A Receptive and Inhibitory Field Based Approach for Image Processing

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Abstract This paper presents some models developed to accomplish a pattern recognition task using the concepts of receptive and inhibitory fields. Some discussions about these concepts and its applications are made. Finally, it is presented some future works.

Keywords: Pattern recognition, image processing, neural networks, receptive fields

At the beginning of the 60's, an important region of neurons in the human brain was found. Such region was called receptive field and its actuation was presented in many functionalities of the human brain, it has already been identified in many parts of the human brain, like the auditory, somatosensory and visual systems.

A receptive field is defined by Levine and Shefner [1] as an area in which the presence of an appropriate stimulus might lead to a response of a sensitive neuron.

Many works were presented using the concepts of receptive fields in image processing. A very important one is the work done by Phung and Bouzerdoum [2], where they proposed a new artificial neural network called PyraNet, proposed to accomplish visual pattern recognition tasks. The PyraNet gets as input an image 2-D and outputs its classification. Such neural network is composed in its basis by 2-D layers of neurons, where each neuron is connected to a receptive field in the previous layer. The 2-D layers are responsible by the feature extraction and data reduction of the image. On the top of the PyraNet the neurons are organized in 1-D layers and are responsible by the pattern classification.

In the work done by Phung and Bouzerdoum [2], the PyraNet was applied over a face detection and a gender recognition tasks. The PyraNet obtained good results in such tasks, achieving a high classification tax with short processing time and consuming little memory.

On the other hand, in the work made by Rizzolatti and Camarda [3] was demonstrated that another stimulus, simultaneously to the receptive field stimulus, can also have effect over the sensitive neuron. Such stimulus was called the non-classical receptive field (non-CRF), having an inhibitory effect in most of the times, then we might refer to it as inhibitory field.

The inhibitory field was successfully applied in a contour detection task by Grigorescu [4].

Then, taking in consideration that the PyraNet only consider the excitatory stimulus of the receptive fields, Fernandes et al. [5] proposed the I-PyraNet, a hybridization between the PyraNet and the concepts of inhibitory fields.

The main benefit of the use of the inhibitory concepts in the I-PyraNet is that a same neuron will be able to produce two different outputs according to its spatial position. The presence of a neuron in a inhibitory field will affect only its output, inverting its signal. It is important to note that the PyraNet might be considered a special case of the I-PyraNet where all the sizes of the inhibitory fields are equal to 0.

Also, in the work done by Fernandes et al. [5] it was proposed a supervised image segmentation model based on the concepts of receptive fields, called Segmentation and Classification with Receptive Fields. Then, both, the SCRF model and the I-PyraNet, were applied together with successful in the accomplishment of a forest detection task in satellite images. In this case, the I-PyraNet reached the lowest error rate among all the classifiers tested, including the combination between the SCRF model and the PyraNet.

The I-PyraNet was also applied over a face detection [6] task and obtained, one more time, a better classification rate than the PyraNet. However, in this application the best result was achieved with a Support Vector Machine (SVM). While the I-PyraNet achieved an area of 0.83 In a ROC curve, the SVM achieved an area of 0.9. Although the I-PyraNet have reached a worse error rate than the SVM, the I-PyraNet classification speed was 175 times faster than the SVM, taking only 0.04 milliseconds to classify a pattern. This fact might motivate the use of the I-PyraNet in embedded systems, where the processing time is a big issue in comparison with other kinds of systems. On the other hand, the results of the I-PyraNet can be improved if the classification gets repeated many times without interfering very much in the total classification time in comparison to the SVM.

However, in none of the works cited above was proposed any method to find out the best I-PyraNet configuration, including its receptive and inhibitory fields sizes. Such research field is one of the future works that are going to be studied by us.

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