Near-Regular Texture Synthesis

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Abstract. This paper describes a method for seamless enlargement or editing of difficult colour textures containing simultaneously both regular periodic and stochastic components. Such textures cannot be successfully modelled using neither simple tiling nor using purely stochastic models. However these textures are often required for realistic appearance visualisation of many man-made environments and for some natural scenes as well. The principle of our near-regular texture synthesis and editing method is to automatically recognise and separate periodic and random components of the corresponding texture. Each of these components is subsequently modelled using its optimal method. The regular texture part is modelled using our roller method, while the random part is synthesised from its estimated exceptionally efficient Markov random field based representation. Both independently enlarged texture components from the original measured texture are combined in the resulting synthetic near-regular texture. In the editing application both enlarged texture components can be from two different textures. The presented texture synthesis method allows large texture compression and it is simultaneously extremely fast due to complete separation of the analytical step of the algorithm from the texture synthesis part. The method is universal and easily viable in a graphical hardware for purpose of real-time rendering of any type of near-regular static textures.

1 Introduction

Physically correct virtual models require object surfaces covered with realistic nature-like colour textures to enhance realism in virtual scenes. Satisfactory models require not only complex 3D shapes accorded with the captured scene, but also realistic surface materials visualisation. This will significantly increase the realism of the synthetic generated scene. We define near-regular textures as textures that contain global, possibly imperfect, regular structures as well as irregular stochastic structures simultaneously. This is more ambitious definition than to view [1] a near-regular textures as a statistical distortion of a regular texture. Near regular textures are difficult to synthesise, however, these textures are ubiquitous in man-made environments such as buildings, wallpapers, floors, tiles, fabric but even some fully natural textures such as honeycomb, sand dunes or waves belong to this texture category. These textures can be modelled in simplified smooth or more precise rough (also referred as the bidirectional texture function - BTF [2]) representation. The rough textures do not obey the Lambert law and their reflectance

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is illumination and view angle dependent. Both types of such near-regular texture representations occur in virtual scenes models. The 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. The related texture modelling approaches may be divided primarily into sampling and model-based-analysis and synthesis, but no ideal texture modelling method exists. Each of the existing approaches or texture models has its advantages and limitations simultaneously and it is applicable for a restricted subset of possible textures only. Model-based texture synthesis [3, 4, 5] requires non-standard multidimensional (3D for static colour textures or even 7D for static BTFs) models. Such models are non trivial and they suffer with several unsolved problems which have to be circumvented (e.g. optimal parameters estimation, efficient synthesis, stability). Model-based methods are also often too difficult to be implemented in contemporary graphical card processors. Sampling approaches [6, 7] rely on sophisticated sampling from real texture measurements. Sampling methods require to store original texture sample, thus they cannot come near the large compression ratio of the model-based methods.

Neither model-based or simple sampling algorithms alone can satisfactorily solve the difficult problem of near-regular texture modelling. Existing methods [1, 8, 9, 10, 11, 12, 13, 14, 15] usually try to overcome this problem by user assisted modelling of the regular structures and then rely on regular tiling. However Lin et al. [11] experimentally observed that several of these general purpose sampling algorithms fail to preserve the structural regularity on more than 40% of their tested regular textures. Tiling-based synthesis algorithms [9, 12] identify the underlying lattice of the input texture either automatically or by user selection of two translation vectors and use slightly modified image quilting method [7] for synthesis. Texture replacement method [10] can replace selected regular texture while preserving its lighting using a Markov random field model and slow iterative Markov chain Monte Carlo solution. Another interactive tiling method [1] requires user assistance to identify a coarse texture lattice structure. The method [15] separates the global regular structure from the irregular structure using fractional Fourier analysis similarly to our method. However the synthesis is performed by generating a fractional Fourier texture mask from the extracted global regular structure which is used to guide pixelwise and time consuming sample-based synthesis. All mentioned near-regular texture modelling methods suffer with drawbacks inherent to the tiling approach. They do not allow texture editing, near-regular BTF textures, unmeasured textures applications and have very limited compression ratio. Tiling approaches cannot eliminate visible repetitions even if they use several tiles which are randomly combined such as [2].

The presented fully automatic method proposes to combine advantages of both basic texture modelling approaches by factoring a texture into factors that benefit best from each of two basic different modelling concepts. The principle of the method is to separate texture regular and stochastic parts, to enlarge both parts separately and to combine these results (texture enlargement) or results from several different textures (texture editing) into the required resulting texture. The proposed solution is not only fully automatic, very fast due to strict separation of the analytical and very efficient synthesis steps, but it also allows significant data compression. Due to its stochastic modelling it completely eliminates visible repetitions (contrary to all mentioned tiling approaches) because there are never used two identical tiles in a scene. Finally the method can be easily used to near-regular texture editing by either combining texture parts from different measurement or by changing stochastic model parameters.

2 Periodic and Non-periodic Texture Separation

The prerequisite for the method is that near-regular input textures have distinct amplitude spectrum parts for both periodic and random components. Otherwise the method, schematised in Fig.1 and outlined in the following sections, would not be able to separate both texture parts. Periodic and non-periodic texture part are detected in the simplified monospectral texture space. The input colour texture is spectrally transformed using the principal component analysis (PCA). Let the digitised colour texture $\bar{Y}$ is indexed on a finite rectangular three-dimensional $M \times N \times d$ underlying lattice I, where $M \times N$ is the image size and d is the number of spectral bands. The original centered data space $\tilde{Y}$ is transformed into a new data space with PCA coordinate axes Y. This new basis vectors are the eigenvectors of the $d \times d$ second-order statistical moments matrix $\Phi = E\{\tilde{Y}_{r,\bullet}\tilde{Y}_{r,\bullet}^T\}$ where d is the number of spectral bands and the multiindex r has two components $r = [r_1, r_2]$ (the row and column index). The projection of random vector $\tilde{Y}_{r,\bullet}$ (the notation $\bullet$ has the meaning of all possible values of the corresponding index) onto the PCA coordinate system uses the transformation matrix $T = [u_1^T, \ldots, u_d^T]^T$ which has single rows u_j that are eigenvectors of the matrix Φ: $\bar{Y}_{r,\bullet} = T\tilde{Y}_{r,\bullet}$. The periodic texture part (Fig. 2) is detected on the most informative transformed monospectral factor, which corresponds to the largest Φ eigenvalue.

2.1 Textural Periodicity Direction

Near-regular measured textures can have arbitrary periodicity directions (Fig.1-top right), not necessarily simple axis aligned periodicity. The periodicity in two directions is detected from the spatial correlation field restricted with the help of Fourier amplitude spectrum (Fig.1-right). The method finds two largest Fourier amplitude spectrum coefficients provided that they do not represent parallel directions. Tolerance sectors (Fig.1- right), which accommodate for possible localisation imprecision of local amplitude spectra maxima, are specified and for all their indices the corresponding spatial correlations are evaluated. Local spatial correlation field maxima, larger than a threshold, are detected and the minimal periodicity maximum is selected. Detected periodicity $(\delta^{h^*}, \delta^{v^*})$ and its direction allows to rotate measured texture to have axis aligned periodicity which simplifies further analytical steps. Detected periodicity and directions specify a rhomboid which contains the largest periodic part from the input texture. The

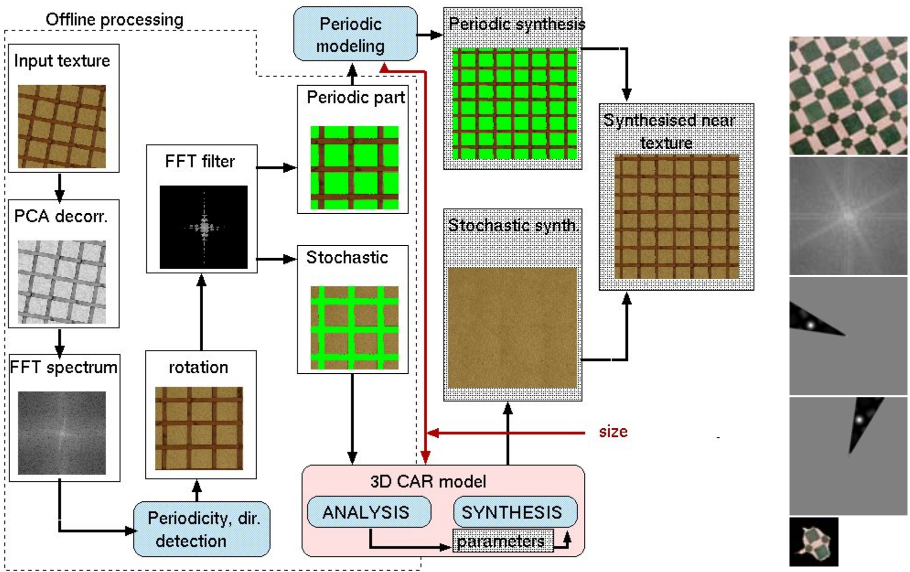

Fig. 1. Presented method overall schema, right from above - original measured texture, its amplitude spectrum, detected spatial correlation sectors, and the resulting toroidal tile (bottom)

rhomboid is further inscribed into the $\hat{M} \times \hat{N}$ rectangle which is cut out from the input texture. Although the double toroidal tile can be searched directly from the rhomboid the rectangular shape restriction simplifies this detection step.

2.2 Amplitude Spectrum Filter

The texture cutout is re-sampled to the lattice size of the power of two required by the fast Fourier transformation (FFT) based filter $\dot{M} \geq \hat{M}$, $\dot{M} = 2^i$, $\dot{N} \geq \hat{N}$, $\dot{N} = 2^j$, where i, j are minimum possible values. Let $A_{\max}$ is the Fourier amplitude spectrum maximum coefficient detected from the Fourier amplitude spectrum (Fig.1- right). The filter removes such coefficients, for which any of the following conditions holds: $A_r < k\,A_{\max}$, $A_r \notin \mathcal{M} \wedge r \notin I_m$, where $\mathcal{M}$ is a set of amplitude spectrum local maxima, $k \in \langle 0; 1 \rangle$ is a parameter and I_m is a contextual neighbourhood (we use the hierarchical neighbourhood of the first or the second order) of such a local maximum. Applying the inverse FFT and re-sampling the filtered tile back to the original $\hat{M} \times \hat{N}$ size we get the filtered cutout $\dot{Y}$ (Fig. 2- even images). FFT can be alternatively replaced by the rotated FFT from the section 2.1 but this option would introduce sampling errors into the filter. The filtered tile $\dot{Y}$ is binarized $(\check{Y})$ using a threshold $t_{bin} \in \langle 0; 1 \rangle$. One label determines the periodic texture part and the other the stochastic part. To find the labels correspondence to both periodical and non-periodical parts of the original texture Fig.2 - odd img., the binary image $\check{Y}$ is

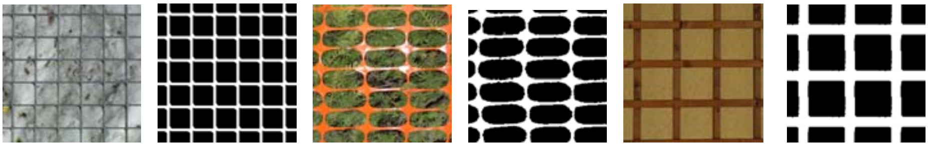

Fig. 2. Near-regular measured textures (odd) and their detected periodic parts

tested for periodicity δ^{h^*}, δ^{v^*}. The majority label complying to the periodicity test denotes the original texture periodic sites (Fig.2- even img.). When both periodic and stochastic parts are separated they can be independently modelled and enlarged to any required size as it is detailed in two following sections. The required near-regular texture is simple composite of both synthetic parts.

3 Periodic Texture Modelling

The regular part of the texture is enlarged using a simplification of our previously published [16] method. The roller method [2,16] is based on the overlapping tiling and subsequent minimum error boundary cut. One or several optimal double toroidal texture patches are seamlessly repeated during the synthesis step. This automatic method starts with the minimal tile size detection which is limited by the size of texture measurements, the number of toroidal tiles we are looking for and the sample spatial frequency content. The optimal horizontal and vertical edges cuts are searched using the dynamic programming method. These optimal vertical and horizontal cuts constitute a toroidal tile as is demonstrated on the Fig.1 - bottom right. Some textures with dominant irregular structures cannot be modelled by simple single tile repetition without clearly visible and visually disturbing regular artefact. Such textures exploit multiple toroidal tiles which share identical border but differ in their interior. Finally, the periodic texture enhancement is simple repetition of one or several randomly alternating double toroidal tiles in both directions until the required texture size is generated.

4 Random Texture Modelling

The random part of a texture is synthesised from the original input texture from where the detected periodic component was removed as described in section 2. If the stochastic texture patches are too small (few hundred pixels area) to reliably learn the random field model statistics, we replace occluded stochastic texture areas by using a modification of the image quilting algorithm [7]. The random part of the texture is synthesised using an adaptive probabilistic spatial model, a multiresolution 3D causal autoregressive model (CAR) [17], which is an exceptionally efficient type from the Markov random field (MRF) family of models. This model allows extreme compression (few tens of parameters to be stored only) and can be speedily evaluated directly in a procedural form to seamlessly fill an infinite texture space. The resulting near-regular texture is simple combination of both regular and stochastic synthesised factors.

5 Results

We have tested the presented method on near-regular textures from our extensive texture database, which currently contains over 1000 colour textures. Tested near-regular textures were either man-made such as two textures on Fig.4 or combinations of man-made structures with natural background (Fig.3) such as grass, wood, plants, snow, sand, etc. Both part of modelling were separately

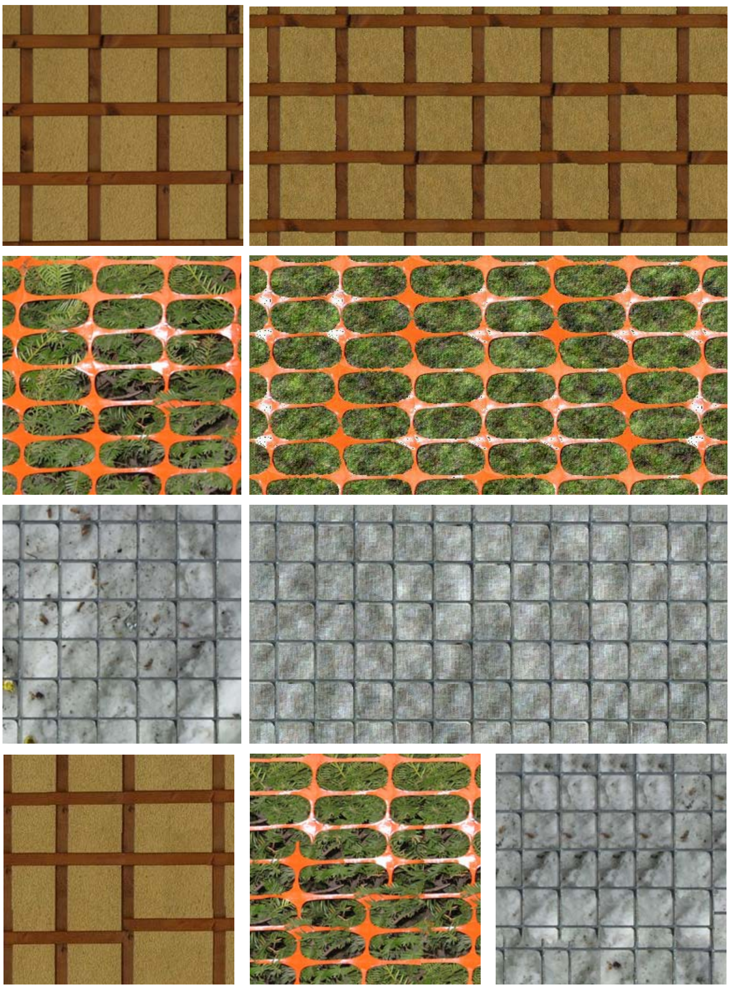

Fig. 3. Near-regular textures and their synthesis (right), image quilting [7] results (bottom row)

Fig. 4. Near-regular texture editing. Measured textures (three leftmost) and edited textures (three rightmost).

successfully tested on hundreds of colour or BTF textures with results reported elsewhere ([16]). Such unusually extensive testing was possible due to simplicity and efficiency of both crucial parts of the algorithm and it allowed us to get insight into the algorithm properties. The method is even capable to synthesise some near-regular textures combined from two distinctive types of regular structures provided they can be adequately separated in the Fourier domain. Resulting textures are mostly surprisingly good for such a fully automatic fast algorithm. Textures in Fig.3 were synthesised in real time ($\approx 1\,[s]$) while using the image quilting method [7] the synthesis took $90\,[s]$ on the same PC. Obviously there is no optimal texture modelling method and also the presented method fails on some near-regular textures with similar (and thus faultlessly unseparable) amplitude spectrum parts of both periodic and random components.

6 Conclusions

Our test results on available near-regular texture data are encouraging. The overall method is fully automatic and extremely fast due to strict separation of the analytical and very efficient synthesis steps. The regular part modelling is easily implementable even in the graphical processing unit. The method offers larger compression ratio than alternative tiling methods for transmission or storing texture information due to the periodic part modelling approach. The MRF based random part model can reach a huge compression ratio itself, hence its storage requirements are negligible, and simultaneously eliminates visible repetitions typical and unavoidable for tiling approaches. The overall method has negligible computation complexity for the periodic model and exceptionally efficient computational model for the random part as well. The method's extension for alternative texture types, such as BTF textures or some other spatial data such as the reflectance models parametric spaces is straightforward. Finally, the method can be easily used to near-regular texture editing by either combining texture parts from different measurement or by changing stochastic model parameters.

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References

1. Liu, Y., Lin, W.C., Hays, J.: Near-regular texture analysis and manipulation. ACM Transactions on Graphics 23(3), 368–376 (2004)
2. Haindl, M., Hatka, M.: BTF Roller. In: Texture 2005. Proceedings of the 4th Int. Workshop on Texture Analysis, pp. 89–94. IEEE, Los Alamitos (2005)
3. Besag, J.: Spatial interaction and the statistical analysis of lattice systems. Journal of the Royal Statistical Society, Series B B-36(2), 192–236 (1974)
4. Haindl, M.: Texture synthesis. CWI Quarterly 4(4), 305–331 (1991)
5. Haindl, M., Havlícek, V.: A multiresolution causal colour texture model. In: Amin, A., Pudil, P., Ferri, F., Iñesta, J.M. (eds.) SPR 2000 and SSPR 2000. LNCS, vol. 1876, pp. 114–122. Springer, Heidelberg (2000)
6. Efros, A.A., Leung, T.K.: Texture synthesis by non-parametric sampling. In: Proc. Int. Conf. on Computer Vision (2), Corfu, Greece, pp. 1033–1038 (1999)
7. Efros, A.A., Freeman, W.T.: Image quilting for texture synthesis and transfer. In: Fiume, E. (ed.) ACM SIGGRAPH 2001, pp. 341–346. ACM Press, New York (2001)
8. Guo, C.E., Zhu, S.C., Wu, Y.N.: Modeling visual patterns by integrating descriptive and generative methods. Int. J. of Computer Vision 53(1), 5–29 (2003)
9. Liu, Y., Collins, R.T., Tsin, Y.: A computational model for periodic pattern perception based on frieze and wallpaper groups. IEEE Trans. Pattern Anal. Mach. Intell. 26(3), 354–371 (2004)
10. Tsin, Y., Liu, Y., Ramesh, V.: Texture replacement in real images. In: CVPR, pp. 539–544. IEEE Computer Society, Los Alamitos (2001)
11. Lin, W.C.C., Hays, J.H., Wu, C., Kwatra, V., Liu, Y.: A comparison study of four texture synthesis algorithms on regular and near-regular textures. Technical report, CMU Robotics Institute, Carnegie Mellon University (2004)
12. Liu, Y., Tsin, Y., Lin, W.C.: The promise and perils of near-regular texture. International Journal of Computer Vision 62(1-2), 145–159 (2005)
13. Karthikeyani, V., Duraiswamy, K., Kamalakkannan, P.: Texture analysis and synthesis for near-regular textures. In: ICISIP, pp. 134–139. IEEE Computer Society, Los Alamitos (2005)
14. Lin, W.C., Hays, J., Wu, C., Liu, Y., Kwatra, V.: Quantitative evaluation of near regular texture synthesis algorithms. In: CVPR, pp. 427–434. IEEE Comp. Soc., Los Alamitos (2006)
15. Nicoll, A., Meseth, J., Müller, G., Klein, R.: Fractional fourier texture masks: Guiding near-regular texture synthesis. Computer Graphics Forum 24(3), 569–579 (2005)
16. Haindl, M., Hatka, M.: A roller - fast sampling-based texture synthesis algorithm. In: Proceedings of the 13th International Conference in Central Europe on Computer Graphics, Visualization and Computer Vision, Plzen, February 2005, pp. 93–96. UNION Agency - Science Press (2005)
17. Haindl, M., Havlíček, V.: A multiscale colour texture model. In: Proceedings of the 16th International Conference on Pattern Recognition, pp. 255–258. IEEE Computer Society, Los Alamitos (2002)
18. Hays, J., Leordeanu, M., Efros, A.A., Liu, Y.: Discovering texture regularity as a higher-order correspondence problem. In: Leonardis, A., Bischof, H., Pinz, A. (eds.) ECCV 2006. LNCS, vol. 3952, pp. 522–535. Springer, Heidelberg (2006)
19. Lin, W.C., Liu, Y.: A lattice-based mrf model for dynamic near-regular texture tracking. IEEE Trans. on Pattern Analysis and Machine Intelligence 29(5), 777–792 (2007)