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Texture Enhancement Using fractional Brownian Motion Evaluation Method


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ABSTRACT:

Single image super resolution has attracted attention in recent years. Moving to texture enhancement it is still an ongoing challenge, even though considerable progress was made in recent years. More effort is devoted to enhancement of regular textures, but stochastic textures that are in natural images are posing difficulty. The objective of this method is to restore lost image details while acquisition. Based on fractional brownian motion (FBM) a texture model is used. This model is global in entire image and does not entail using patches present in image.

The FBM is stochastic process with properties like self-similarity and long range dependencies between pixels. Self similarity is used to characterize a wide range of natural textures. This model based on FBM is evaluated and regularized super resolution algorithm with only one image as input is derived. A wide range of textures and images can be enhanced by applying this algorithm. An algorithm which increases the further performance is proposed by changing the parameters involved in diffusion process. Finally by the help of quality assessment parameters like Structural similarity Index Matrix, Peak Signal To Noise Ratio, Correlation Coefficient quality of image evaluated with reference to the input image.

KEYWORDS:

Stochastic Texture, Super resolution, Fractional Brownian Motion.

INTRODUCTION:

Super Resolution of natural images has conquered great advancement where as coming to textures it's an ongoing challenge. Specifically stochastic texture enhancement provides the opportunity to recover lost details during acquisition time[1]. Traditional approaches often yield cartoon like images and even quality may be compromised. So an approach using Fractional Brownian Motion (FBM) for characterizing stochastic textures is proposed in this paper. This has wide range of applicability in Satellite Imaging and many other applications. In satellite imaging for any object identification and classification the image must be of more clarity. By super resolution it can be made easy. Super resolution concept has significant scope in medical imaging and also in forensic analysis. For textured images, State- of- art methods like example- based super resolution[9], sample patch algorithm etc mainly emphasizes edges but do not restore other textural missing details.

A.Texture and its types :

Texture is an important cue in human visual perception, texture processing has become more important in computer graphics, computer graphics, computer vision and image processing. . A texture is a measure of the variation of the surface intensity, and quantifying properties such as density, regularity. Image texture is defined as the function of the spatial variation in pixel intensities (gray values). In image processing texture is a bunch of metrics calculated and designed to quantify the perceived texture of image.

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The spatial arrangement of colour or intensities in an image or selected region of an image is obtained by texture. Textures in general can be classified into two classes: Regular, or structured and stochastic[2]. The initial one is defined as spatially resembled parts of a single or several repetitive patterns. One example of regular texture is a brick wall. Stochastic textures don't contain a specific pattern and these textures are not modelled as same as regular textures. As conceptually and visually two textures are different enhancement techniques are also differed. Unlike regular textures, [3]stochastic textures are not characterized by repetitive patterns, instead defined by their statistical properties. This stochastic texture exhibits statistical properties such as non-local, long-range dependencies and self-similarity, as their pixel distribution remains the same across.Regular textures are enhanced by using methods of edge enhancement, in the stochastic texture such edges don't exist.

So by attempting to apply edge enhancement to such a texture , might in some cases create a stair casing effect, while smoothens out the clear details in the neighbourhood of the newly-created edge. Regular and stochastic texture enhancement is differed by a different approach called texture synthesis. Texture synthesis is a process where a patch is utilized to create a new image of bigger size and visually same as the original one. Even though such methods show similar results to the original visually, they are less effective in de convolution problems such as super resolution, in which the high resolution estimate has to represent the low resolution image. Further in case of stochastic textures such synthesis based on local-dependencies may fail to capture the every detail in the texture. Example based techniques combined with texture synthesis also exist for texture enhancement.

PROBLEM STATEMENT:

The theoretical framework and algorithms presented in this study are concerned with superresolution of fully textured images, wherein the texture incorporates both stochastic and structured elements. The superresolution paradigm considered here is the so-called single-image superresolution, where only one image is available as an input. Considering first the more challenging aspect of the granularity and non-stationarity of structures often encountered in natural textures, a stochastic texture model has been developed, based on fBm. PDE-based regularization has been introduced in order to capture anisotropic texture details, and a diffusion-based singleimage superresolution scheme was derived. As is the case in similar underdetermined problems, the emphasis is on side information, inherent in the underlying image model. The results obtained in our study, encourage the use of global fBm-based model (rather than patch-based) for natural textured images, as a method for reconstruction of degraded textures.

Drawbacks:

1)The empirical image, $Y\varphi(\eta1, \eta2)$, is initially derived from the degraded image, $Y(\eta1, \eta2)$. However, as the diffusion advances and the image is refined, it is beneficial to update $Y\varphi(\eta1, \eta2)$ as well. Due to the time consuming LS it entails, this is performed periodically after several iterations of the diffusion process.

2) The parameters of this algorithm are H, α, β and the number of diffusion iterations or stopping condition. H is estimated based on the degraded image itself . The other parameters have fixed values for all images. The diffusion process is completed when H(i), estimated in the ith iteration, is equal to H

PROBLEM DEFINITION:

The proposed model and concomitant algorithm are based on the empirical observation that stochastic textures are characterized by the property of self-similarity. An appropriate random process is estimated with reference to the existing lowresolution image. The initial restoration of missing details is based on an arbitrary realization of an fBm image. One may, therefore, expect different results for different evaluations. However, due to the phase matching and optimization, results for different random seeds yield almost identical results. In our current study, we attempt to remove the formal dependency on an initial arbitrary image, and obtain a model which depends on the fBm statistics.

The following form of the superresolution problem is considered: A high-resolution (HR) image is degraded by a blurring filter, representing, for example, the PSF of an optical sensor. It is subsequently subsampled.

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Noise is then additively mixed with the blurred and subsampled image to create the available low-resolution (LR) image. Let X(η1, η2) and Y (η1, η2) denote the original (HR) image and observed (LR) noisy image, respectively. The imaging model can be represented as follows:

$$Y(\eta_1, \eta_2) = D((X\ b)(\eta_1, \eta_2)) + N(\eta_1, \eta_2),$$

The proposed model has been exploited for solving the SR problem. It can also be used for other image enhancement problems, such as denoising or in-painting. This is a challenge in the case of textures, due to the overlap in the frequency range with that of the noise, and due to the lack of local, small-scale, smoothness.

It should be emphasized that existing denoising algorithms usually succeed in restoring edges and smooth segments, but not in the recovery of fine details. Preliminary results show that the fBm, used as a prior in MAP estimation, can effectively act as a regularizer which performs denoising on fBm-based images.

IMPLEMENTATION:

Anisotropic Diffusion:

A brief review of the anisotropic diffusion that will suffice for our application is provided. This diffusion, although commonly referred to anisotropic, is in fact non-linear but isotropic. This has been noted by Weickert, who introduced a truly anisotropic diffusion process, commonly referred to as tensor diffusion: This formulation allows for different types of diffusion to be performed in different orientations within the image. In edge enhancing diffusion, for instance, only the diffusion coefficient perpendicular to the edge orientation will assume a significant value.

This method further emphasizes edges while smoothing noisy image areas. Instead of a single diffusivity function,two functions are used - one for each eigenvalue.Using PDE-based methods allows for adaptive filtering of an image, with low computational complexity. The following PDE equation suitable for image processing was introduced in this context by Perona and Malik :

$$I_t = \nabla \cdot (g(\nabla I)\nabla I),$$

Texture-Based Tensor Diffusion:

One cannot expect to represent a natural texture using a single parameter. Instead of using a general function, we use a structure function generated from the degraded image itself. This yields an image which contains the details of the degraded image, along with correlations introduced according to the specific structure of the non-stationary field. We refer to the structure function derived from the degraded image as the empirical structure function (ESF). The method to recover the ESF from a given, degraded, image is based on an inverse procedure to the method of obtaining the image from the structure function. Using the ESF, it is possible to obtain an image,from the degraded image, by calculating the autocorrelation of the first- and second-order increments, solving the LS problem is to obtain a structure function and using the synthesis algorithm. The resulting image is referred to as the empirical image.The method to recover the ESF from a given, degraded, image is based on an inverse procedure to the method of obtaining the image from the structure function, devised in [36]. Let Y (η1, η2) be a degraded image. The increments in the x = η1 and y = η2 orientations are defined as:

$$Y_{\eta 1}(\eta_1,\eta_2)=Y(\eta_1,\eta_2)-Y(\eta_1-\eta_1, \eta_2),$$
$$Y_{\eta 2}(\eta_1,\eta_2)=Y(\eta_1,\eta_2)-Y(\eta_1,\eta_2-\eta_2).$$

To obtain the empirical structure function, it is therefore required to invert the equations, and produce φ(η1, η2), given the increment autocorrelation functions of Y (η1, η2).
Substitutingη1= η2 = 1, it follows that the 1D autocorrelation functions can be represented usingconvolution equations with derivative filters:
$$R_{\eta 1}(\eta_1, \eta_2) = (\varphi\ f_d)(\eta_1, \eta_2),$$
$$R_{\eta 2}(\eta_1, \eta_2) = (\varphi\ f^T_d)(\eta_1, \eta_2),$$

Tensor Diffusion:-

We now consider the modifications required to enable the tensor diffusion to perform superresolution on natural textures. This allows for the introduction of missing texture details, while still emphasizing the edges of a degraded texture image.

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We now consider the modifications required to enable the tensor diffusion to perform superresolution on natural textures. The tensor, D(I), introduced earlier, is set instead to be D((It + αYφ(η1, η2))), where Yφ(η1, η2) is the empirical image, and α is a weight parameter. This allows for the introduction of missing texture details, while still emphasizing the edges of a degraded texture image.The superresolution algorithm is presented by considering the following energy functional, in column-stacked image representation:

E(X, X) = (B X – Y) 2 + (Xˆ H P – HH P X) 2 + β(| X + αYφ| 2)dxdy

STRUCTURAL SIMILARITY BASED IMAGE QUALITY ASSESSMENT:

Natural image signals are highly structured: Their pixels exhibit strong dependencies, especially when they are spatially proximate, and these dependencies carry important information about the structure of the objects in the visual scene. The Minkowski error metric is based on point wise signal differences, which are independent of the underlying signal structure. Although most quality measures based on error sensitivity decompose image signals using linear transformations, these do not remove the strong dependencies, as discussed in the previous section. The motivation of our new approach is to find a more direct way to compare the structures of the reference and the distorted signals.

SSIM Index:

For image quality assessment, it is useful to apply the SSIM index locally rather than globally. The structure similarity index matrix (SSIM) is a method for measuring the similarity between two images. The SSIM index is a full reference metric in other words, the measuring of image quality based on an initial uncompressed or distortion free image as reference. It is designed to improve on traditional methods like peak signal to noise ratio whish have proven to be inconsistent with human eye perception. SSIM considers image degradation as perceived change in structural information which is the idea that the pixels have strong inter dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene. The SSIM index can be viewed as a quality measure of one of the images being compared, provided the other image is regarded as of perfect quality. It is an improved version of the universal image quality index proposed before. First, image statistical features are usually highly spatially non-stationary. Second, image distortions, which may or may not depend on the local image statistics, may also be space-variant. Third, at typical viewing distances, only a local area in the image can be perceived with high resolution by the human observer at one time instance And finally, localized quality measurement can provide a spatially varying quality map of the image, which delivers more information about the quality degradation of the image and may be useful in some applications.The PSNR block computes the peak signal to noise ratio between two images. This ratio is often used as a quality measurement between the original and a compressed image.The higher the PSNR, the better the quality of the compressed or reconstructed image.Image enhancement or improving the visual quality of a digital image can be subjective, saying that one method provides a better quality image. For this reason, it is necessary to establish quantitative / empirical measures to compare the effects of image enhancement algorithms on image quality. The higher the PSNR, the better degraded image and better, the reconstructed to match the original image and the better the reconstructed image. In general, a higher PSNR value should correlate to a higher quality image. However PSNR is a popular quality metric because its easy and fast to calculate.

Example-based super resolution:

Example based super resolution refers to learning LR/HR patch correspondence from known LR/HR image pairs in a database, which provides a good prior on the predicted HR patch for a given LR patch. This technique is not guaranteed to recover the actual high frequency details and may lead to 'hallucination'. Limitations of classical-SR can be overcome using example-based SR. In example based SR, correspondence between HR/LR patches is learned from a database of LR/HR image pairs. A new LR image can be resolved at higher scale by using the LR/HR correspondence learned. However, since enough patch repetitions occur across scales of an image, we can use different scales of the given input LR image to learn HR/LR patch correspondence without any external database.

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CONCLUSION:

In this paper Fractional Brownian Motion is applied to stochastic textures and natural images also. There by considering every detail of the image natural images can also be further enhanced effectively. The parameters involved in FBM are modified and there by the processing time is reduced and the number of iterations are reduced. So by this proposed super resolution algorithm performance can be increased. In the future work this method can be extended to anisotropic textures. Fractional Brownian Motion has been widely used as a model of image structure, it is in fact suitable for modelling natural textures, but it is not congrous with image structures comprised of the edges and contours. Future work is nonetheless encouraged for in an attempt expand the model to better model anisotropic textures also.

FUTHER SCOPE:

Further research is nonetheless called for in an attempt to expand the model to better model anisotropic textures as well, and to minimize thereby the need for regularization. Such a model may yield other enhancement algorithms suitable for a broader class of stochastic textures. Despite of the above goal, yet to be accomplished, the proposed PDE-based regularization is interesting and important on its own merits The empirical structure function is obtained via an ill-posed scheme, and better solutions for this problem may result in better understanding of textures and yield thereby better enhancement results.

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