An Novel FFT Based Error Reduction Algorithm For Textured Image

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Abstract: This paper presents a reconstruction of missing textures based on error reduction algorithm using fourier transform magnitude estimation method. 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 error reduction algorithm. In this method the errors are monitoring in the error reduction algorithm, the fourier transform magnitude of known patches are similar to that of target patch. After that, the fourier transform magnitude of the target patch is estimated from those of the selected known patches and their corresponding errors. So this method has to estimate both the fourier transform magnitudes and phases by using error reduction algorithm to reconstruct the missing areas.

Keywords: error reduction algorithm, fourier transform magnitude estimation, texture analysis, phase retrieval, image reconstruction.

I. Introduction

In digital images the missing areas are restoration can be used in many applications. The applications are removal of unnecessary objects, super imposed text in the image and error concealment. There are many methods for realizing these applications have been proposed. Restoration of digital images can be classified into two categories. They are structure based reconstruction and texture based reconstruction. In this, we focus on the texture based reconstruction. But this type of reconstruction limited to gray scale images.

In texture reconstruction method the missing areas are estimated by using statistical features of known textures within the target image. Patches within the target image approximate to lower dimensional subspace and derive the inverse projection for the corruption to estimate missing intensities. In this scheme, several multivariate analyses such as PCA [3], [4] and sparse representation [5] have been used for obtaining low dimensional subspaces. In addition to above reconstruction schemes, many texture synthesis based reconstruction methods have been proposed.

In conventional methods the calculation of texture feature vectors is depended on the intensities in the clipped patches. The texture feature elements are obtaining raster scanning the intensities in the clipped patches. However, when the patches are clipped in interval different from periods of texture, 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 the clipping interval and periods of textures. Thus it becomes difficult to generate subspace that can correctly approximate the clipped patches in low dimension. Then the reconstruction ability of missing textures also becomes worse.

In order to solve the above problem, we propose a novel fft based error reduction algorithm. This method first given to the known fourier transform magnitude of a target image. The error reduction algorithm retrieves its phase from an image domain constraint to estimate its unknown intensities. In our method, we focus 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.

II. Related works

The filling regions of missing data in digital images can be done by the method of filling in joint interpolation of vector fields and gray levels. This method is based on joint interpolation of the gray levels and gradient/ isophotes direction, 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 decent flow, which leads to a set of coupled second order partial differential equation, one for the gray levels and one for the gradient orientations. The process underlying this approach can be considered as an interpolation of the Gestaltist's principle of good continuation. No limitation 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 super imposed text like dates, subtitles, or publicity.

The texture synthesis also can be used in the filling the missing regions. That method is a texture synthesis by nonparametric sampling. The texture synthesis process grows a new image outwards from the initial seed, one pixel at a time. A Markov random field is assumed and the conditional distribution of pixel given all its neighbors synthesized so far is estimated by querying the sample image and finding all similar neighborhoods. The degree of randomness is controlled by a single perceptually intuitive parameter. This method aim at preserving as much local structure as possible and produce a good results for a wide variety of synthetic and real world textures.

Sparse representation of signals have drawn considerable interest in recent years. The assumption that natural signals, such as images, admit a sparse decomposition over 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 KSVD has been recently proposed for this task and shown to perform very well for various gray scale image processing tasks. In this paper, the problem of learning dictionaries for color images and extend the KSVD based grayscale 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 color image denoising, demosaicing, and impainting, as demonstrated in this method.

The completing the missing parts caused by the removal of foreground or background elements from an image. Our goal is 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 composite adaptive image fragments into the image. Values of inverse of matte are used to compute a confidence and a level set that direct and 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 likelihoods increases along with the mean confidence of the image, until reaching a complete image. We demonstrate our method by completion of photographs and paintings.

III. Proposed Algorithm

The texture reconstruction method based on error reduction algorithm. The error reduction algorithm which is a fourier transform algorithm and is widely used for phase retrieval during process of reconstruction of target image by iteratively applying both Fourier and image constraints. In the proposed method we first clip the patches in the target image. Each patch has a size of w x h. In the clipping patches have both distorted and undistorted regions are present. In the distorted region the missing textures are estimated from the other known areas. Then we apply the fourier transform to the both distorted and undistorted regions. When we apply the fourier transform to the patches we have magnitude and phase spectrum are obtained. The magnitude spectrum represents the intensity values present in the patch. The magnitude spectrum of undistorted region is gives the correct values. But the magnitude spectrum of the distorted region is not correct values.

So in the distorted patch we have to take the phases. The phase spectrum gives an information about the orientation of intensity values along the two directions. So we have to create a estimate patches with the help of both distorted and undistorted patches we have to taken. The distorted patch we take phase of that patch and undistorted patch we take magnitude of the patch. After that we apply the inverse fourier transform to the estimated patch. Then compare the distorted patch with undistorted patch by using the error reduction algorithm. This process is iteratively apply all to patches. So error reduction algorithm is a iterative process. After some iterations which patch has the minimum error that patch we are called estimated patch. The estimated patch is can be used in the reconstruction process. In the reconstruction process we have to take care of location of the where the distorted patch has removed. That is reconstructed with the help of phase retrieval. When we apply the fourier transform the phase also be considered in the reconstruction process.

Fourier Transform Magnitude:

The fourier transform magnitude target image can be estimated the with the help of the target patch. First we select the patches whose fourier transform magnitude is similar to the the missing area is present in the patch. And then calculate the distances of the fourier transform magnitudes between the target patch and selected patch. But the true distances of the fourier transform magnitudes cannot be directly calculated for the target patch f since it contains the missing area. So the proposed method utilizes the error reduction algorithm under the following two constraints.

Fourier constraint: the fourier transform magnitude of undistorted patch is similar to the distorted patch.

Image constraint: the intensities in the undistorted patch is known, these values are fixed.

Error Reduction Algorithm:

The error reduction originally invented by Gerchberg-Saxton.The method is invented for the purpose of connection with the problem of reconstructing phase from two intensity measurements. This algorithm consists of the following four steps. 1) Fourier transform an estimate of the object 2) replace the modulus of the resulting computed Fourier transform with the measured Fourier modulus to form an estimate of the Fourier transform 3) inverse Fourier transform the estimate of the Fourier transform; and 4) replace the modulus of the resulting computed image with the measured object modulus to form a new estimate of the object. The error reduction algorithm which is one of the iterative fourier transform algorithm which is used for reconstructing the target image by using both fourier and image domain constraints. The mth iteration of the error reduction algorithm consist of following steps.

Fourier transform: the fourier transform of mth estimated image is given by

$$G_m(u,v)=\left|Gm(u,v)\right|\exp[i\theta m(u,v]$$

$$=F\left|gm(x,y)\right|$$

where $|Gm(u,\ v)|$ and $\theta m(u,\ v)$ are the magnitude and phase of the Fourier transform respectively.

Application of fourier constraint: the distorted region fourier transform magnitude is replaced with undistorted region of the target image.

$$G'_m(u,v)=\left|F(u,v)\right|\exp[i\theta m(u,v]$$

Inverse fourier transform: the inverse fourier transform is applied to the formed fourier transform

$$g'_m(x,y)=F^{-1}\left|G'm(u,v)\right|$$

Application of image constraint: the estimated image is given by

$$g_{m+1}(x,y)=\begin{cases} g'_m(x,y) & (x,y)\in D \\ 0 & (x,y)\notin D \end{cases}$$

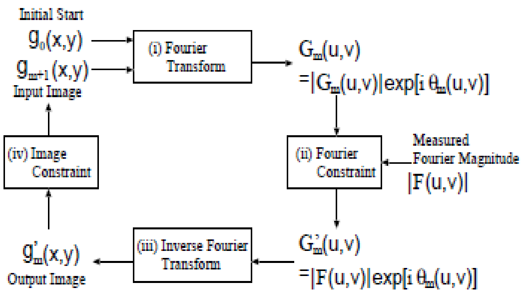

Fig.1: Block Diagram of Error Reduction Algorithm

The error after some iteration in the error reduction algorithm can be calculated as

$$e^i=\sum_{u=1}^{w}\sum_{v=1}^{h}\left(\left|F_{T1}(u,v)\right|-\left|Fi(u,v)\right|\right)^2$$

where $\left|F_{T1}(u,v)\right|$ represents the fourier transform magnitude of the target patch obtained after T1 iteration.

Error measurements: error generation from the fourier space error can be calculated by

$$R_F=\frac{\sum_k\left|\left|Fe(\bar{k})\right|-\gamma\left|F_{j+1}(\bar{k})\right|\right|}{\sum_k\left|Fe(\bar{k})\right|}$$

Where γ is a scaling factor and $F_{j+1}(\bar{k})$ is the fourier transform of, $\rho j+1(\bar{x})$ and difference between the reconstruction and model using real space error defined as

$$Rreal=\frac{\sum_x\left|\rho_{recon}(x)-\rho_{model}(\bar{x})\right|}{\sum_x\left|\rho_{model}(\bar{x})\right|}$$

Where $\rho_{recon}(\bar{x})$ represents the final reconstruction by each algorithm.

IV. Experimental Results

The performance of proposed method is better than the already existing methods. The proposed method takes the distorted image and then crates the patches then apply the fourier transform to the patches. Then compare the distorted region with undistorted region which has the minimum error that patch has the estimated patch. The proposed method utilizes the fourier transform magnitudes to estimate the distorted regions in the image. But in the other conventional methods the missing areas are reconstructed with the help of raster scanning. In conventional methods there is a mismatch between the texture features because of raster scanning. The conventional methods are benchmarking and state of the art methods which directly use the intensity values within the patches, they are suitable for comparison with our method using fourier transform magnitudes as texture features.

Fig.2: Original Image

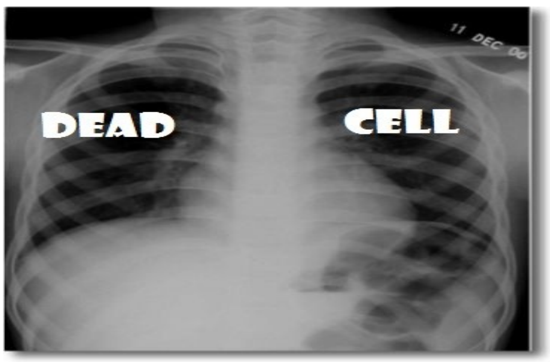

Fig.3: Distorted Image

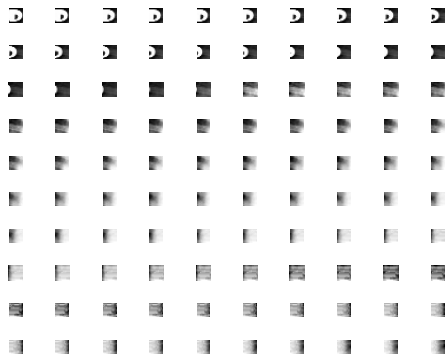

Fig.4: patches of the distorted region

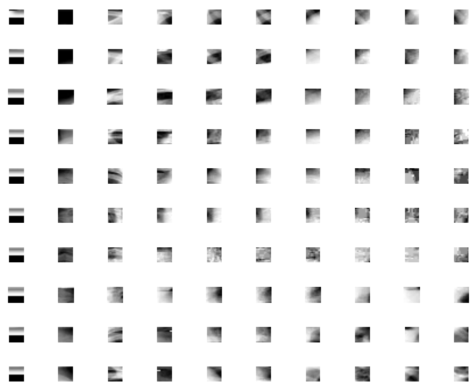

Fig.5: patches of the undistorted region

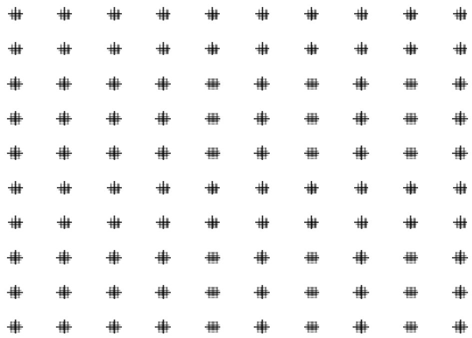

Fig.6: Fourier Transform Magnitude of the undistorted patches

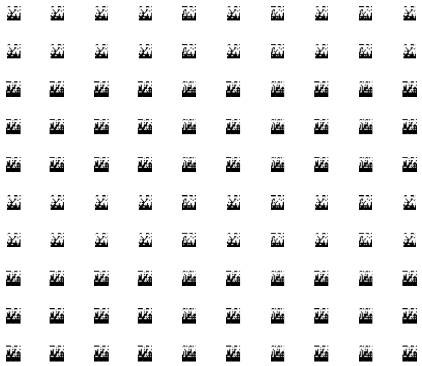

Fig.7: phases of the distorted patches

Fig. 8: reconstruction results

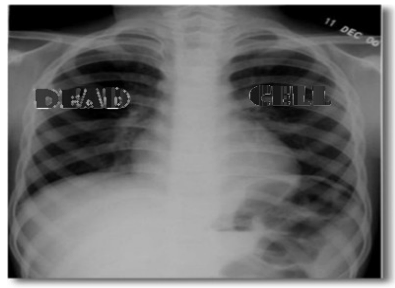

Fig.9: Reconstruction of the degraded image

Conclusion: The texture reconstruction based on error reduction algorithm using fft can be used here. This method utilizes fourier transform magnitudes as texture features and enables missing texture reconstruction by retrieving their phases based on the error reduction algorithm. In this we using the fourier transform magnitude estimation approach to reconstruct the textures and also minimize the errors with the help error reduction algorithm. This method can be estimated the accurate texture features and enables the reconstruction of missing areas.

V.References

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