TexRet: A Texture Retrieval System Using Soft-Computing

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ABSTRACT

The TEXRET-System, a texture retrieval system based on soft-computing technologies is being developed. The importance of this kind of system is increasing due to the massive access to digital image databases, which also demand the existence of systems that can understand human high-level requests. The TEXRET system has the following features: (i) direct access from the Internet, (ii) high interactivity, (iii) texture retrieval using human-like or fuzzy description of the textures, (iv) content-based texture retrieval using user-feedback, and (v) synthesis or generation of the requested textures when these are not found in the database, which allows a growing of the database. One of the main system features is synthesis of the requested textures when these are not found in the database, which allows a growing of the database. Missing textures are synthesized interactively using Markov Random Fields and interactive genetic algorithms. This paper is centered on the texture synthesis of the textures.

Keywords: Color Features Extraction (CFE), Fuzzy Interface, Hue-Saturation-Luminosity (HSL), TexRet, Texture Generation, Textural Features Extraction (TFE)

1. INTRODUCTION

Textures are homogeneous visual patterns that we perceive in natural and synthetic scenes. They are made of local micropatterns, repeated somehow, producing the sensation of uniformity. Texture perception plays an important role in human vision. It is used to detect and distinguish objects, to infer surface orientation and perspective, and to determine shape in 3D-scenes (Khan & Venkatapuram, 1993). An interesting psychological observation is the fact that human beings are not able to describe textures clearly and objectively, but only subjectively by using a fuzzy characterization of them. On the other hand, with the new advances in communication and multimedia computing technologies, accessing mass amounts of digital information (image databases) is becoming a reality. In this context, textures, due to their esthetical properties, play today an important role in the consumer-oriented design, marketing, selling and exchange of products and/or product information. For this reason, systems that allow the search and retrieval of textures in image databases are of increasing interest. This work is an effort to construct of the TEXRET-System, a texture retrieval system.

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based on soft-computing technologies. The TEXRET-System has the following features: (i) direct access from the Internet, (ii) texture queries using humanlike or fuzzy description of the textures, and (iii) synthesis or generation of the requested textures when these are not found in the database, which allows a growing of the database. This article is centered on this last feature of the system.

Texture Synthesis has been an increasingly active research field in computer graphics. Many different approaches have been used to generate textures, but till now no fully successful generation model has been found.

Among the most interesting models we can distinguish structural models, reaction-diffusion like models and probabilistic models. In this last group, Markov random fields stands out for their large versatility and performance. For this reason, in this work Markov random fields are chosen to implement the generation of textures.

The paper is structured as follows. The TEXRETSystem is outlined in Section 2. In Sections 3 and 4, the system modules dealing with the synthesis of textures are described. Finally, in Sections 5 and 6 some preliminary results and conclusions are given.

2. THE TEXRET-SYSTEM

The TEXRET-System, whose block diagram is shown in Figure 1, is made of the FI (Fuzzy Interface), the Q2TPT (Qualitative to Quantitative Textural Properties Transformation), the TR (Texture Retrieval), the TG (Texture Generation), and the EPA (Evolutionary Parameter Adjustment) modules. The on-line phase of the texture retrieval process works as follows: A human user makes a query of a texture using a subjective, linguistic or human-like texture description. The FI module enters this description into the system using a fuzzy representation of it. The Q2TPT module interprets the query and translates it into a quantitative texture description that is implemented using Tamura Descriptors. This qualitative description is used by the TR module to search the texture in the database. In the case that the texture is not found in the database, the user can choose the automatic generation of it. The TG module generates the texture using Markov Random Fields (MRF). The parameters of the MRF are calculated from the Tamura descriptors and then the textures are generated. As a result of this generation process a set of textures is presented to the user. If the user considers that one of the generated textures satisfy his query, the process finishes here. If not, the user enters into an iterative process. The iterative generation of the textures is implemented using interactive evolutionary computation (EPA module). It should be pointed out that the subjective or humanlike texture description that the system accepts, was determined by a psychological study in texture perception, performed by co-workers of the authors, and that will be presented elsewhere.

In the next two sections the modules dealing with the generation of textures are presented.

3. THE FI AND Q2TPT MODULES

The function of the Q2TPT module is to interpret subjective textural properties and to translate them into objective features. The FI module allows obtaining an internal representation of these subjective textural properties using fuzzy logic. The Q2TPT is implemented by using a Neuro-Fuzzy architecture, whose training phase is shown in Figure 2.

3.1. Neuro-Fuzzy Network

The implemented architecture corresponds to a modified variant of the Khan (1996) network. This network is based on a variation of the Multilayer Back-Propagation Network (MBPN). In the original description it consists of seven layers, which also do fuzzification and rule approximation.

In the modified variant, the product-sums of the MBPN formulas are replaced by multiplications and the learning rule is modified appropriately.
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