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Texture recognition of medical images with the ICM method

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Abstract

The Integrated Cortical Model (ICM) is based upon several models of the mammalian visual cortex and produces pulse images over several iterations. These pulse images tend to isolate segments, edges, and textures that are inherent in the input image. To create a texture recognition engine the pulse spectrum of individual pixels are collected and used to develop a recognition library. Recognition is performed by comparing pulse spectra of unclassified regions of images with the known regions. Because signatures are smaller than images, signature-based computation is quite efficient and parasites can be recognized quickly. The precision of this method depends on the representative of signatures and classification.

Our experiment results support the theoretical findings and show perspectives of practical applications of ICM-based method. The advantage of ICM method is using signatures to represent objects. ICM can extract the internal features of objects and represent them with signatures. Signature classification is critical for the precision of recognition.

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1. Introduction

Many texture recognition algorithms have been previously proposed of which some will be reviewed in the next section. Many of these algorithms rely on statistical analysis of image segments. We will propose a new approach that relies on pulse-image spectra. Basically, the image is processed by a higher-order network and cooperative pulsations are indicative of the image texture. Thus, comparisons of pulse spectra with a library can classify regions of the image according to its texture. We will present results comparing the proposed system with previously proposed algorithms. The standardized texture database contains images that consist of only texture. Thus, we will also present the proposed algorithm's performance on a microscopic image of a secretion cell. Finally, while it is possible for the algorithm to extract texture information there still is a need for a decision engine. We will demonstrate that an associative memory improves the classification of image pixels over the traditional statistical decision process.

2. Texture extraction

In Ref. [1] several methods of texture analysis were applied to a standard texture database. Thus,

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we will compare the proposed method against these previous analyses on the same dataset.

2.1. The variety of previous methods

Singh analyzed eight different methods for texture analysis. We will briefly mention each method and an associated letter code which associates each method to the results shown in the tables. The auto-correlation (ACF) method measures the similarity of texture primitives using auto-correlations. The shape of the correlation response is an indication of the inherent texture. The co-occurrence method (CM) [2] measures the joint probability distribution as a function of the distance between pixels. The edge frequency (EF) method basically sends the image through an edge enhancing operation and computes the frequency of edges by summing regions of varying size d. Law's Method (LM) [3] uses small masks to compute statistical qualities such as mean, deviation, skewness, kurtosis, and energy over specified regions. The run length (RL) method counts the length of runs of pixels that have the same intensity level. The binary stack method (BSM) [4] separates the image by grey levels of intensity. Then computations are performed on each grey level to determine the type of connected regions that exist. The method of texture operators (TO) [5] uses several small binary-element matrices to measure the connectivity of pixels in different directions (vertical, horizontal, slant, etc.). Finally, the texture spectrum (TS) [6] method measures the frequency of texture units.

2.2. Pulse-image spectra

The method that is proposed here uses *pulse-image* generators to eventually determine the *pulse spectrum* of each pixel. These spectra are then used to classify the pixels. Pulse images [7] are a set of images generated from a single input image. Basically, each pixel (or neuron) contains a coupled oscillator consisting on an internal state (F) and a dynamic threshold (Θ). It is mathematically convenient to group the F's of all of the pixels into a single 2D array, $\mathbf{F}$. Similarly, the thresholds are also described as an array. The pulse images tend to isolate the segments, textures, and edges that are contained in the input image.

The process receives an input image and produces a pulse image at each iteration. In the initial iterations the neurons tend to pulse synchronously dependent on the input. As the iterations progress the collective pulse segments tend to de-synchronize. The iterations are stopped after 20 iterations due to the de-synchronization. The process iterates over the following three equations:

$$\mathbf{F}[n+1] = f\mathbf{F}[n] + \mathbf{S} + W\{\mathbf{Y}\} \tag{1}$$

$$Y_{ij}[n+1] = \begin{cases} 1 & \text{if } F_{ij}[n+1] > \Theta_{ij}[n] \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$\Theta[n+1] = g\Theta[n] + h\mathbf{Y}[n+1]. \tag{3}$$

The input is a 2D array of image intensities ($\mathbf{S}$), the connections between the neurons are described by the function $\mathbf{W}$, and the output of each iteration is $\mathbf{Y}[n]$. The scalars f and g are slightly less than 1.0 and $f<g$. The scalar h is usually quite large. The connection function $\mathbf{W}$ has traditionally been a smoothing operation with a small kernel. However, more recent work has developed a *centripetal autowave* model [8] in which the communications between neurons adjusts after each iteration. The neurons strengthen their communications based upon a *curvature flow* model in which the borders of the previous $\mathbf{Y}$ define segment boundaries. The communications strengthen towards the local center of curvature of these boundaries.

2.3. Pulse spectra

Neurons with similar intensities and with neighbors of similar intensity will tend to pulse during the same iterations. Thus, neurons with similar textures will pulse in unison. Furthermore, the de-synchronization of collective pulse segments is dependent upon the image textures. A pulse spectrum of a single pixel is defined as the pulse activity of that pixel versus the iteration index n. In order to accentuate the texture a local smoothing operation is applied to each $\mathbf{Y}$ before the spectrum is extracted.

A library of spectra is created by manually isolating regions of specified texture. The spectra from each region are collected. Simple statistics such as the average spectra are calculated for each region. A classification of a pixel of unknown texture can be as simple as finding which average spectrum within the library the unknown most closely resembles.

For images with more complicated textures the process of identification is more complicated. In a medical image a specific region may have several textures and therefore would be represented by several members of the library. A more complicated searching method such as an associative memory can then be employed to perform the classification.

2.4. Pulse spectra and the standard texture test

The images used by Singh were collected and converted to their pulse spectra. A simple library of textures was established and comparisons of unknown spectra were performed using simple matching. These results can therefore be directly compared to the methods explored by Singh. Table 1 displays the results of several tests. The individual tests used the k-nearest neighbor method and the different values of K indicate the number of nearest neighbors used in obtaining the classification. As can be seen the pulse spectra (denoted by ICM) outperformed most methods and was either the best or close to the best for different values of K. This test justifies the pursuit of pulse spectra as a method for extracting texture information.

3. Medical image application

The image explored here contains a secretion cell surrounded by other matter on the slide. The intent is to select small regions for training and then classify all of the pixels within the image. The image is shown in Fig. 1.

The cell itself contains several different textures. There are several epithelial cells within the gland each containing a nucleus (near the perimeter) and cytoplasm. The middle region (no texture) is the lumin, the secretion section is the highly textured region just above and to the right of the lumin. As can be seen there is also a variety of items on the outside.

3.1. Spectra distribution

The plot in Fig. 2 displays the average and deviation of spectra for manually selected regions. Within each region there were between 100 and

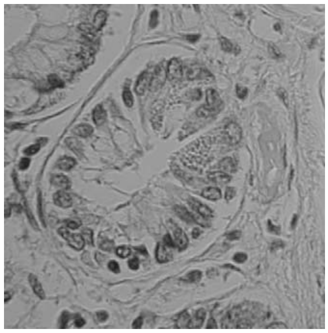

Fig. 1. A secretion cell.

Table 1

Texture analysis methods	$K = 1$ (%)	$K = 3$ (%)	$K = 5$ (%)	$K = 7$ (%)	$K = 9$ (%)
ICM	94.8	94.2	93.9	92.1	91
ACF	79.3	78.2	77.4	77.5	78.8
CM	83.5	84.1	83.8	82.9	81.3
EF	69	69	69.3	69.7	71.3
LM	63.3	67.8	69.9	70.9	69.8
RL	45.3	46.1	46.5	51.1	51.9
BSM	92.9	93.1	93	91.9	91.2
TO	94.6	93.6	94.1	93.6	94
TS	68.3	67.3	67.9	68.5	68.1

200 pixels selected for training. The plots indicate that there are differences between the classes that far exceed the similarities within the class. Thus, classification via the spectra is possible.

3.2. Statistical identification

The spectrum for each pixel was calculated and compared to the library. The library consisted of the same regions used in the previous section. The images in Fig. 3 pictorially display the classification. The first class is the epithelial nuclei and so the white pixels in Fig. 3a show display those pixels classified as epithelial nuclei. Fig. 3b displays those pixels classified as cytoplasm. Fig. 3c display those pixels classified as the secretion segment.

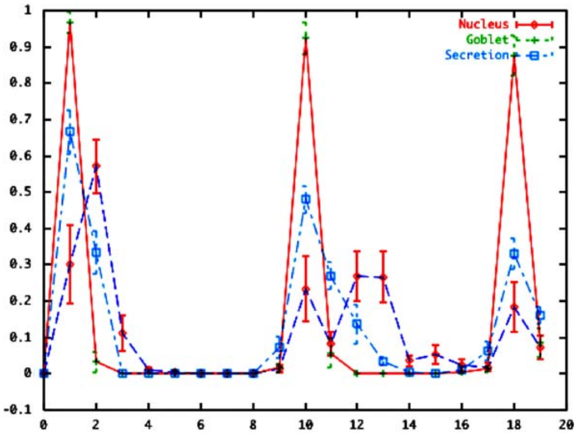

Fig. 2. The average and deviation of spectra from selected regions.

Of course, the system was not perfect, but large segments of the image are classified correctly. No attempt at anti-training was used in this method. To improve classification a more complicated recognition scheme was employed.

3.3. Classification using an associative memory

An improvement in recognition can be realized by employing an associative memory. The FAAM (fast analog associative memory) [9] was employed here to recognize pulse spectrum from several training examples. It classifies each pixel as Yes (white), No (black), or Undecided (grey) (Fig. 4).

4. Conclusions

The pulse spectra of an image are indicative of the texture-contained therein. Therefore, a library

Fig. 3. Classification of pixels as epithelial nuclei, cytoplasm, or secretion.

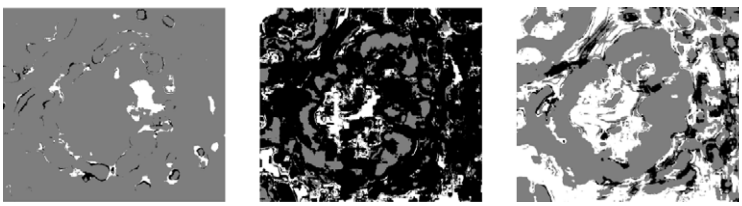

Fig. 4. Results from the use of an associative memory.

of pulse spectra can be created and used to classify unknown spectra via simple matching of associative memories. Shown here an complicated image containing several textures was classified using this method. Small regions were manually selected as training regions. From these regions the spectra were collected and formed the library. The spectra of all of the other pixels were then classified according to the similarity of those within the library. Results indicate that the pulse spectra are a viable method for texture classification.

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