Signal Processing: *Image Communication* 32 (2015) 106–120

Contents lists available at ScienceDirect

Signal Processing: *Image Communication*

journal homepage: www.elsevier.com/locate/image

On the usage of the 2D-AR-model in texture completion scenarios with causal boundary conditions: A tutorial

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ARTICLE INFO

Article history:
Received 21 April 2014
Received in revised form
27 January 2015
Accepted 27 January 2015
Available online 4 February 2015

Keywords:
Texture completion
Texture synthesis
Inpainting
Autoregressive model
Image reconstruction

ABSTRACT

In recent years, significant progress has been witnessed in several image and video completion scenarios. Given a specific application, these methods can produce, reproduce or extend a given texture sample. While there are many promising algorithms available, there is still a lack of theoretical understanding on how some of them are designed and under which conditions they perform. For that, we analyze and describe the technique behind one of the most popular parametric completion algorithms: the autoregressive (AR) model. Furthermore, we address important implementation details, complexity issues and restrictions of the model. Beyond that, we explain how the performance of the AR model can be significantly improved. In summary, this paper aims to achieve three major goals: (1) to provide a comprehensive tutorial for experienced and non- experienced readers, (2) to propose novel methods that improve the performance of the 2D-AR completion, and (3) to motivate and guide researchers that are interested in the usage of the AR model for texture completion tasks.

1. Introduction

Texture understanding and representation have been a research focus for many years in human perception, computer graphics and computer vision. Recently a substantial portion of research activities in this area emphasize on two main topics: texture synthesis [1] and inpainting [2].

1.1. Definitions

Texture synthesis refers to the generation process of a novel texture pattern from a limited sample. An arbitrarily large output texture is generated that is perceptually similar to the input sample. Hence, this method is a way to create textures for different applications (e.g. texture mapping on surfaces). On the other side, the term inpainting stands for approaches that regenerate missing or damaged image areas using information from the rest of it. Most of the work on inpainting focused on applications such as image/video restoration (e.g. scratch removal), object removal (e.g. removal of selected image elements) and error concealment (e.g. filling-in image blocks lost during data transmission). The main difference between texture synthesis and inpainting is that inpainting techniques are better suited for complex images containing both texture and dominant structures.

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http://dx.doi.org/10.1016/j.image.2015.01.010
0923-5965/

Table 1
Overview on texture completion approaches [3], visual quality and complexity limitations.

Category	Models	Completion of texture classes	Limitations	Complexity
Parametric	AR, MA, ARMA	Rigid and non-rigid	Structures	Medium
PDE-based	PDE	Rigid, thin, elongated regions	Structures, smooth results	Medium
Non-parametric	MRF	Rigid and non-rigid	Prone to error	High

In this paper, we will use the generic term “texture completion” to describe the seamless reconstruction of missing texture samples of a given picture or part of texture sample.

1.2. Classification of texture completion approaches

Texture completion algorithms can be divided into three main categories: (1) parametric, (2) partial-differential-equations-based (PDE), and (3) non-parametric. An overview of texture completion categories is given in Table 1 (cf. also Ndjiki-Nya et al. [3]).

Parametric completion approaches approximate the probability density function (PDF) of the texture source using a compact model with a fixed parameter set [4–13]. That is, these methods extract statistics from the given input texture that are modeled based on a compact parameter set. Such approaches also provide information relating to the underlying texture properties, which can be relevant in identification and recognition applications. Some of the most commonly used parametric methods are based on the autoregressive (AR), the moving average (MA) and the autoregressive moving average (ARMA) models.

The second texture completion methods category, named PDE-based algorithms, employs a diffusion process to fill the missing image parts in a visually plausible manner. These techniques commonly use non-linear or high order partial-differential-equations to propagate information from the boundary towards the interior of the unknown area. Several approaches based on PDE have been developed in the last decade [14–17].

The last class of methods, non-parametric completion approaches, does not explicitly model the PDF, but instead measure it from an available texture sample. In general, in this completion category, a best match is determined from a source region and copied to a target region [18–24].

1.3. Contributions

In this paper, we will describe the technique behind the autoregressive-based texture completion strategy. Our interest is to present a low complexity usage of the AR model. Hence, the focus lies in using the prediction equations to extrapolate/synthesize texture very efficient given a visually pleasing quality rather than attempting to find an optimal but high complex solution for the texture filling problem. Furthermore, we are specifically addressing applications where the known data are on the top and left of the missing region (causal model). This is for example true in video coding scenarios at the decoder side. A theoretical understanding of the AR model will be provided through the detailed explanation of issues like how the AR approach can be implemented, how correct results can be reproduced and how complexity and other restrictions apply. Furthermore, new contributions to further improve the AR technique will also be presented. They relate to the adaptive definition of a training area, pre- and post-processing steps, a consistency criterion and a regularization procedure. In this work, we will describe a robust, multi-application, texture completion method that can be integrated in texture completion applications and as well in inpainting scenarios as a sub-module (due to the limitation of the AR model to reconstruct structures, cf. Table 1). In addition, we will emphasize the faster computational performance of the AR framework in comparison to the state-of-the-art, while remaining visually pleasing completion results.

The remainder of this paper is organized as follows. In Section 2, an overview on the state-of-the-art in AR-related research topics is introduced. Next, the texture completion problem is explained in Section 3. The overall AR-based completion framework is presented in Section 4. A detailed description of 2D-AR texture completion together with a proposal on adaptive training area definition can be found in Section 5. The experimental results followed by various application scenarios are provided in Sections 6 and 7 respectively. Finally, conclusions and future steps are given in Section 8.

2. State-of-the-art of AR modelling

Three decades ago, the autoregressive model, traditionally used on temporal signals, started being utilized for image processing (e.g. in the area of image and video texture completion). The AR models have been successfully used for texture representation. In the work of Chellappa et al. [7], a 2D non-causal autoregressive (NCAR) model was used to synthesize different texture samples sized 64×64 with several neighbor sets and parameters. The authors showed that the AR model can reproduce natural textures. A similar contribution by Deguchi [8] focused on texture characterization and completion of gray-level textures, using the same NCAR model as [7]. The basic properties of the model, the algorithm and the model identification problem are discussed. Furthermore, the work of Deguchi was at the time an innovative texture segmentation approach, where blocs with similar AR parameters were merged iteratively. The work of Tugnait [9] investigated the suitability of 2D NCAR models with asymmetric support for completion of 128×128 real life textures. Here the AR model is fitted to textures with abstracted mean value, i.e. with zero mean. The removed mean is added back in the synthetic image. In [10], the