FILLING-IN GAPS IN TEXTURED IMAGES USING BIT-PLANE STATISTICS

E. Ardizzone, H. Dindo and G. Mazzola
Dipartimento di Ingegneria Informatica (DINFO) dell'Università degli Studi di Palermo

Keywords: Digital Restoration, Inpainting, Texture Synthesis, Bit-Plane Slicing.

Abstract: In this paper we propose a novel approach for the texture analysis-synthesis problem, with the purpose to restore missing zones in greyscale images. Bit-plane decomposition is used, and a dictionary is build with bit-blocks statistics for each plane. Gaps are reconstructed with a conditional stochastic process, to propagate texture global features into the damaged area, using information stored in the dictionary. Our restoration method is simple, easy and fast, with very good results for a large set of textured images. Results are compared with a state-of-the-art restoration algorithm.

1 INTRODUCTION AND PREVIOUS WORKS

Filling-in gaps in a digital image, often known as digital inpainting, is one of the most active field in image processing research. Restoration of damaged or unknown areas in an image is an important topic for applications as: image coding(e.g. recovering lost blocks); removal of unwanted objects (e.g. scratches, spots, superimposed text, logos); video special effects; 3D texture mapping. There are two different main approaches for a filling-in problem in literature: PDE (Partial Differential Equation) methods, and constrained texture synthesis.

PDE methods (Bertalmio et al. 2000; Chan and Shen 2002) give impressive results with natural images but introduce blurring, that is more evident for large regions to inpaint. They are computationally expensive and not suitable for textured images.

Texture synthesis methods reconstruct an image from a sample texture. For inpainting purposes, region to fill-in is the area into which synthesize the texture, and information to replicate comes from the surrounding pixels. Most of these methods use Markov Random Fields (Cross and Jain, 1983) as theoretical model to represent a texture. That is, for each pixel, color (or brightness) probability distribution is determined by a limited set of its surrounding pixels. Heeger and Bergen (1995) proposed a method which synthesizes textures by matching histograms of a set of multiscale and orientation filters. Portilla and Simoncelli (2001) proposed a statistical model based on a wavelet decomposition. Efros and Leung (1999) synthesized one pixel at time, matching pixels from target image with the input texture. The "image quilting" technique (Efros and Freeman 2001) used constrained block-patching for the synthesis process. Wei and Levoy (2000) proposed a multi-resolution texture synthesis algorithm, based on gaussian pyramid decomposition. Kokaram (2002) proposed a 2D autoregressive statistical model for filling-in and texture generation. Criminisi et al. (2004) proposed an hybrid "exemplar-based" method for removing large objects from digital images. All these methods are extremely time consuming and many of them failed to reconstruct highly-structured texture.

We propose a novel approach to analyze and synthesize textures, in order to make the restoration process easier and faster with respect to other methods. Different is the application: instead of synthesizing the whole image starting from a sample, we want to fill-in a missing area of the image using surrounding information.

Ardizzone E., Dindo H. and Mazzola G. (2008).
FILLING-IN GAPS IN TEXTURED IMAGES USING BIT-PLANE STATISTICS.
In *Proceedings of the Third International Conference on Computer Vision Theory and Applications*, pages 122-127
DOI: 10.5220/0001081401220127

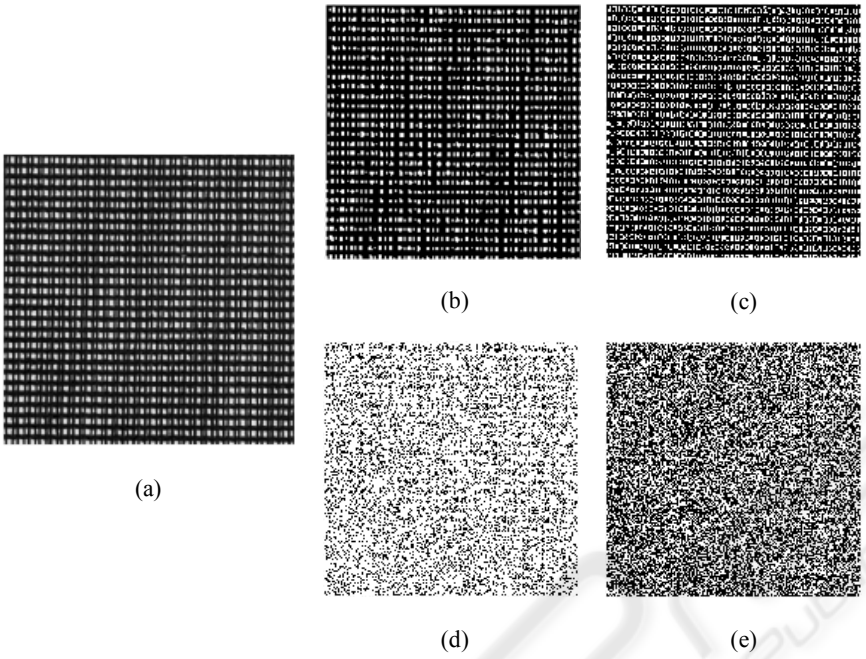


Figure 1: Image bit-plane decomposition: (a) original image, (b-c) most significant, (d-e) less significant bit-planes (details of image D21 from Brodatz set). Most significant bit-planes are more structured than less significant ones. Lower planes are quite similar to pure noise.

2 OUR METHOD

The key point is to observe image features in a simple domain, the bit-plane representation. Images are split with a bit-plane decomposition and bits of each plane are processed. Working with bits is faster and simpler than working with pixels, both in the analysis and synthesis phase.

Our approach does not focus on automatic damage detection. The user must select a region to restore to create an input matrix, with the same image size, in which all the pixels are labeled as good or damaged. Starting from this input matrix, our method can be divided into three sub-phases:

- Decomposition and Gray-coding
- Information analysis
- Reconstruction

2.1 Image Decomposition

None of the related works, to our knowledge, has proposed a method to store information about pixels statistics in an image, because it is an hard task, both for memory usage and access time problems. Typically a search for the needed information is recomputed at each step of the restoration process, with a waste of execution time. Our method splits the image in bit-plane slices, and each plane is Gray-coded in order to decorrelate information between different planes. Working with bit sequences, rather than pixels, helps to save memory space and to speed-up access time, making information memorization and recovering easier and faster. Note that in the restoration step, each plane cannot be reconstructed independently from the others, since annoying artefacts would be visible into the reassembled image. In the next subsection a method will be presented to link information coming from different planes. Note also that since most part of information is stored in the most significant planes (see fig.1), lower planes can be processed roughly (e.g. using smaller window size), speeding-up the process without losing quality in the restored image.

2.2 Information Analysis

Our texture model is based on the Markov Random Field (MRF) theory, since it has proven to be satisfactory in representing a wide set of texture

types. We consider textures as instances of a stationary random model, in which each pixel is statistically determined by its neighborhood.

The purpose of this step is to build a dictionary to store uncorrupted information, which will be used in the reconstruction step. A square window W_N (where N is the window size set by the user) runs along each bit plane. Bit-planes are processed from the most significant to the less. For each undamaged bit $b^i(x,y)$ in a bit-plane, an index is created with the scan-ordered bit sequence inside the window W_N. A corresponding index is created with information from the previous significant bit plane, using a M-size square window set at the same position, and added as a header to the first index:

$$k(x,y)=\left[\sum_{(x_j,y_j)\in W_M{}^{i+1}} b^{i+1}(x_j,y_j)\cdot 2^j\right]\cdot 2^{N\cdot N}+\sum_{(x_l,y_l)\in W_N{}^i} b^l(x_l,y_l)\cdot 2^l \quad (1)$$

where $b^i(x,y)$ are bits from the current bit-plane i, $b^{i+1}(x,y)$ are bits from the previous significant bit-plane i+1. We create a histogram, our "dictionary", which stores the frequency of these sequences into the bit-planes. Each value represents the a posteriori probability of a bit sequence in a i-plane, conditioned by the corresponding sequence in the previous (i+1)-plane.

$$H(i,k)=P\left(W_N{}^i \mid W_M{}^{i+1}\right) . \quad (2)$$

The most significant plane is processed as a special case, with no contribution from a previous plane.

2.3 Reconstruction

According to the 2D-Wold decomposition model for homogeneous random fields (Liu and Picard, 1996), the most important features for human texture perception are: periodicity, directionality and randomness. Two competing processes work to reproduce these features from the global image into the damaged area: a bit-by-bit constrained random generation process, which aims to reproduce texture directionality and randomness of the global image, and a patching process to replicate texture periodicity.

Note that the order in which pixels (or bits) are synthesized strongly affects results, because it sets the neighborhood used to reconstruct the damaged area. With a simple scan order the restoration process tends to reproduce up-to-down left-to-right diagonal shapes. Our algorithm processes bits along a direction that depends on image average gradient vector. This solution helps us to reconstruct the natural bias of the image.

The reconstruction phase is the dual process of the dictionary building process. As in the previous phase, bit planes are processed from the most significant to the less one. For each damaged bit in each plane an N square window is considered, which will contain uncorrupted, corrected and damaged bits. The corresponding M square window is considered in the previous plane, in which the whole information is known (bits are either undamaged or corrected).

The bit-by-bit generation process at first computes the probability that the central bit of the window is 1 or 0, given the known neighbour bits in the plane and the bits in the previous plane. The statistics of each of the submasks of a window can be computed building up those of all the possible statistics of the windows which share that submask:

$$P\left(\hat{W}_N{}^i \mid W_M{}^{i+1}, b_c=0\right)=\sum P\left(W_j{}^i \mid W_M{}^{i+1}, b_c=0\right) \quad (3)$$

$$P\left(\hat{W}_N{}^i \mid W_M{}^{i+1}, b_c=1\right)=\sum P\left(W_j{}^i \mid W_M{}^{i+1}, b_c=1\right) . \quad (4)$$

$$W_{j_1}{}^i \cap W_{j_2}{}^i = \hat{W}_N{}^i$$

The two statistics we are looking for:

$$S_0{}^i(x,y)=\sum_{p=0}^{2^{N_D}-1} H\left[i, B^i{}_p(x,y)\right]=P\left(\hat{W}_N{}^i \mid W_M{}^{i+1}, b_c=0\right) \quad (5)$$

$$S_1{}^i(x,y)=\sum_{p=0}^{2^{N_D}-1} H\left[i, W^i{}_p(x,y)\right]=P\left(\hat{W}_N{}^i \mid W_M{}^{i+1}, b_c=1\right) \quad (6)$$

where H[i,k] is the dictionary built in the analysis phase, N_D is the number of the damaged bits in the window, B^i_p is the index for the sequence with a "black" (zero) central bit in the window, and W^i_p is the sequence with a "white" (one) central bit, b_c is the central bit of the mask in the i-plane. Both of these indexes contain bits from the $\hat{W}_N$ submask.

The second sub-step of the reconstruction step is a random generation, conditioned by the statistics computed in eq.5 and eq.6, in order to choice which information (0/1) to put in the central position of the window. The two statistics are weighted with weights that depend on an user-defined parameter α :

$$P_0 = w_0 \cdot \frac{S_0}{S_0+S_1} \quad P_1 = w_1 \cdot \frac{S_1}{S_0+S_1}$$
$$w_0, w_1 = f_{0,1}\left(\max\left(P_0, P_1\right), \alpha\right) \quad (7)$$

By setting α close to 1, this process is the same as a random process with the two probabilities:

$$P_0 = \frac{S_0^{\,i}(x,y)}{S_1^{\,i}(x,y)+S_0^{\,i}(x,y)} \quad P_1 = \frac{S_1^{\,i}(x,y)}{S_1^{\,i}(x,y)+S_0^{\,i}(x,y)} \tag{8}$$

which fits for synthesizing highly stochastic textures. When α>>1 the bit value is simply set as the most frequent bit in the window central position with that surrounding conditions. That is suitable for strongly oriented textures. In this way our method can control the randomness and directionality of the generated texture.

To avoid the "growing garbage" problem, if no statistics match the current sequence in the dictionary, a random generation process is used with the following probabilities:

$$\begin{aligned} P_0 &= P\left(b^i(x,y)=0 \mid b^{i+1}(x,y)\right) \\ P_1 &= P\left(b^i(x,y)=1 \mid b^{i+1}(x,y)\right) \end{aligned} \tag{9}$$

At the same time, a second competing process works to propagate global texture features into the area to restore. A patching process aims to reproduce texture periodicity. For each damaged bit, the two most frequent sequences (one with 0 as its central bit, one with 1), which share the known bit submask, are extracted from the dictionary:

$$W^i_{0\max}(x,y) = \arg\max P\left(W_j^{\,i} \mid W_M^{\,i+1}, b_c = 0\right) \tag{10}$$

$$W^i_{1\max}(x,y) = \arg\max P\left(W_j^{\,i} \mid W_M^{\,i+1}, b_c = 1\right) \cdot \tag{11}$$

$$W_{j_1}^{\,i} \cap W_{j_2}^{\,i} = \hat{W}_N$$

If one of the statistics is much greater than the other, the bit-by-bit generation process is disabled and the whole window is filled with the most frequent sequence. The activation threshold of this process, that is what we mean for "much greater", is set by an user defined parameter. As we discussed in this section, less significant bit planes have a more random global structure. So patching is useless or harmful to process these planes, and it is disabled. Filling-in the whole window, rather than bit-by-bit, extremely speeds up the execution time, and helps in replicating texture periodicity, if it is at a scale either equal or smaller than the window size.

After all planes are restored, bit planes are merged to reconstruct the whole image, and a soft edge-preserving smooth filter is applied to remove the residual high-frequency noise due to this reassembling phase.

3 COMPUTATIONAL COST

Computational cost depends on damaged area size and on the windows size:

$$\begin{aligned} &O(n-d)+O\left(d\cdot 2^{S-T}\right) \\ &S = N\times N + M\times M \end{aligned} \tag{12}$$

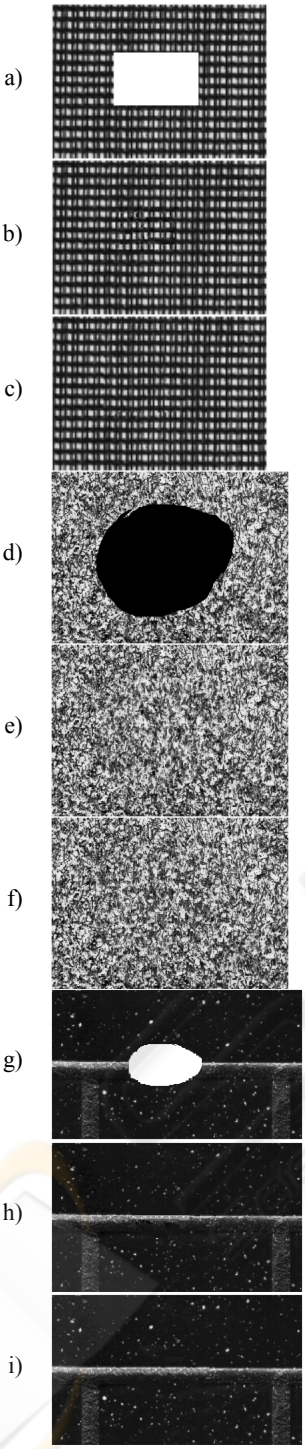
where d is the number of the damaged pixels, n is the image size, N and M the size of the two masks.

The first term of eq. 12 results from the dictionary building phase. It also depends on windows size. The second term is the computational cost of the reconstruction phase. Exponential term is due to the structure we use to store information in the analysis step. Our dictionary is stored in a hash table, with collision lists, which is the best solution to speed-up the access time. T is the table size. If d<<n and windows are small, first term is predominant and computational cost is O(n). Increasing M, N and d, computational cost becomes exponential in the worst case, that is much far from the real execution time measured with our experiments.

4 EXPERIMENTAL RESULTS

Tests had been made on over 30 640x640 images from the Brodatz texture set. Each image is arbitrarily damaged to create an area to fill-in (note that to create consistent statistics hole size must be much lower than image size, which is usually the case in real-world images). The algorithm has been implemented in ANSI-C, and executed on an Intel Core Duo PC (1,83 GHz, 2 GB RAM). Execution time is about 1 sec, for stochastic texture and small holes, and rises up to 5-6 minutes, for highly-structured textures and large-sized holes, processed with larger-sized masks.

Figure 2 shows some results obtained with our algorithm, compared with those obtained with the Criminisi (2004) inpainting algorithm. Both visual and numerical comparison are provided. We measured significant statistical parameters in order to compare images before and after restoration. Visual comparison shows that our results are very similar to those obtained with Criminisi algorithm. No remarkable differences in statistical features measured for the two methods (in respect to the parameters of the original image). We noted only some difference in the S\N parameter for small region to fill. This can be explained by considering that the Criminisi algorithm is based on a patching method. Our method, on the other hand, is one or two order of magnitude faster than the Criminisi method, depending on the damaged area size. An earlier version of the algorithm had been tested (Ardizzone et al. 2007) on images from a photographic archive of digitized old prints.



stats	original	damaged	our method	Criminisi
m	**76,9864**	**77,6598**	**76,9071**	**76,9819**
σ	**64,4647**	**65,2693**	**64,4709**	**64,4647**
s	**1,0717**	**1,0745**	**1,0704**	**1,0716**
k	**2,7908**	**2,8105**	**2,7889**	**2,7906**
S/N		**22,7384**	**24,7963**	**29,5066**
d		**1552 (0,38%)**		
t(s)			**an. 4,5** **syn. 3,4**	**29.6**

stats	original	damaged	our method	Criminisi
m	**130,8099**	**122,0571**	**130,9902**	**130,7417**
σ	**61,2621**	**67,3885**	**60,8456**	**61,6086**
s	**0,0749**	**0,0396**	**0,0772**	**0,0673**
k	**1,7097**	**1,8936**	**1,7085**	**1,7180**
S/N		**4,4710**	**8,8456**	**8,5823**
d		**28626 (7%)**		
t (s)			**an. 1,5** **syn. 1,1**	**618,5**

stats	original	damaged	our method	Criminisi
m	**35,0554**	**36,0589**	**34,8039**	**35,0759**
σ	**35,8527**	**39,9498**	**35,5104**	**35,8855**
s	**3,46605**	**3,4968**	**3,4508**	**3,4582**
k	**15,3146**	**15.5208**	**15,1343**	**15,2490**
S/N		**6,2192**	**17,0377**	**22,9851**
d		**3091 (0,75%)**		
t(s)			**an. 1,8** **syn. 9,2**	**213.9**

Figure 2: (a,d,g) corrupted images (details from D21, D9, D25 from the Brodatz set, with superimposed damages); restored images with our method (b,e,h) and with Criminisi inpainting algorithm (c,f,i). A set of significant statistical parameters is provided to compare the two methods: m= mean, σ= standard deviation, s= skewness, k= kurtosis. d=number of damaged.pixels. S/N (dB)=signal to noise ratio between original-damaged and original-restored images. Execution time is shown for both analysis and synthesis phase (our method) and for the whole Criminisi process.

5 REMARKS AND FUTURE WORKS

The most evident limitation of our approach is about the window size. There are two problems with large-sized windows: the larger the window, the higher the execution time is and the less consistent the statistics stored in the dictionary is. Due to these two reasons, tests have been made with a maximum window size of 7x7. This is not a problem for processing stochastic texture (a 3x3 window performs well). Textures that have periodicity in larger scale are harder to reconstruct. However, fine tuning of parameters in many cases is enough to achieve good results. Note that only the most significant bit-planes need larger windows. Lower planes are randomly structured, and if higher planes are well-reconstructed, they can be restored using smaller windows.

We are working to extend our approach to process a larger set of texture types. We also plan to study a method to eliminate dependence from the user-defined parameters. Texture features could be estimated during a pre-analysis phase, and parameters suggested for the restoration process.

6 CONCLUSIONS

Bit-plane slices are used as a simple domain, into which analyse texture features and synthesize missing pixels to fill-in gaps, while respecting boundary conditions. Two competing methods, a conditional stochastic process and a patching method, work together to reconstruct the missing texture features. With this purpose, our approach is simple and efficient, and good results are achieved for a wide set of textured images. Results are compared with those obtained with a state of the art restoration algorithm. Minor loss in the quality of the results, with a high gain in execution time.

ACKNOWLEDGEMENTS

This work has been partially funded by the MIUR (Italian Ministry of Education, University and Research) project FIRB 2003 D.D. 2186–Ric, December 12th 2003.

REFERENCES

Ardizzone, E., Dindo H., Mazzola G., 2007. Restoration of Digitized Damaged Photos Using Bit-Plane Slicing. In *ICME 2007, IEEE International Conference on Multimedia and Expo, Proceedings of*, pp. 1643-1646.

Bertalmio, M., Sapiro, G., Caselles, V., and Ballester, C. 2000. Image inpainting. In *SIGGRAPH 2000, Proceedings of*, pp. 417–424.

Chan, T. F., and Shen, J., 2002. Mathematical models for local non-texture inpaintings. *SIAM Journal of Applied Mathematics*, vol. 62, no. 3, pp. 1019–1043.

Criminisi, A., Perez, P., Toyama, K., 2004. Region Filling and Object Removal by Exemplar-Based Inpainting. *IEEE Transactions on Image Processing* vol. 13, no. 9, pp. 1200-1212.

Cross, A. C., and Jain, A. K., 1983. Markov Random Field Texture Models. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 5 , pp. 25–39.

Efros, A. A., and Freeman, W. T., 2001. Image quilting for texture synthesis and transfer. *In SIGGRAPH 2001, Proceedings of,* pp. 341–346.

Efros, A. A., and Leung, T. K., 1999. Texture synthesis by non-parametric sampling. In *ICCV '99, IEEE International Conference on Computer Vision Proceedings of,* vol. 2, pp. 1033–1038.

Heeger, D. J., and Bergen, J. R., 1995. Pyramid-based texture analysis/synthesis. In *ICIP '95, IEEE International Conference on Image Processing, Proceedings of,* pp. 648–651.

Kokaram, A. 2002. Parametric texture synthesis for filling holes in pictures. In *ICIP 2002, International Conference on Image Processing, Proceedings of*, vol. 1, pp. 325- 328.

Liu, F., Picard, R. W., 1996. Periodicity, Directionality, and Randomness: Wold Features for Image Modeling and Retrieval. *IEEE Transaction on Pattern Analysis and Machine. Intelligence.* vol, 18, no. 7, pp. 722-733.

Portilla, J., and Simoncelli, E. P., 2000. A Parametric Texture Model based on Joint Statistics of Complex Wavelet Coefficients. *International Journal of Computer Vision,* vol. 40, no. 1, pp. 49–71.

Wei, L., Levoy, M., 2000. Fast Texture Synthesis using Tree-structured Vector Quantization, *In SIGGRAPH 2000, Proceedings of,* pp. 479-488.