DESIGN OF AN ALGORITHM TO ANALYSE AND RECOGNIZATION FOR REASSEMBLING OF TEXTURE IMAGE

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***Abstract* - A missing texture reconstruction method based on an error reduction (ER) algorithm, including a novel estimation scheme of Fourier transform magnitudes is presented in this brief. In this method, Fourier transform magnitude is estimated for a target patch including missing areas, and the missing intensities are estimated by retrieving its phase based on the ER algorithm. Specifically, by monitoring errors converged in the ER algorithm, known patches whose Fourier transform magnitudes are similar to that of the target patch are selected from the target image. In the second approach, the Fourier transform magnitude of the target patch is estimated from those of the selected known patches and their corresponding errors. Consequently, by using the ER algorithm, both the Fourier transform magnitudes and phases can be estimate to reconstruct the missing areas.**

Index Terms – Fourier, Error Reduction

I. Introduction

Restoration of missing areas in digital images has been intensively studied due to its many useful applications such as removal of unnecessary objects and error concealment. Therefore, many methods for realizing these applications have been proposed. A missing texture reconstruction method based on an error reduction (ER) algorithm using a new Fourier transform magnitude estimation scheme is been proposed here as a solution to previously existing limits.

Given a known Fourier transform magnitude of a target image, the ER algorithm retrieves its phase from an image domain constraint to estimate its unknown intensities. In this method, focus is on a unique characteristic of Fourier transform magnitudes, shift invariant characteristic. The Fourier transform magnitudes of patches clipped from the same kinds of textures become similar to each other.

Therefore, Fourier transform magnitudes can be effectively utilized as texture features, and the mismatch between clipping interval and periods of textures can also be represented by the phases. In order to reconstruct missing textures, the proposed method introduces the following two novel approaches into the ER algorithm. First, proposed method enables selection of similar known patches, which are optimal for the reconstruction of target patches including missing areas, based on errors converged by the ER algorithm. Next, from the selected known patches and their corresponding errors, the proposed method performs the estimation of the Fourier transform magnitudes of target patches. Then, from the estimated Fourier transform magnitudes, we retrieve their phases based on the ER algorithm and enable successful reconstruction of missing areas.

II. RELATED WORK

In this paper a variational approach for filling-in regions of missing data in digital images is introduced. The approach is based on joint interpolation of the image gray levels and gradient/isophotes directions, smoothly extending in an automatic fashion the isophote lines into the holes of missing data. This interpolation is computed by solving the variational problem via its gradient descent flow, which leads to a set of coupled second order partial differential equations, one for the gray-levels and one for the gradient orientations. The process underlying this approach can be considered as an interpretation of the Gestaltist's principle of good continuation. No limitations are imposed on the topology of the holes, and all regions of missing data can be simultaneously processed, even if they are surrounded by completely different structures. Applications of this technique include the restoration of old photographs and removal of superimposed text like dates, subtitles, or publicity. Examples of these applications are given.

In [2], a non-parametric method for texture synthesis is proposed. The texture synthesis process grows a new image outward from an initial seed, one pixel at a time. A Markov random field model is assumed, and the conditional distribution of a pixel given all its neighbours synthesized so far is estimated by querying the sample image and finding all similar neighbourhoods. The degree of randomness is controlled by a single perceptually intuitive parameter. The method aims at preserving as much local structure as possible and produces good results for a wide variety of synthetic and real-world textures.

1. "Sparse representation for colour image restoration".

Sparse representations of signals have drawn considerable interest in recent years. The assumption that natural signals, such as images, admit a sparse decomposition over a redundant dictionary leads to efficient algorithms for handling such sources of data. In particular, the design of well adapted dictionaries for images has been a major challenge. The K-SVD has been recently proposed for this task and shown to perform very well for various greyscale image processing tasks. In this paper, the problem of learning dictionaries for color images and extend the K-SVD-based greyscale image denoising algorithm that appears in literature is addressed. This work puts forward ways for handling non-homogeneous noise and missing information, paving the way to state-of-the-art results in applications such as colour image denoising, demos icing, and imprinting, as demonstrated in this paper.

2. "Fragment-based image completion".

This paper presents a new method for completing missing parts caused by the removal of foreground or background elements from an image. Our goal is to synthesize a complete, visually plausible and coherent image. The visible parts of the image serve as a training set to infer the unknown parts. Our method iteratively approximates the unknown regions and composites adaptive image fragments into the image. Values of an inverse matte are used to compute a confidence map and a level set that direct an incremental traversal within the unknown area from high to low confidence. In each step, guided by a fast smooth approximation, an image fragment is selected from the most similar and frequent examples. As the selected fragments are composited, their likelihood increases along with the mean confidence of the image, until reaching a complete image. We demonstrate our method by completion of photographs and paintings.

Most algorithms, which focus on texture reconstruction, estimate missing areas by using statistical features of known textures within the target image as training patterns. Specifically, they approximate patches within the target image in lower-dimensional subspaces and derive the inverse projection for the corruption to estimate missing intensities. In this scheme, several multivariate analyses such as PCA and sparse representation have been used for obtaining low-dimensional subspaces. In addition to the above reconstruction schemes, many texture synthesis based reconstruction methods have been proposed in literature.

It should be noted that conventional methods generally calculate texture feature vectors whose elements are raster scanned intensities in clipped patches. However, when the patches are clipped in intervals different from the periods of the textures, the obtained feature vectors become quite different from each other even if they are the same kinds of textures. This is always caused by the mismatch between clipping interval and periods of textures. Thus, it becomes difficult to generate subspaces that can correctly approximate the clipped patches in low dimensions or find best-matched examples. Then the reconstruction ability of missing textures also becomes worse.

III. PROPOSED METHOD.

The ER algorithm, which is one of the iterative Fourier transform algorithm and is widely used for phase retrieval, enables reconstruction of a target image by iteratively applying both Fourier and image constraints. In the proposed method, a patch f ($w \times h$ pixels) including missing areas is clipped from the target image, and its missing textures are estimated from the other known areas. For the following explanations, we denote two areas whose intensities are unknown and known within the target patch f as Ω and $\overline{\Omega}$, respectively. Furthermore, the proposed method utilizes known patches f^i ($i = 1, 2. . . N$) that are clipped from the target image in the same interval, where N is the number of clipped patches.

Note that we simply clip training patches in a raster scanning order from the upper-left of the target image. In the proposed method, we first estimate the Fourier transform magnitude of the target patch f based on converged errors in the ER algorithm. Next, reconstruction of the target patch f is realized by using the ER algorithm from the estimated Fourier transform magnitude.

1. Reduction Algorithm.

The error reduction or Gerchberg–Saxton algorithm solves the signal equation for $f(x)$ by the iteration of a four-step process. In the first step, an estimate of the object $f(x), g_k(x)$ undergoes Fourier transformation:

$$G_k(u) = |G_k(u)|e^{i\phi_k(u)} = \mathcal{F}(g_k(x)) \quad (1.1)$$

The experimental value of $|F(u)|$, calculated from the diffraction pattern via the signal equation, is then substituted for $|G\_k(u)|$, and giving an estimate of the Fourier transformation:

$$G'_k(u) = |F(u)|e^{i\phi_k(u)} \quad (1.2)$$

Next, the estimate of the Fourier transformation $G'_k(u)$ is inverse Fourier transformed:

$$g'_k(u) = |g'_k(x)|e^{i\theta'_k(x)} = \mathcal{F}^{-1}(G'_k(u)) \quad (1.3)$$

g'_k (x)then must be changed so that the new estimate of the object, $g'_{\{k+1\}}(x)$ satisfies the object constraints. $g'_{\{k+1\}}(x)$ is therefore defined piecewise as:

$$g'_{k+1}(x) \equiv \begin{cases} g'_k(u) & x \notin \gamma \\ 0 & x \in \gamma \end{cases} \quad (1.4)$$

where γ is the domain in which $g'_k(x)$ does not satisfy the object constraints. As the calculated image, $g'_k(x)$, is complex valued, $|g'_k(x)|$ is replaced by the experimental value of $|f(x)|$, to give the new estimate of the object.

$$g_{k+1}(x) = |f(x)|e^{i\theta'_{k+1}(x)} \quad (1.5)$$

This process is continued until both the Fourier constraint and object constraint are satisfied. Theoretically, the process will always lead to a convergence, but the large number of iterations needed to produce a satisfactory image (generally

>2000) results in the error-reduction algorithm being unsuitably inefficient for sole use in practical applications.

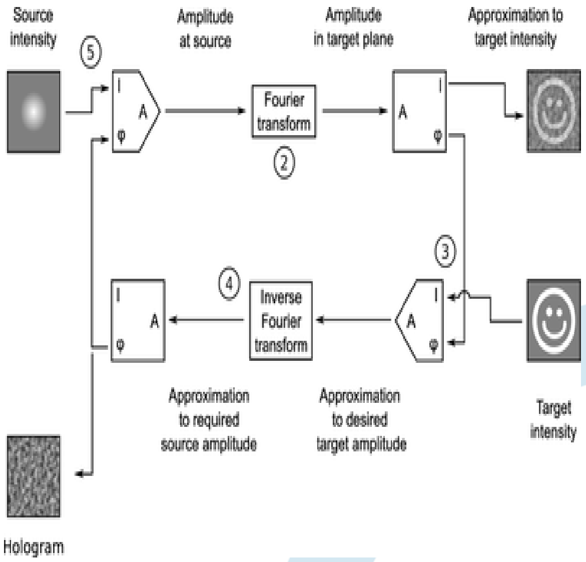

Fig 1. Schematic view of the error reduction algorithm for phase retrieval

2. Estimation of Fourier Transform Magnitude

In this subsection, the algorithm for estimating the Fourier transform magnitude of the target patch f is explained. In order to estimate the Fourier transform magnitude, we first select patches whose Fourier transform magnitudes are similar to that of f from $f^i(i = 1,2\ldots N)$ and calculate the distances of the Fourier transform magnitudes between the target patch f and the selected patches. Unfortunately, the true distances of the Fourier transform magnitudes cannot be directly calculated for the target patch f since it contains the missing area Ω.

Therefore, the proposed method utilizes the errors converged in the ER algorithm under the following two constraints as new criteriae$^i(i = 1,2\ldots N)$. Fourier Constraint: The Fourier transforms magnitude of f is the same as that of $f^i|F^i(u,v)|(u = 1,2,\ldots,w,h = 1,2,\ldots,h)$.

Image Constraint: Since the intensities in the area $\overline{\Omega}$ of the target patch f are known, these values are fixed. Then the error converged after T1 iterations in the ER algorithm is calculated as follows:

$$e^i = \sum_{u=1}^{w}\sum_{v=1}^{h}\left(\left|F_{T_1}(u,v)\right| - \left|F^i(u,v)\right|\right)^2 \ldots\ldots\ldots\ldots\ldots \quad (2.1)$$

Where $F_{T_1}(u,v)$ represents the Fourier transform magnitude of the target patch f obtained after T1 iterations. The ER algorithm is one of the steepest descend algorithms that minimize the errors of Fourier transform magnitudes under the image domain constraint. Therefore, we can regard the error $e^i(i = 1,2,\ldots,N)$ converged in the ER algorithm as the minimum distance of the Fourier transform magnitude between the two patches f and f^i. Then M patches whose criteria e^i are smaller than those of other known patches are selected. For the following explanation, the selected patches and their calculated distances e^i are respectively denoted as f^jande^j $(j = 1,2,\ldots,M)$. From the above procedures, we can select M known patches f^j similar to f in terms of Fourier transform magnitudes and their minimum distancee^j . By using the known Fourier transform magnitudes $|F^j(u,v)|$ of f^j and their corresponding distances are as of e^j $(j = 1,2,\ldots,M)$, the proposed method estimates the Fourier transform magnitude of the target patch f based on the idea of MDS.

First, we define a vector ξ^j whose elements are the raster scanned values of each Fourier transform magnitude $|F^j(u,v)|$. Similarly, the vector of the Fourier transform magnitude of the target patch f is denoted as ξ. From the matrix Ξ $(= [\xi^1,\xi^2,\ldots,\xi^M])$, we can obtain the following singular value decomposition:

$$\Xi H = U\Lambda V^T = UZ \quad (2.2)$$

In the above equation, Λ is a $q \times q$ singular value matrix, where q is the rank of Ξ, and U and V are $wh \times q$ and $M \times q$ orthonormal matrices, respectively. Vector/matrix transpose is represented by thesuperscript ^{T}. The matrix $Z = [z^1,z^2,\ldots,z^M]$ satisfies $Z = \Lambda V^T$. Furthermore, $H = I - \frac{1}{M}11^T$ is a $M \times M$ centering matrix, where I is the identity matrix and $1 = [1,1,\ldots,1]^T$ is a $M \times 1$ vector.

$$-2Z^T z = \left(e^2 - e_0^2\right) - \frac{1}{M}11^T\left(e^2 - e_0^2\right) \quad (2.3)$$

is satisfied. The vector z in the above equation is

$$z = U^T\left(\xi - \bar{\xi}\right) \quad (2.4)$$

where$\bar{\xi} = 1/M\sum_{j=1}^{M}\xi^j$. Furthermore, e^2 is an $M \times 1$ vector whose $j-$th element corresponds to $\hat{e}^j$, and $e_0^2 = [\|z^1\|^2,\|z^2\|^2,\ldots,\|z^M\|^2]$. Then the estimation result $\hat{\xi}$ of ξ is realized by the following procedures. First,

$$\begin{aligned}\hat{z} &= -\frac{1}{2}\left(ZZ^T\right)^{-1}Z\left(e^2 - e_0^2\right)\\ &= -\frac{1}{2}\Lambda^{-1}V^T\left(e^2 - e_0^2\right).\end{aligned} \quad (2.5)$$

Therefore, from Eq. (3.10), the estimation result $\hat{\xi}$ is obtained as follows:

$$\xi = U\hat{z} + \bar{\xi} \quad (2.6)$$

By using the above equation, we can finally obtain the estimation result $|\hat{F}(u,v)|$ of the Fourier transform magnitude for the target patch f.

3. *Texture Reconstruction Algorithm*

The ER algorithm in the literature survey, which is one of the iterative Fourier transform algorithm and is widely used for phase retrieval, enables reconstruction of a target image by iteratively applying both Fourier and image constraints. In the proposed method, a patch f (w×h pixels) including missing areas is clipped from the target image, and its missing textures are estimated from the other known areas. For the following explanations, we denote two areas whose intensities are unknown and known within the target patch f as Ω and $\bar{\Omega}$, respectively. Furthermore, the proposed method utilizes known patches f^i $(i = 1, 2, \ldots, N)$ that are clipped from the target image in the same interval, where N is the number of clipped patches. Note that we simply clip training patches in a raster scanning order from the upper-left of the target image. In the proposed method, we first estimate the Fourier transform magnitude of the target patch f based on converged errors in the ER algorithm. Next, reconstruction of the target patch f is realized by using the ER algorithm from the estimated Fourier transform magnitude.

3.1 Estimation of Fourier Transform Magnitude

In this subsection, we explain the algorithm for estimating the Fourier transform magnitude of the target patch f. In order to estimate the Fourier transform magnitude, we first select patches whose Fourier transform magnitudes are similar to that of f from f i (i = 1, 2, . . . , N) and calculate the distances of the Fourier transform magnitudes between the target patch f and the selected patches. Unfortunately, the true distances of the Fourier transform magnitudes cannot be directly calculated for the target patch f since it contains the missing area _. Therefore, the proposed method utilizes the errors converged in the ER algorithm under the following two constraints as new criteria e^i $(i = 1, 2, \ldots, N)$ Fourier Constraint: The Fourier transform magnitude of f is given by $|F^i(u, v)|$ $(u = 1, 2, \ldots, w, \, h = 1, 2, \ldots, h)$ Image Constraint: Since the intensities in the area ._ of the target patch f are known, these values are fixed. Then the error converged after T1 iterations in the ER algorithm is calculated as follows:

3.2. Texture Reconstruction

The algorithm for texture reconstruction of the missing area Ω within the target patch f by using the estimated Fourier transform magnitude $|\hat{F}(u,v)|$ is presented in this subsection. Based on the ER algorithm under the following two constraints, the proposed method recovers the phase of f to reconstruct the missing texture in Ω.

Fourier Constraint: The Fourier transform magnitude of the target patch f is $|\hat{F}(u,v)|$.
Image Constraint: Since the intensities in the area $\overline{\Omega}$ of the target patch f are known, these values are fixed.

By applying the above two constraints to the target patch f in T_2 times, we try to retrieve its phase. Note that the estimated Fourier transform magnitude $|\hat{F}(u,v)|$, generally contains errors, so that f tends not to satisfy the Fourier constraint. In such a case, the reconstruction results within Ω may be degraded due to these errors. Therefore, the proposed method simply introduces an alternative procedure that renews $|\hat{F}(u,v)|$. utilized as the Fourier constraint into the ER algorithm. Specifically, the renewal of the Fourier transform magnitude used as the Fourier constraint is performed after every $T_3 (T_3 < T_2)$iterations as follows

$$|\hat{F}_{m+1}(u,v)| = |\hat{F}_m(u,v)| + \beta \left\{ |F_m(u,v)| - |\hat{F}_m(u,v)| \right\}$$

wherem represents mth iteration in the ER algorithm, and $|\hat{F}_m(u,v)|$ is the Fourier transform magnitude used as the Fourier constraint in mth iteration. Note that the initial values of $|\hat{F}_0(u,v)|$ become those of $|\hat{F}(u,v)|$in our method. Furthermore, $|F_m(u,v)|$ represents the Fourier transform magnitude of the target patch f in mth iteration.

The value β is a positive constant. In the above equation, $|\hat{F}_m(u,v)|$ is renewed in such a way that the distance from the Fourier transform magnitude $|F_m(u,v)|$ of the target patch satisfying the image constraint is minimized. Then, by iterating this modified ER algorithm, phase retrieval satisfying the above two constraints can be realized. Therefore, we can reconstruct the missing area Ω within the target patch f.

Finally, the proposed method clips patches including missing areas and performs their reconstruction to estimate all missing intensities in the target image. It should be noted that in order to realize this scheme, we have to determine the order in which patches along the fill-front of missing areas are filled. We call this order “patch priority”. The proposed method can retrieve the phase of the target patch f to reconstruct the missing area Ω. As shown in the previous subsection, we can estimate the Fourier transform magnitude, and the rest unknown component is only its phase.

Therefore, the phase must be retrieved from the obtained Fourier transform magnitude under the constraint of the known intensities within $\overline{\Omega}$. As described above, it is well known that the ER algorithm is one of the steepest descend algorithms which minimize the mean square error between the known Fourier transform magnitude and that of the target patch. Furthermore, if we assume that the Fourier transform magnitude of the target patch f can be perfectly estimated by the previous subsection, the ER algorithm is the best one to estimate its phase. Therefore, in this subsection, we adopt the ER algorithm-based scheme for retrieving the phase of the target patch f to reconstruct the missing area Ω.

IV. CONCLUSION AND FUTURE WORK

A new missing texture reconstruction method based on the ER algorithm including a Fourier transform magnitude estimation scheme is presented in brief. The proposed method utilizes Fourier transform magnitudes as texture features and enables missing texture reconstruction by retrieving their phases based on the ER algorithm. In this algorithm, we newly introduce the Fourier transform magnitude estimation approach by the errors converged in the ER algorithm. This approach realizes accurate texture feature estimation and enables successful reconstruction of the missing areas. Consequently, some improvements of the proposed method over the previously reported methods are confirmed.

In future work, we have to adopt a new scheme in order to realize successful structure reconstruction. Some researchers have reported simultaneous reconstruction approaches of structural and texture parts that enable selection of a suitable reconstruction method for each area in the literature survey.

This means they can adaptively select the two reconstruction methods which respectively perform accurate structure and texture restoration. Thus, this scheme may provide one solution to the above problem. We also have to realize an improved method which can reconstruct color images successfully. Furthermore, the reduction of the computation costs in the proposed method should also be realized. We need to complement the above points in subsequent studies.

References

[1] C. Ballester, M. Bertalmio, V. Caselles, and G. Sapiro, *"Filling-in by joint interpolation of vector fields and gray levels,"IEEE Trans. Image Process., vol. 10, no. 8, pp. 1200–1211, Aug. 2001.*

[2] A. A. Efros and T. K. Leung, *"Texture synthesis by nonparametric sampling," in Proc. IEEE Int. Conf. Comput. Vis., Corfu, Greece, Sep. 1999, pp. 1033–1038.*

[3] T. Ogawa and M. Haseyama, *"POCS-based texture reconstruction method using clustering scheme by kernel PCA," IEICE Trans. Fundam., vol. E90-A, no. 8, pp. 1519–1527, Aug. 2007.*

[4] I. Drori, D. Cohen-Or, and H. Teshurun, *"Fragment-based image completion," in Proc. SIGGRAPH, 2003, pp. 303–312.*

[5] T. Amano and Y. Sato, *"Image interpolation using BPLP method on the eigenspace," Syst. Comput.Jpn., vol. 38, no. 1, pp. 87–96, Jan. 2007.*

[6] J. Mairal, M. Elad, and G. Sapiro, *"Sparse representation for color image restoration," IEEE Trans. Image Process., vol. 17, no. 1, pp. 53–69, Jan. 2008.*

[9] Z. Xu and J. Sun, *"Image inpainting by patch propagation using patch sparsity," IEEE Trans. Image Process., vol. 19, no. 5, pp. 1153–1165, May 2010.*

[10] I. B. Fidaner. (2008). *A Survey on Variational Image Inpainting, Texture Synthesis and Image Completion [Online]. Available: http://www.scribd. com/ doc/ 3012627/ A-Survey-on Variational-Image-Inpainting-Texture-Synthesis-and-Image-Completion.*