig. 1. The parameters of the neural network were calculated according to the methods given in [11, 12]. In the course of experiments the original image has been compared with its near-duplicates images and also with the images of completely different objects which bear no resemblance to it. As the near-duplicate images we used the original images with Gaussian blur of their pixels brightness. It was identified that the high-quality rank distributions of the brightness clusters cardinality of the original image and its duplicates has a good match up to a certain threshold value of the blur radius. This radius has been determined from the estimate of the cosine distance according to the formula (1) between the rank distributions of the original and duplicate images. It was identified that the near-duplicate grayscale images are successfullly recognized up to the radius of their Gaussian distortions equal to 8-11 pixels. The threshold distance of the successful recognition hereby possessed the value $d_o = 0.157$ that corresponds to the angle value of 10% from the angle in $\pi/2$, wherein the n–dimensional vectors of the images being compared are orthogonal, i.e. the images are completely different.

Moreover, experiments set up in [15] have shown that the method enables to successfully recognize the original image by its reduced duplicate distorted by Gaussian blur.

Experiments have also proved a good recognition selectivity. The images of the objects which beared no resemblance to the original images provided the cosine distance substantially exceeding the recognition threshold.

Thus, experiments with the graycsale images have shown the successful application of the rank distributions of the brightness clusters cardinality in order to solve the specified problem.

5. Experimental results by recognition of color duplicate images

We have applied the aforementioned method to recognize color images too. Herewith, the color image was preliminary transformed into grayscale as follows. As the pixel brightness of the grayscale we used a brightness component of the color model YUV applied in [16]. In this model the image brightness component Y contains the basic image information, whereas the color difference components U and V are less meaningful. Therefore, for segmentation and recognition only the brightness Y of the original and duplicate images has been clustered, whereas the color difference components were disregarded in recognition. The brightness component Y of the color model YUV has already contained an indirect information about the color since it is the weighted sum of the color components of the RGB-model $Y = 0,299R + 0,587G + 0,114B$.

Otherwise, the color image recognition is similar to the aforesaid recognition of the grayscale images.

In experiments we have used a series of color images and simulated the creation of their duplicate images by Gaussian distortions of pixel brightness of the master image performed by means of Adobe Photoshop software.

In these experiments the original and duplicate images were presented both in gray– and color scales. The following combinations were compared: gray original image – gray duplicate images, gray original image – color duplicate images, color original image – gray duplicate images, color original image – color duplicate images.

Fig. 3, b) and d) show those color and gray duplicate images which can still be recognized at the specified recognition threshold $d_0 = 0.157$.

The quantitative estimation of the distance dependences between the master and duplicate images and the radius of Gaussian distortions is shown in Fig. 4.

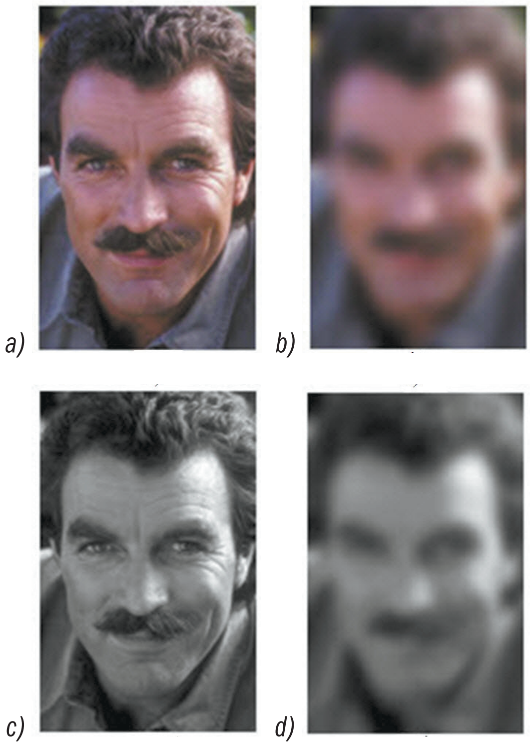

Fig. 3. The original and duplicate images: a) the original color image from [17]; b) the Gaussian image distortion (the distortion radius is12 pixels); c) the gray original image; d) the Gaussian image distortion (the radius is 10 pixels)

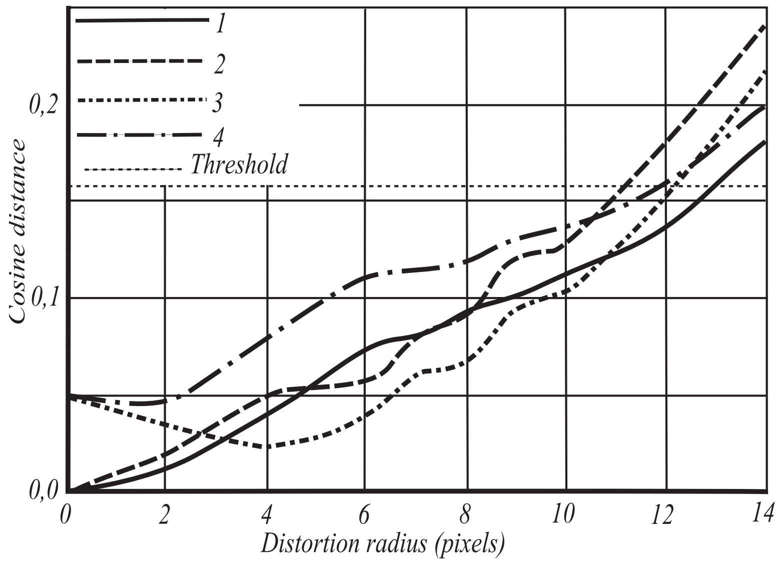

Fig. 4. Dependence of the cosine distance between the master image and its duplicate images on the Gaussian distortion radius in the case of color images; 1)color original image – color duplicate images; 2) gray original image – gray duplicate images; 3) color original image – gray duplicate images; 4) gray original image – color duplicate images

The above figure indicates that when $d_0 = 0.157$ the recognition for all specified combinations is performed for rather large values of the distortion radius, approximately, up to 11–13 pixels. Moreover, it is obvious that the recognition is also related to the combination of color representations of the original and duplicate images. The most distorted duplicate images (about 13 pixels) are recognized for the combination 'color original image – color duplicate images. In combinations 'gray original image – gray duplicate images' the successful recognition is to be completed with less distortions (about 11 pixels). Combinations of different color representations provide the threshold distance at intermediate distortions. However, in all studied cases the degree of visual distortion of the duplicate images is significant (Fig. 3).

Conclusions

The multi-stage segmentation performed by means of the recurrent neural network allows us to create the image pattern based on the rank distribution of the brightness clusters cardinality obtained in segmentation.

1. The rank distribution of the brightness clusters cardinality in the segmented images is the characteristic feature which is sufficient to recognize the near-duplicate original images.
2. The successful recognition depends on the combination of representation scales (color and gray) of the original and duplicate images.
3. When the specified recognition threshold is $d_o = 0.157$, the recognition based on the rank distribution allows us to define the near-duplicate color images up to the radius of their Gaussian distortions equal to 11–13 pixels.

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