Colorado Beetles Recognition with Neural Networks

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Abstract

In this article we describe our approach to recognize Colorado beetles in digital images. Colorado beetles are one of the main threats for potatoes fields. The Colorado beetles recognition is a task for artificial vision systems. The main characteristic that was analyzed is image texture because of the beetles have very specific yellow-black strips. For texture recognition task we applied Random Threshold neural classifier (RTC). In this article we describe the RTC structure and algorithms. We analyze the obtained results.

1. Introduction

There are many articles devoted to the texture recognition [1], [2], [3], [4]. Different methods can be used for texture recognition.

Recognition of objects based on their images is one of the central problems in modern Computer Vision. We consider objects as being described by their geometric, photometric and texture properties. While a vast literature exists on recognition based on geometry and photometry, less has been said about recognizing scenes based upon their textures.

For texture recognition different approaches are developed and exist. Sometimes local features are chosen or optical flow is computed. Sometimes, statistical models are generated on the base of images sequences that are analyzed [1]. It is very popular the principal component analysis (PCA). PCA is based on second order statistical dependencies. Sometimes, independent component analysis (ICA) can be used to obtain a basis whose components are maximally independent. Sometimes local spatial filters are used for multichannel texture analysis [5]. This computational approach is used for analyzing visible textures. Textures are modeled as irradiance patterns containing a limited range of spatial frequencies, where mutually distinct textures differ significantly in their dominant characterizing frequencies. By encoding images into multiple narrow spatial frequency and orientation channels, the slowly-varying channel envelopes (amplitude and phase) are used to segregate textural regions of different spatial frequency, orientation, or phase characteristics. Thus, an interpretation of image texture as a region *code,* or currier of region information, is emphasized. For texture detection the 2-D Gabor filters were used.

The standard model features (SMF) was proposed in [3]. The SMFs are based on combining the output of Gabor filters over scale and position. This combination is done using a max operation, resulting in a set of features which are position- and scale-tolerant edge pattern detectors. The SMF were introduced as an implementation of the feed-forward model in neuroscience, and are successors to previous quantifications of it [4].

Texture recognition is useful in dynamic textures recognition. Dynamic textures are sequences of images that exhibit some form of temporal stationarity, such as waves, steam, and foliage [1]. The authors pose the problem of recognizing and classifying dynamic textures in the space of dynamical systems where each dynamic texture is uniquely represented. Since the space is non-linear, a distance between models must be defined. They examined three different distances in the space of autoregressive models and assess their power.

The texture recognition method can combine with shape-based object detection and context understanding to obtain the power recognition system [2]. Sometimes it is useful to recognize texture to identify scenes after very brief exposures [6].

There are investigations when neural network algorithms are used for texture recognition [7]. A model-based texture recognition system used the nearest neighbor neural network which classifies image textures seen from different distances and under different light directions. In [7] there were used the textures form [8].

In this paper we consider the problem of recognizing textures on the Colorado beetles images that help us to recognize if beetles are presented or not on the plants. We use neural network model to build the adaptive recognition system.

2. RTC neural classifier

The RTC neural classifier is presented in Fig.1.

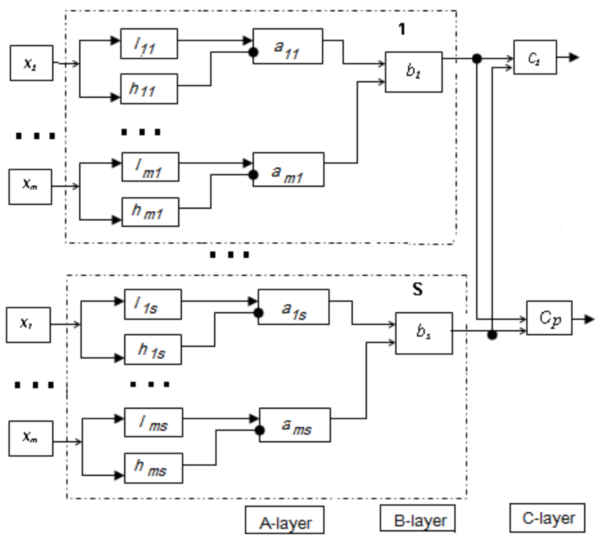

Figure 1: RTC structure.

We developed this neural classifier for different recognition tasks: in micromechanical areas, tissue recognition for chaga disease, etc. [9], [10].

The input signals are *Xi* (*i*=1 … *n*). They correspond to the characteristics of the image. Then the neurons with the thresholds l_{ij} and h_{ij} (low and high respectively) are presented. The index *i* represents the characteristic and the index *j* represents the neural group. The thresholds l_{ij} and h_{ij} are chosen in a random way fulfilling always the rule that l_{ij} is less than h_{ij}:

$$l_{ij} < h_{ij}\,. \tag{1}$$

2.1. Basic layout features

The neurons with thresholds l_{ij} and h_{ij} are connected to the neuron a_{ij}. The neuron a_{ij} is excited when X_i belongs to the diapason $[l_{ij}, h_{ij}]$. All neurons a_{ij} (*A*-layer) from one group will be connected to the neuron b_j (*B*-layer), where *j* is a group number. This neuron works as AND operation. All the neurons a_{ij} must be excited to obtain the response in the neuron b_j. All neurons b_j are connected with all neurons c_j (*C*-layer). The neurons c_j corresponds to the class under recognition, *p* is the number of classes (in our case we have only two classes: healthy tissue and infected tissue).

The weights of connections between neurons of *B*-layer and *C*-layer will be changed during the training process as is proposed in the Rosenblatt perceptron [11].

2.2. Realization of the RTC neural net

The RTC neural classifier is programmed in C++, Borland. The program menu was developed and is presented in Fig. 2.

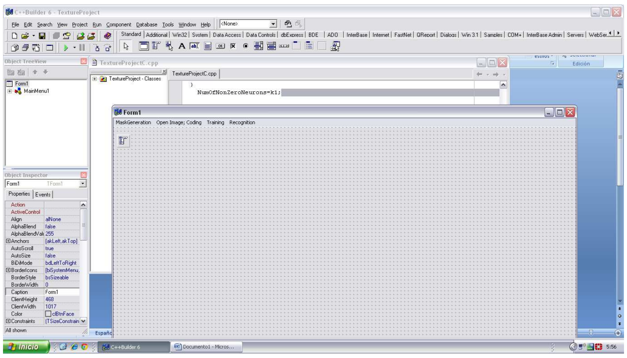

Figure 2: RTC realization

The main menu contains the following commands: Mask Generation, Open image and Coding, Training and Recognition. Before explanation of the obtained results we will briefly describe the image data set that was used in our investigations.

3. Image database

Our image data base contains 25 images of Colorado beetles, every image has the size of (250 x 180) pixels. All images are presented in *bmp* format. An example of the image set is presented in Fig.3.

Figure 3: Image example.

The RTC classifier has a supervised training so we needed to mark the images for training process. In Fig.4 we present the example of marked image. For mark we selected white color (if we use 8 bits to code the color the white color corresponds to 255 of brightness).

Figure 4: Marked image.

The background of the images is very different but beetles texture has very characteristic features.

Figure 5: Images with different background.

The process of neural classifier training initiates with image scanning with window of (*h* x *w*) pixels. Every window is the sample for the RTC neural classifier training. For every window the program calculates input parameters as brightness histogram, for example, for neural classifier. The step of window movement is half of its size.

4. Preliminary results

For the first experiment the system randomly selected 10 images from 25 images for training. The scan window had the size of (20 x 20) pixels. The step of window movement is 10 pixels. The results for 30 cycles of training are shown in Table 1.

Table 1: Error number for training process (20x20)

Training Cycle	Error Number
1	1125
5	709
10	524
15	483
20	460
25	438
30	405

After the training process the system tried to recognize other 15 images that did not participate in training. In this case we obtained the recognition result of 2192 errors or 32.47 %. It means that the recognition rate was 67.53 %.

It is preliminary results for this database. It is interesting investigate the recognition rate for different window sizes. So in future we want to investigate the recognition rate for the window of (30x30) and (40x40) pixels.

5. Conclusions

We describe our approach to recognize Colorado beetles in digital images as texture recognition task. For texture recognition task we applied Random Threshold neural classifier (RTC). The RTC structure and algorithms are described. The preliminary results demonstrate the possibility of RTC application for beetle texture recognition. These investigations have to be improved in future

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7. References

[1] Saisan, P., Doretto, G., Nian Wu, Y. and Soatto, St.., "Dynamic Texture Recognition", *In Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 2001*, 2: II-58-II-63, 2001.

[2] Bileschi, St. and Wolf, L., "A unified system for object detection, texture recognition, and context analysis based on the standard model feature set", *British Machine Vision Conference (BMVC*), 11, 2005.

[3] Serre, T., Wolf, L. and Poggio, T., "Object Recognition with Features Inspired by Visual Cortex". In *CVPR*, 2005, San Diego, June 2005.

[4] Riesenhuber, M. and Poggio, T., "How visual cortex recognizes objects: The tale of the standard model", *The Visual Neurosciences*, 2:1640–1653, 2003.

[5] Bovik, A., Clark, M. and Geisler W., "Multichannel texture analysis using localized spatial filters". *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(1): 55–73, 1990.

[6] Walker Renninger, L., and Malik, J., 'When the scene identification just texture recognition?', *Vision Research*, 44:2301-2311, 2004.

[7] Lladó Bardera X., Texture recognition under varying imaging geometries, Chapter 5. Texture recognition, PhD Thesis, University of Girona, Spain, 2004.

[8] Brodatz P., Textures: A phjotographic album for artists and designers, Dover Publications, New York, 1966.

[9] Baidyk T., Kussul E., Redes neuronales, visión computacional y micromecánica, Editoriales ITACA-UNAM, 2009, pp.158.

[10] Kussul E., Baidyk T., Wunsch D., Neural Networks and Micro Mechanics, Springer-Verlag, 2010, pp.210.

[11] F. Rosenblatt, *Principles of Neurodynamics*, Spartan Books, New York, 1962, 215 pp.