DETECTION OF OBJECT WITH USING NEURAL NETWORK AS SYMPTOM CLASSIFIER

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ABSTRACT

This article deals with detection of spores in visual data obtained from a microscope. Classification process and its steps are explained. Furthermore, the article analyses the usage of neural network as symptomatic classifier. Characteristics of classification are shown on two concrete model-systems. Models are also evaluated.

1. INTRODUCTION

In the past decade, the processing and analysis of visual data with the use of intelligent mechanisms has been increasingly becoming the focal point of interest, not only of those who engage in theoretical research but also of those who are concerned with the related practical applications. The continual enhancement of hardware performance and its innovative solutions enable much more sophisticated computations, which in turn facilitate a much greater complexity of processing and the handling of increasingly challenging real-time based tasks. This makes it possible to use neural networks to generate classification, because neural networks modeling requires a lot of time for computing operations to be performed. This paper brings together a practical application of visual data processing and the capabilities of a neural network as a symptom classifier.

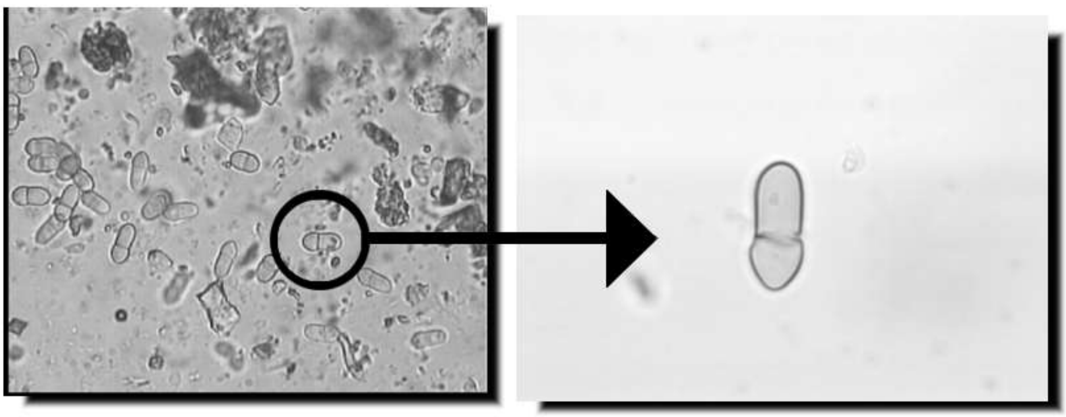

Fig. 1: Venturia inaequalis in a microscopic and filtered image

Venturia inaequalis (Fig. 1) is the ascospore of a fungus disease, which attacks leaves, blossoms, and the fruits of apple trees [4]. The aim of this application is to identify this disease by analyzing microscopic images and finding such objects which correspond to this ascospore. The whole classification process can be divided into three independent parts. First of all, the collected data has to be preprocessed and segmented. The result of the first part is a vector of symptoms which are represented by real numbers. The second part of the procedure is basically a classification with the selected method. This is followed by the interpretation of the obtained results and possibly by a specification of the next step.

2. THE CLASSIFICATION PROCEDURE

The entire classification and evaluation process represents separate functional operations that form a sequential chain of processing operations (Fig. 2). First, we employ a microscope equipped with a scanning device in the form of a chip to secure a digital image of the examined object. As you can see in Fig. 1 (on the left), the image is a little bit noisy and contains a lot of mess, therefore preprocessing is needed.

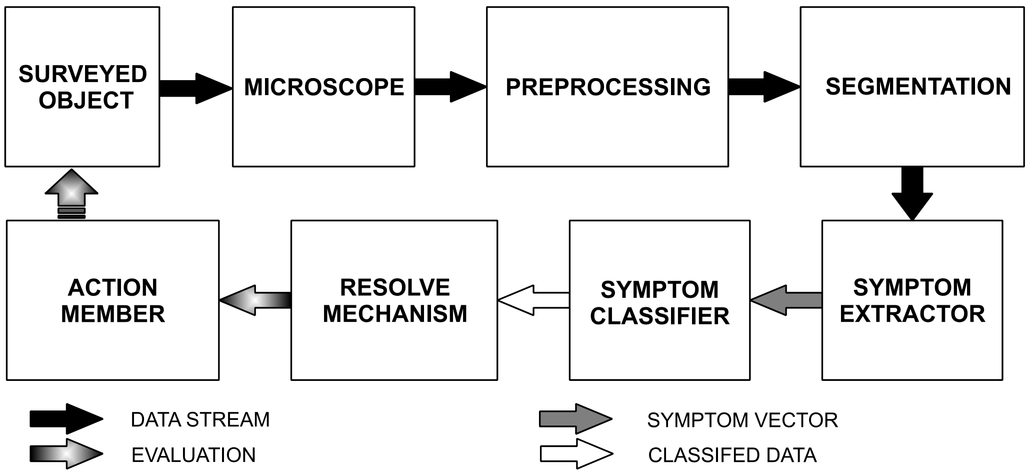

Fig. 2: Identification process functional diagram

Once the image is properly modified and preprocessed, the segmentation process comes next to identify sectors within the image, which possibly contain the spore objects. The symptom extractor is able to extract values, which describe geometrical characteristics of those objects. The extractor passes this vector to the symptom classifier; i.e. the neural network in our case. The classification results lead to the determination of a subsequent action or the termination of the entire identification process.

3. PREPROCESSING

In order to ensure efficient classification, it is necessary carry out certain operations to remove superfluous information from the image and thus enable easy identification of the spores. Such operations are commonly known as preprocessing. First, the color depth should be reduced because it does not contain any information that would be useful for the classification. Other useful operations include histogram equalization [3] or a contrast increase. Noise reduction, if needed, is possible through an adaptive median or a Gaussian filter [3]. Furthermore, the preprocessed data is submitted to the segmentation process. The simplest segmentation is thresholding. Under ideal circumstances, the result of thresholding is a completely segmented image with a focus on the important parts or sectors of the image. In the other case, we must use an advanced method, such as edge detection. It is possible to take into consideration the edge detector based on zero-crossing second-order derivative brightness function or Canny edge detector [4].

For every segment, we shall find specific features, which can possibly make it easier to distinguish between the individual objects sought. Geometrical moments such as the surface area of the object, the center of gravity [2], central and normative central moments represent an example of such features. The representative numbers allows us to differentiate between spore and other objects.

4. SYMPTOM CLASSIFICATION WITH USING NEURAL NETWORK

Geometric moments represent a symptom vector, which in turn is the input of the neural network (NN) at the same time. The NN divides the input space into sections, each with substantially different output values. The determination of the number of outputs and the number of the proposed classes enables the NN to meet the requirement of efficient classification. The term “class” refers to a group of input patterns that correspond to one target pattern. We have chosen 3 classes: the spore, black, and all others. Only the spore means successful detection. Each of the classes also represented the maximum output value of one output neuron while the other neurons’ output values are minimal. The input vector had to be normalized and significantly corrected before it was used for batch training (Fig. 3).

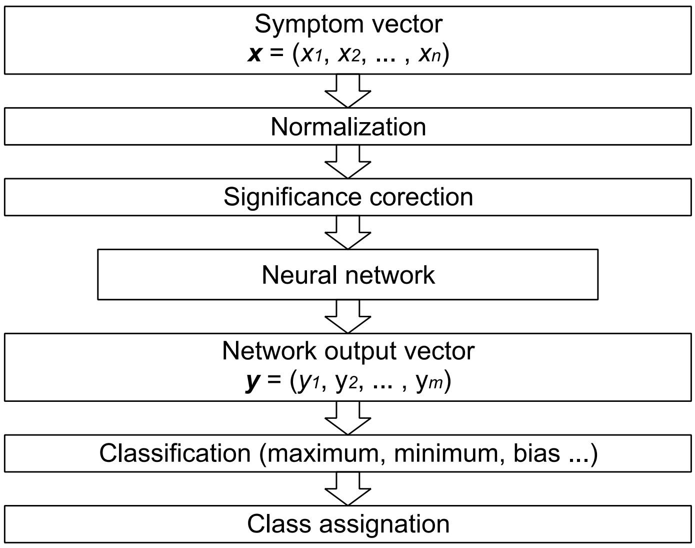

Fig. 3: Process of evaluation with using neural network

5. PERCEPTRON NETWORK

Perceptron is a very simple mathematical model of a biological neuron. We can evaluate its inner potential ξ as a scalar product of input vector $\boldsymbol{x} = (x_1, x_2, \dots, x_m)$ representing real values and the vector of weights $\mathbf{w} = (w_1, w_2, \dots, w_m)$. The output value of the transfer function with ξ as an argument represents an output value of the neuron itself. The most frequent transfer functions are logistic and tangential sigmoid. In our case, the number of relevant symptoms was established at ten. The output layer of the network contained three neurons representing three classes. The number of neurons in the hidden layer was experimentally chosen to be ten as well. Finally, the transfer function logistic sigmoid with steepness λ equal to one was selected as the activation function. The results show that the NN was able to adapt its weights to all training patterns within a relatively short time period. Nonetheless, the rate of successful classification fluctuated around 90%.

6. RBF NETWORK

Local units RBF use radial basic functions. These units are similar as perceptrons. Their input vector is $\boldsymbol{x} = (x_1, x_2, \dots, x_m)$, where the parameter (weight) c_i is assigned to each member. The RBF unit also has the real output y and parameter b, which represents an imaginary width of the radial area. The transfer function differs from the perceptron. According to the theoretical assumptions, the determination of RBF networks was much faster compared to the previous model. The rate of successful classification of untrained patterns was as high as 95%. The number of RBF units was the same as the number of trained ones. The RBF network had better results, both in the rate of adaptation and the final classification.

7. CONCLUSION

Both of NN models can be used as a symptom classifier. The only difficulty is the number of training and testing patterns which affect the classification efficiency. If we were to achieve a higher reliability, we would have to analyze a greater number of samples, which would end up being rather time-consuming. The RBF units were eventually more suitable. The rate of determination was higher, just as was the rate of successful classification. The perceptron NN was also capable of meeting the requirements yet at the cost of a greater time needed for the adaptation.

ACKNOWLEDGEMENTS

The paper has been prepared with the support of the research plan MSM0021630529 “Intelligent systems in automation”.

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