A Compound MRF Texture Model

Michal Haindl Vojtěch Havlíček

Institute of Information Theory and Automation
of the ASCR, 182 08 Prague, Czech Republic
Email:{haindl,havlicek}@utia.cz

***Abstract*—This paper describes a novel compound Markov random field model capable of realistic modelling of multispectral bidirectional texture function, which is currently the most advanced representation of visual properties of surface materials. The proposed compound Markov random field model combines a non-parametric control random field with analytically solvable widesense Markov representation for single regions and thus allows to avoid demanding Markov Chain Monte Carlo methods for both parameters estimation and the compound random field synthesis.**

***Keywords*-compound Markov random field; bidirectional texture function;**

I. Introduction

Physically correct virtual models require not only complex 3D shapes accorded with the captured scene, but also object surfaces covered with realistic nature-like colour textures to enhance realism in virtual scenes. Because the appearance of real materials dramatically changes with illumination and viewing variations, any 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 Bidirectional Texture Function (BTF) [1]. 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. BTF function is represented by thousands of measurements (images) per material sample, thus its modelling prerequisite is simultaneously also significant compression capability [2].

Compound random field models (CMRF) consist of several submodels each having different characteristics along with an underlying structure model which controls transitions between these submodels [3]. CMRF models were successfully applied to image restoration [3]–[5] or segmentation [6], however these models always require demanding numerical solutions with all their well known drawbacks.

We propose a CMRF model which combines a non-parametric and parametric analytically solvable MRFs and thus we can avoid using some of time consuming iterative Markov Chain Monte Carlo (MCMC) method for both CMRF model parameters estimation as well as CMRF synthesis.

II. Compound Markov 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 $Y_{r,j} \in \mathcal{R}$ 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 (BTF) observed texture $\tilde{Y}$ (composed of d spectral planes) can be modelled by a compound Markov random field model, where the principal Markov random field (MRF) X controls switching to a regional local MRF 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 MRF type. They differ only in their contextual support sets ${}^{i}I_r$ and corresponding parameters sets ${}^{i}\theta$. The CMRF model has posterior probability

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

and the corresponding optimal MAP solution is:

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

where Ω_X, Ω_Y are corresponding configuration spaces for random fields (X, Y). To avoid iterative MCMC MAP solution, we propose the following two step approximation:

$$\begin{aligned} (\breve{X}) &= \arg \max_{X \in \Omega_X} P(X \mid \tilde{Y}) \ , \\ (\breve{Y}) &= \arg \max_{Y \in \Omega_Y} P(Y \mid \breve{X}, \tilde{Y}) \ . \end{aligned}$$

This approximation significantly simplifies CMRF estimation because it allows to take advantage of simple analytical estimation of regional MRF models.

A. Region Switching Markov Model

The principal MRF $(P(X \mid \tilde{Y}))$ can be, for example, represented by a flexible $K-$state Potts random field [7], [8]. Instead of this or some alternative parametric MRF, which require a MCMC solution, we suggest to use simple

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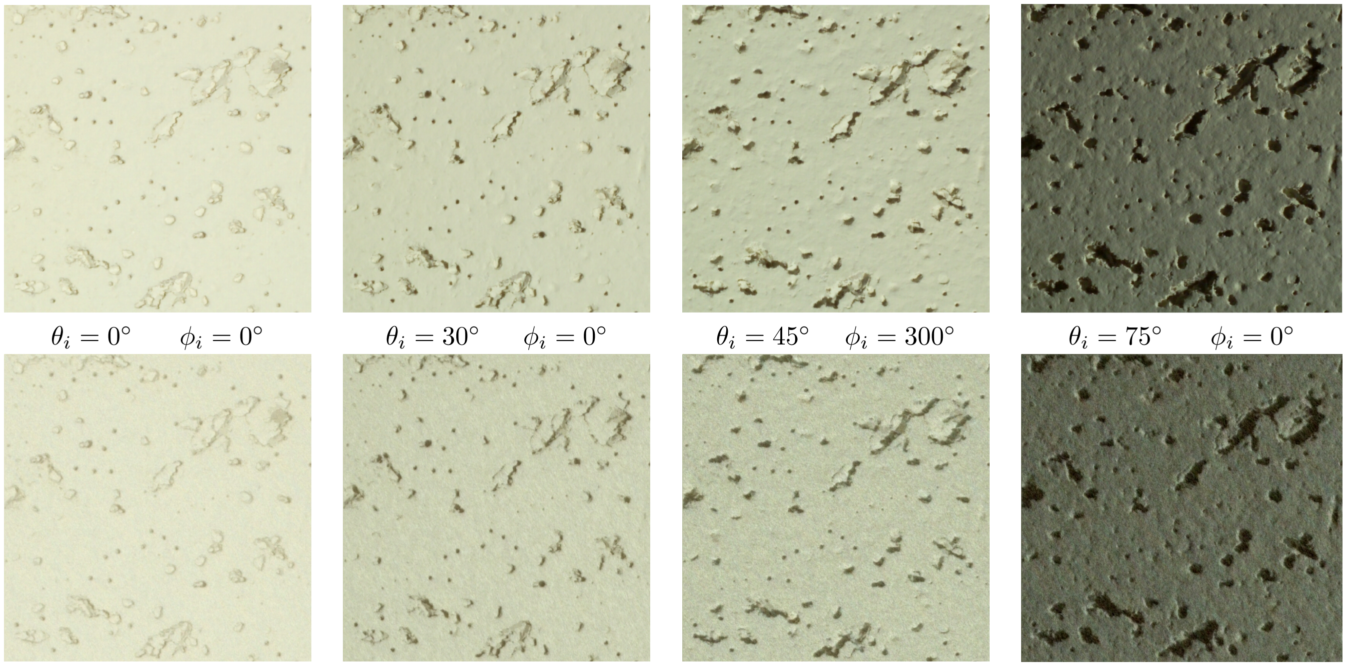

Figure 1. BTF ceiling panel texture measurements (upper row) and their synthetic counterparts for various elevation (θ_i) and azimuthal (ϕ_i) illumination angles.

non-parametric approximation based on our roller method [9], [10].

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.

The roller method is subsequently used for optimal $\breve{X}$ compression and extremely fast enlargement to any required field size. The roller method [9], [10] 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.

B. Local Markov Models

Local i-th texture region (not necessarily continuous) is represented by the adaptive 3D causal autoregressive random (3DCAR) field model [11], [12] because this model can be analytically estimated as well as synthesised. Alternatively we could use spectrally decorrelated 2D CAR or Gaussian Markov random field (GMRF) models [13], [14]. All these models allows analytical synthesis (see [13] for the corresponding conditions) and they can be unified in the following matrix equation form (i-th model index is further omitted to simplify notation):

$$Y_r = \gamma Z_r + \epsilon_r \ , \tag{1}$$

where

$$Z_r = [Y_{r-s}^T : \forall s \in I_r]^T \tag{2}$$

is the $\eta d \times 1$ data vector with multiindices r, s, t, $\gamma = [A_1, \ldots, A_\eta]$ is the $d \times d\,\eta$ unknown parameter matrix with submatrices A_s. In the case of d 2D CAR / GMRF models stacked into the model equation (1) the parameter matrices A_s are diagonal otherwise they are full matrices for general 3DCAR models [12]. The model functional contextual neighbour index shift set is denoted I_r and $\eta = cardinality(I_r)$. GMRF and CAR models mutually differ in the correlation structure of the driving noise ϵ_r (1) and in the topology of the contextual neighbourhood I_r (see [13] for details). As a consequence, all CAR model statistics can be efficiently estimated analytically [11] while the GMRF statistics estimates require either numerical evaluation or some approximation ([13]).

Given the known 3DCAR process history $Y^{(t-1)} = \{Y_{t-1}, Y_{t-2}, \ldots, Y_1, Z_t, Z_{t-1}, \ldots, Z_1\}$ the parameter estimation $\hat{\gamma}$ can be accomplished using fast, numerically robust and recursive statistics [11]:

$$
\begin{aligned}
\hat{\gamma}_{t-1}^T &= V_{zz(t-1)}^{-1} V_{zy(t-1)} \ , \\
V_{t-1} &= \tilde{V}_{t-1} + V_0 \ , \\
\tilde{V}_{t-1} &= \begin{pmatrix} \sum_{u=1}^{t-1} Y_u Y_u^T & \sum_{u=1}^{t-1} Y_u Z_u^T \\ \sum_{u=1}^{t-1} Z_u Y_u^T & \sum_{u=1}^{t-1} Z_u Z_u^T \end{pmatrix} \\
&= \begin{pmatrix} \tilde{V}_{yy(t-1)} & \tilde{V}_{zy(t-1)}^T \\ \tilde{V}_{zy(t-1)} & \tilde{V}_{zz(t-1)} \end{pmatrix} \ , \\
\lambda_{t-1} &= V_{yy(t-1)} - V_{zy(t-1)}^T V_{zz(t-1)}^{-1} V_{zy(t-1)} \ ,
\end{aligned}
$$

where V_0 is a positive definite matrix (see [11]). Although, an optimal causal (for (2D/3D)CAR models) functional contextual neighbourhood I_r can be solved analytically by a straightforward generalisation of the Bayesian estimate in [11], we use faster approximation which does not need to evaluate statistics for all possible I_r configurations. This approximation is based on large spatial correlations. We start from the causal part of a hierarchical non-causal neighbourhood and neighbours locations corresponding to spatial correlations larger than a specified threshold (> 0.6) are selected. The i-th model synthesis is simple direct application of (1) for both 2DCAR or 3DCAR models. A GMRF synthesis requires one FFT transformation at best [13]. 3DCAR models provide better spectral modelling quality than the alternative spectrally decorrelated 2D models for motley textures at the cost of small increase of number of parameters to be stored.

III. RESULTS

We have tested the presented novel CMRF model on natural colour textures from our extensive texture database (http://mosaic.utia.cas.cz, Fig.2-bark), which currently contains over 1000 colour textures, CGTextures (http://www.cgtextures.com, Fig.2-grass), and on BTF measurements from the University of Bonn [15] (Fig.1-upper row). Tested textures were either natural, such as two textures on Fig.2, or man-made Fig.1 (ceiling panel). Each BTF material sample included in the University of Bon database [1] is measured in 81 illumination and viewing angles, respectively. A material sample measurements (Fig.1) from this database have resolution of 800×800 and size 1.2 GB. Fig.1-upper row shows four such measurements of ceiling panel material for different illumination angles and fixed perpendicular view (elevation and azimuthal view angles are zero $\theta_v = \phi_v = 0°$). Examples on Figs.1,2 use six level control field $(K = 6)$ and causal neighbourhood derived from the 20th order hierarchical contextual neighbourhood.

Resulting synthetic more complex textures (such as grass with flowers on Fig.2) have generally better visual quality (there is no any usable analytical quality measure) than textures synthesised using our previously published [2], [12]–[14] simpler MRF models (Fig.2-bottom row). Synthetic multispectral textures are mostly surprisingly good

Figure 2. Synthetic enlarged colour maple bark and grass textures (odd rows) estimated from their natural measurements (second row). The last row contains comparative synthesis using single 3DCAR model [12].

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). The BTF-CMRF variant of the model uses similar fundamental flowchart with our Markovian BTF model [2] (i.e. BTF space intrinsic dimensionality estimation, BTF space segmentation, BTF subspace MRF model estimation, subspace MRF model synthesis and interpolation of unmeasured BTF space parts) but allows to avoid its range map estimation, range map modelling and displacement filter steps, respectively. 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 [2].

IV. Conclusions

The presented CMRF (BTF-CMRF) method shows good performance on the most of tested real-world materials. It 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. 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.

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