Alternative Signatures based on Randomized Neural Network for Texture Classification

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***Abstract*—This paper describes two alternative methods for texture signature extraction based on a Randomized Neural Network (RNN), an artificial neural network with a single hidden layer architecture. The proposed signatures are promising ways to increase the discriminating capacity for texture recognition, while also keeping a fast feature building process. Experiments showed that the accuracy of texture classification using the new signatures is higher than other texture description methods in the literature.**

***Index Terms*—computer vision, randomized neural network, texture signature**

I. Introduction

Textures can be understood as characteristics that provide properties such as smoothness, roughness and regularity [1]. In this way, texture allows the characterization of different image regions, especially when color information is not enough to discriminate them. Textures are also usually defined as images built by repeating a rigid (or slightly changing) model over a surface [2]. Although this definition comprises a wide range of textures, especially artificial ones (which means textures that are not produced by nature), it does not generalize well to natural textures such as fog, smoke, wood etc., as they present stochastic patterns, resulting in an appearance similar to a cloud. [3].

Texture feature extraction is one of the most critical steps for texture classification [4]. Even with the lack of a precise definition that encompasses both artificial and natural variations, many methods to describe and discriminate textures can be found in the literature. Many possibilities have been explored to generate these features, such as Local Binary Patterns (LBP) [5], Wavelets [6], Tourist Walks [7], Fractal Dimension [8], [9], Second-Order Statistics [10], Fourier [11] and Gabor filters [12], shortest paths in graphs [13], texture signatures based on Extreme Learning Machines (ELM) [14] and others.

A novel texture feature extraction method, described in [14], proposes the use of an ELM to obtain a texture signature. An ELM is a feedforward neural network (with a single hidden layer), which can be trained very fast (using a closed-form solution, for instance) [15]. It is also called a Randomized Neural Network (RNN) due to the fact that the weights between the input and hidden layers are random.

In this work, we describe alternative methods to generate texture signatures based on RNNs. The proposed methods increase the discriminating capacity of ELM based signatures for both natural and artificial textures in three benchmark datasets.

This paper is organized as follows: Section II contains details about the RNN architecture and how it can be used to produce texture signatures. In Section III, we present alternative approaches to extract features and labels, required as inputs to train the RNN in the signature generation process. Our experiments and results are shown in Section IV, in which we verify the classification accuracies obtained on three datasets and compare them with the performance of other methods in the literature. Finally, we conclude the paper in Section V, while also suggesting possible improvements and expectations for future work.

II. RNN based signature

The method described in [14] uses an RNN to create texture signatures. Unlike the common use, the authors did not employ the neural network for classification or clustering. The neural network was used instead to define a novel descriptor in a texture feature extraction framework. To accomplish this, the authors of [14] considered each pixel of the image as a “class” label and its neighboring pixels as a “feature vector” for that label, both used in the training phase of the RNN. The idea is to create associations between pixels in the image and their neighboring elements, as these were “samples” from the same class.

In the first approach, the feature vectors were built from different pixel window sizes and the central pixel from each window was used as a label. Next, the weights of the output neuron layer of the RNN were used to compose an image signature. The second approach was to combine signatures created by the first approach, using distinct number of neurons in the hidden layer of the RNN, i.e., a concatenation of distinct signatures for the same image, resulting in a new signature with higher dimensionality. In this paper, we focus on the