A Compound Moving Average Bidirectional Texture Function Model

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Abstract. This paper describes a simple novel compound random field model capable of realistic modelling the most advanced recent representation of visual properties of surface materials - the bidirectional texture function. The presented compound random field model combines a non-parametric control random field with local multispectral models for single regions and thus allows to avoid demanding iterative methods for both parameters estimation and the compound random field synthesis. The local texture regions (not necessarily continuous) are represented by an analytical bidirectional texture function model which consists of single scale factors modeled by the three-dimensional moving average random field model which can be analytically estimated as well as synthesized.

Keywords: bidirectional texture function, texture synthesis, compound random field model

1 Introduction

Convincing and physically correct virtual models require not only precise 3D shapes in accord with the captured scene, but also object surfaces covered with genuine nature-like surface material textures with physically correct reflectance to ensure realism in virtual scenes. The primary purpose of any synthetic texture approach is to reproduce and enlarge a given measured texture image so that ideally both natural and synthetic texture will be visually indiscernible. However, the appearance of real materials dramatically changes with illumination and viewing variations. Thus, the only reliable representation of material visual properties requires capturing of its reflectance in as wide range of light and camera position combinations as possible. This is a principle of the recent most advanced texture representation, the seven dimensional Bidirectional Texture Function (BTF) [13]. Compound random field models consist of several sub-models each having different characteristics along with an underlying structure model which controls transitions between these sub models [19]. Compound Markov random field models (CMRF) were successfully applied to image restoration [3, 5, 19, 21], segmentation [24], or modeling [9, 16, 11, 17]. However, these models always require demanding numerical solutions with all their well known drawbacks. The exceptional CMRF [9] model allows analytical synthesis at the cost of a slightly compromised compression rate.

We propose a compound moving average bidirectional texture function model BTF-CMA model which combines a non-parametric and parametric analytically solvable moving average (MA) random fields (RF) and thus we can avoid using some of time consuming iterative Markov Chain Monte Carlo (MCMC) method for both BTF-CMA model parameters estimation as well as BTF-CMA synthesis. Similarly to the previously mentioned CMRF methods, our presented model avoids range map estimation which is required for most RF based BTF models ([15, 8, 12, 14, 18]). Beside texture synthesis, texture editing is another useful application which has large potential for significant speed-up and cost reduction in industrial virtual prototyping [16]. Although some recent attempts have been made to automate this process, automatic integration of user preferences still remains an open problem in the context of texture editing [16]. Proposed method present partial solution of this problem by combining estimated local models from several different source textures or simply editing estimated local models of the original texture.

2 Compound Random Field Texture Model

Let us denote a multiindex $r = (r_1, r_2)$, $r \in I$, where I is a discrete 2-dimensional rectangular lattice and r_1 is the row and r_2 the column index, respectively. $X_r \in \{1, 2, \ldots, K\}$ is a random variable with natural number value (a positive integer), Y_r is multispectral pixel at location r and $Y_{r,j} \in \mathscr{R}$ is its j-th spectral plane component. Both random fields (X, Y) are indexed on the same lattice I. Let us assume that each multispectral or BTF observed texture $\tilde{Y}$ (composed of d spectral planes) can be modelled by a compound random field model, where the principal random field X controls switching to a regional local model $Y = \bigcup_{i=1}^{K} {}^{i}Y$. Single K regional submodels ${}^{i}Y$ are defined on their corresponding lattice subsets ${}^{i}I$, ${}^{i}I \cap {}^{j}I = \emptyset \quad \forall i \neq j$ and they are of the same RF type. They differ only in their contextual support sets ${}^{i}I_r$ and corresponding parameters sets ${}^{i}\theta$. The CRF model has posterior probability

$$P(X, Y \,|\, \tilde{Y}) = P(Y \,|\, X, \tilde{Y}) P(X \,|\, \tilde{Y})$$

and the corresponding optimal MAP solution is:

$$(\hat{X}, \hat{Y}) = \arg \max_{X \in \Omega_X, Y \in \Omega_Y} P(Y \,|\, X, \tilde{Y}) \, P(X \,|\, \tilde{Y}) \ ,$$

where Ω_X, Ω_Y are corresponding configuration spaces for random fields (X, Y).

2.1 Region Switching Model

The principal RF $(P(X \,|\, \tilde{Y}))$ can be, for example, represented by a flexible $K-$state Potts random field [17, 22, 23]. Instead of the Potts RF or some alternative general parametric MRF, which require a Markov chain Monte Carlo (MCMC) solution, we suggest to use simple non-parametric approximation based on our roller method [6, 7].

The control random field $\breve{X}$ is estimated using simple K-means clustering of $\tilde{Y}$ in the RGB colour space into predefined number of K classes, where cluster indices are $\breve{X}_r \quad \forall r \in I$ estimates. The number of classes K can be estimated using the Kullback-Leibler divergence and considering sufficient amount of data necessary to reliably estimate all local Markovian models.

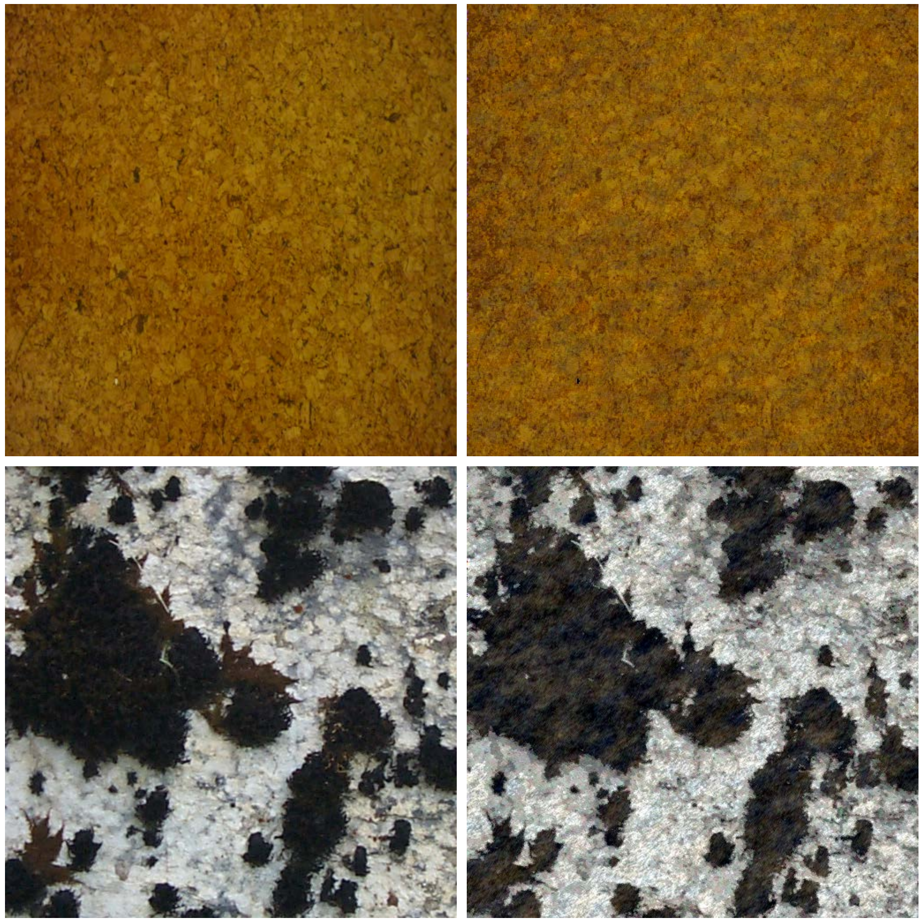

Fig. 1. Examples of the cork texture (upper row) and lichen (bottom row) and their CMRF^{3MA} synthesis (right column).

The roller method is subsequently used for optimal $\check{X}$ compression and extremely fast enlargement to any required field size. The roller method [6, 7] is based on the overlapping tiling and subsequent minimum error boundary cut. One or several optimal double toroidal data patches are seamlessly repeated during the synthesis step. This fully automatic method starts with the minimal tile size detection which is limited by the size of control field, the number of toroidal tiles we are looking for and the sample spatial frequency content. The roller method advantageously maintains the original overall ratio single regions areas, e.g., the average standard deviation for this percentage ratio after four times enlarged texture map was observed to be less than 3 %.

2.2 Spatial Factorization

The spatial factorisation is technique that enables separate modelling of individual band limited frequency components of input image data and thus to use random field models with small compact contextual support. This factorization step is the prerequisite for satisfactory visual quality result of the presented model. Each grid resolution represents a single spatial frequency band of the texture which corresponds to one layer of Gaussian pyramid [13]. The input data are decomposed into a multi-resolution grid and all resolution data factors represents the Gaussian-Laplacian pyramid of level *k* which is a sequence of *k* images in which each one is a low-pass down-sampled version of its predecessor.

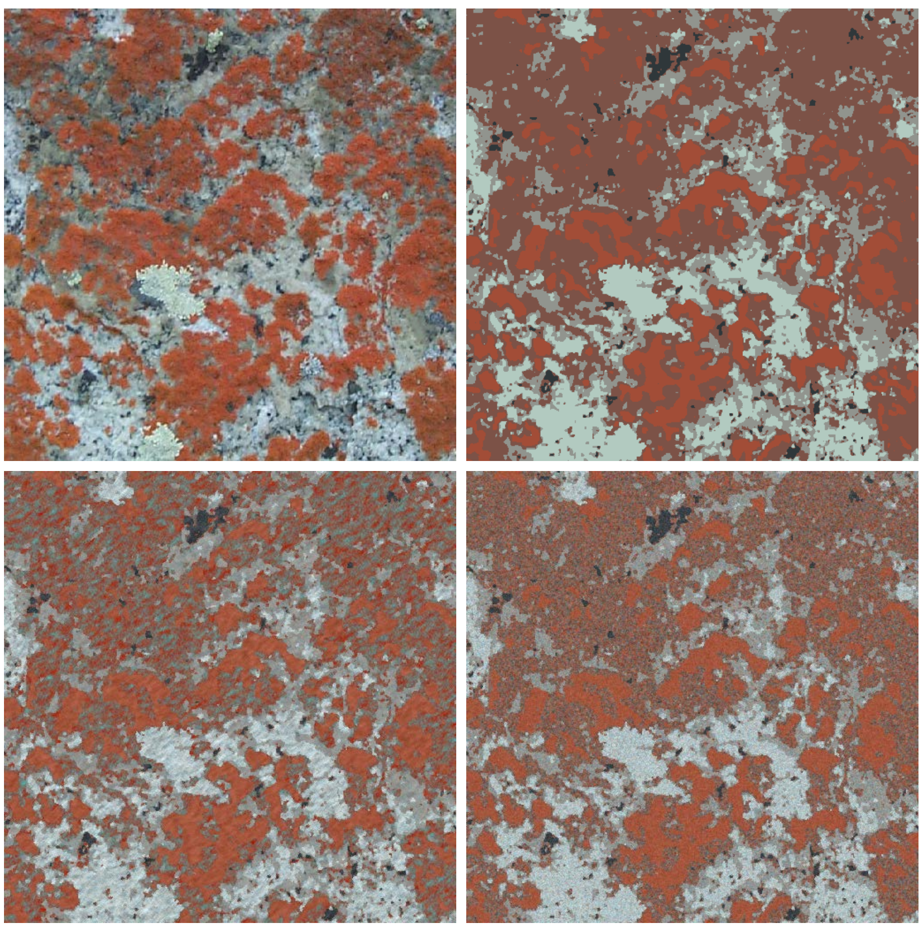

Fig. 2. An example of the lichen texture (upper left), its control field (upper right), the CMRF^{3MA} synthesis (bottom left), and a comparative synthesis using a 3D Gaussian generator.

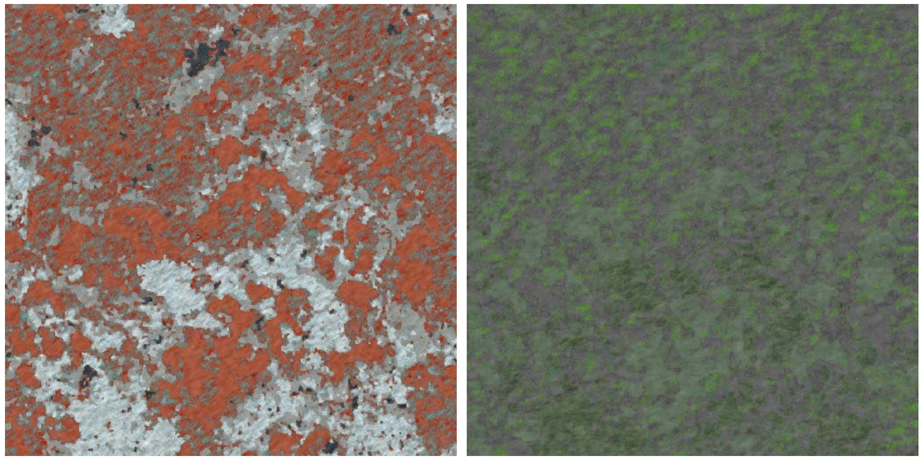

Fig. 3. Synthetic (CMRF^{3MA}) lichen texture and its edited version (right).

2.3 Local Moving Average Models

Single multispectral texture factors are modelled using the extended version ($3DMA$) of the moving average model [20]. A stochastic multispectral texture can be considered to be a sample from 3D random field defined on an infinite 2D lattice. A spatial input factor Y is represented by the $3DMA$ random field model. Y_r is the intensity value of a multispectral pixel $r \in I$ in the image space. The model assumes that each factor is the output of an underlying system which completely characterizes it in response to a 3D uncorrelated random input. This system can be represented by the impulse response of a linear 3D filter. The intensity values of the most significant pixels together with their neighbours are collected and averaged, and the resultant 3D kernel is used as an estimate of the impulse response of the underlying system. A synthetic mono-spectral factor can be generated by convolving an uncorrelated 3D random field with this estimate. Suppose a stochastic multi-spectral texture denoted by Y is the response of an underlying linear system which completely characterizes the texture in response to a 3D uncorrelated random input E_r, then Y_r is determined by the following difference equation:

$$Y_r = \sum_{s \in I_r} B_s E_{r-s} \tag{1}$$

where B_s are constant matrix coefficients and $I_r \subset I$. Hence Y_r can be represented $Y_r = h(r) * E_r$ where the convolution filter $h(r)$ contains all parameters B_s. In this equation, the underlying system behaves as a 3D filter, where we restrict the system impulse response to have significant values only within a finite region. The geometry of I_r determines the causality or non-causality of the model. The selection of an appropriate model support region is important to obtain good results: small ones cannot capture all details of the texture and contrariwise, inclusion of the unnecessary neighbours adds to the computational burden and can potentially degrade the performance of the model as an additional source of noise.

The parameter estimation can be based on the modified Random Decrement technique (RDT) [2, 1]. RDT assumes that the input is an uncorrelated random field. If every pixel component is higher than its corresponding threshold vector component and simultaneously at least one of its four neighbours is less than this threshold the pixel is saved in the data accumulator. The procedure begins by selecting thresholds usually chosen as some percentage of the standard deviation of the intensities of each spectral plane separately. Additionally to that, a 3D MA model requires also to estimate the noise spectral correlation, i.e.,

$$\begin{aligned} E\{E_r E_s\} &= 0 \qquad \forall r_1 \neq s_1 \vee r_2 \neq s_2 \ , \\ E\{E_{r_1,r_2,r_3} E_{r_1,r_2,\bar{r}_3}\} &\neq 0 \qquad \forall r_3 \neq \bar{r}_3 \ . \end{aligned}$$

The synthetic factor can be generated simply by convolving an uncorrelated 3D RF E with the estimate of B according to (1). All generated factors form new Gaussian pyramid. Fine resolution synthetic smooth texture is obtained by the collapse of the pyramid i.e. an inverse procedure of that one creating the pyramid.

The resulting synthesized texture is obtained by mapping individual synthesized local sub textures to the enlarged control field realization. Additional pixel swapping and filtering along the individual region border increases the visual quality of the result as the overall intensity of the borders may be distracting.

Fig. 4. An example of the measured BTF terracotta texture and its synthetic (even images) results, where ϕ, θ are azimuthal and elevation illumination / viewing angles, respectively.

3 Results

Automatic texture quality evaluation is important but still unsolved difficult problem and qualitative evaluation is for now possible only using impractical and expensive visual psycho-physics. We have recently tested [10] on our texture fidelity benchmark (**http://tfa.utia.cas.cz**) several published state-of-the-art image quality measures and also one dedicated texture measure (STSIM) in several variants. We have tested the presented novel $BTF-CMRF^{3MA}$ model on natural colour textures from our extensive texture database (http://mosaic.utia.cas.cz), which currently contains over 1000 colour or BTF textures. Tested textures were either natural, such as two textures on Figs.1,2,5,3 or man-made Fig.4 (terracotta). Tested BTF material samples from our database [4] are measured in 81 illumination and viewing angles, respectively. A material sample measurements (Fig.4) from this database have resolution of 1800×1800 and size 1.2 GB. Fig.4 shows a cutout example from such measurements of a terracotta material and its synthesis for two different illumination and view angle combinations. All presented examples use five level control field $(K = 5)$, the hierarchical contextual neighbourhood of the third order, and the three-layer Gaussian-Laplacian pyramid.

Fig.2 advantageously compares the presented $BTF-CMRF^{3MA}$ model (Fig.2 - bottom left) with local fields modeled by simple multidimensional Gaussian generator (Fig.2-bottom right). The Gaussian generator produces too noisy and spatially uncorrelated synthetic texture (e.g. top right corner). The model can be easily used to create an artificial texture by editing single local sub-textures (Fig.3), which can be either learned from separate sources or their parameters can be manually modified. Fig.5 illustrates a fourfold enlarged stone texture.

Resulting synthetic more complex textures (such as lichen on Figs.1-bottom,2) have generally better visual quality (there is no any usable analytical quality measure) than textures synthesised using our previously published [12, 8, 15] simpler MRF models. Synthetic multispectral textures are mostly surprisingly good for such a fully automatic fast algorithm. Obviously there is no universally optimal texture modelling algorithm and also the presented method will produce visible repetitions for textures with distinctive low frequencies available in small patch measurements (relative to these frequencies). BTF-CMRF is capable to reach huge BTF compression ration $\sim 1:1 \times 10^5$ relative to the original BTF measurements but $\approx 5\times$ lower than [12].

4 Conclusions

The presented CMRF (BTF-CMRF) method shows good visual performance on selected real-world materials. The appearance of such materials should consist of several types of relatively small regions with fine-granular inner structure such as sand, grit, cork, lichen, or plaster. The model offers large data compression ratio (only tens of parameters per BTF and few small control field tiles) easy simulation and exceptionally fast seamless synthesis of any required texture size. The method can be easily generalised for colour or BTF texture editing by estimating some local models on one or several target textures. Both analysis as well as synthesis of the model are exceptionally fast. The model does not compromise spectral correlation thus it can reliably model motley textures. A drawback of the method is that it does not allow a BTF data space restoration or modelling of unseen (unmeasured) BTF space data unlike some fully parametric probabilistic BTF models, and it requires a pyramidal spatial factorization.

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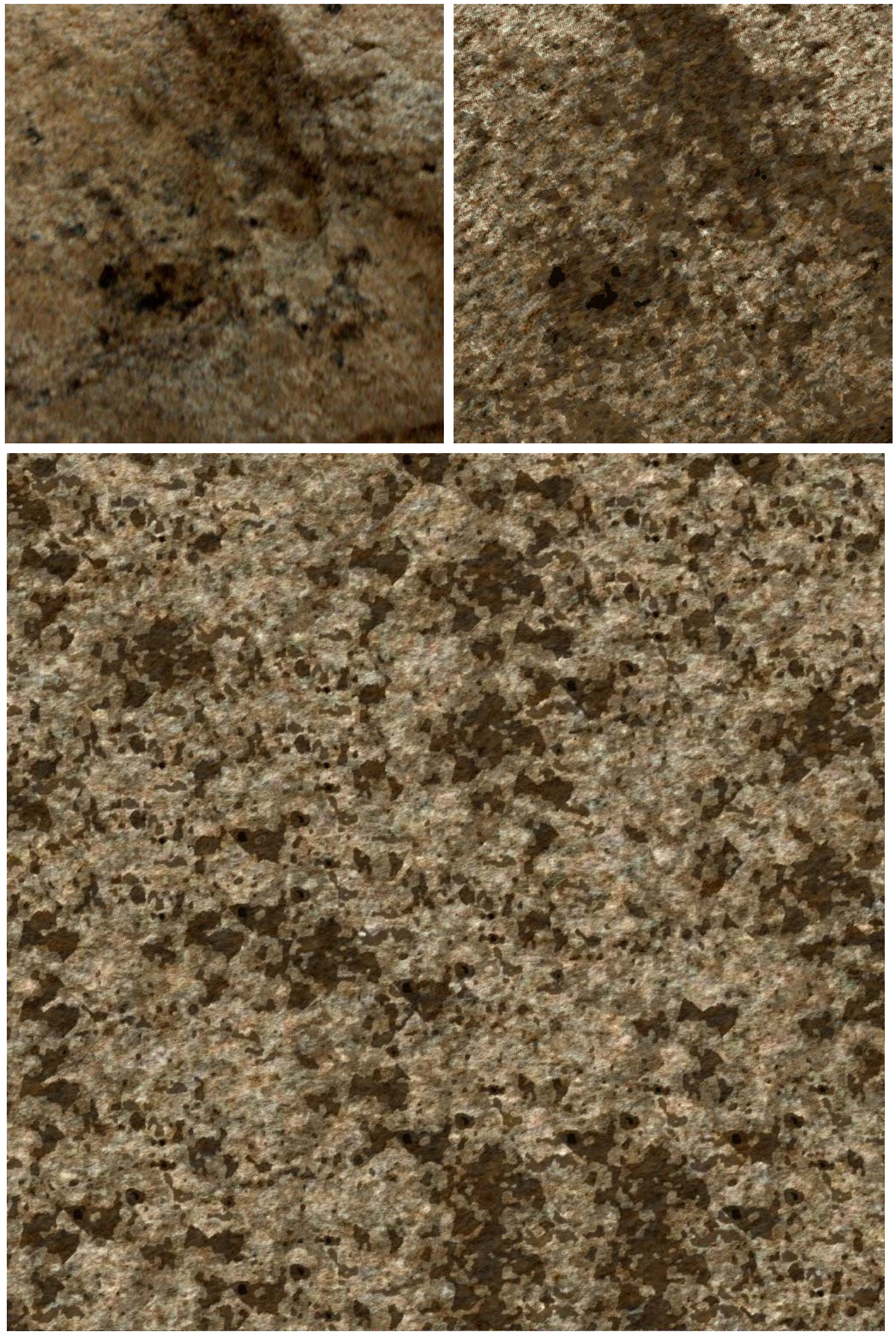

Fig. 5. An example of the stone texture (upper left), its original size (upper right) and fourfold enlarged CMRF^{3MA} synthesis.