BLIND DEBLURRING OF NATURAL STOCHASTIC TEXTURES USING AN ANISOTROPIC FRACTAL MODEL AND PHASE RETRIEVAL ALGORITHM

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ABSTRACT:

The challenging inverse problem of blind deblurring has been investigated thoroughly for natural images. Existing algorithms exploit edge-type structures, or similarity to smaller patches within the image, to estimate the correct blurring kernel. However, these methods do not perform well enough on natural stochastic textures (NST), which are mostly random and in general are not characterized by distinct edges and contours. In NST even small kernels cause severe degradation to images. Restoration poses therefore an outstanding challenge. In this work, we refine an existing method by implementing an anisotropic fractal model to estimate the blur kernel's power spectral density. The final kernel is then estimated via an adaptation of a phase retrieval algorithm, originally proposed for sparse signals. We further incorporate additional constraints that are specific to blur filters, to yield even better results. The latter are compared with results obtained by recently published blind deblurring methods.

1. INTRODUCTION

With the rapid development of the Internet and the popularization of various digital devices, the number of multimedia information in modern society is growing rapidly, which promotes the further prosperity of multimedia information management research. Image data retrieval and management system plays a particularly important role in the research of multimedia information management. Not only is the image the basis of video but also image database technology can be directly applied to many important fields, such as digital library, digital museum, medicine, geographic observation, petroleum geological exploration, public security, and clothing. Image is the main medium for people to communicate with each other and understand the world. It is not only the most intuitive form of important information expression but also the most difficult information content to obtain, transmit, process, realize, and store [1]. Research and statistics show that more than 70% of human information from the outside comes from image information, and the role of image information is difficult to be replaced by other information forms. Image technology covers a wide range and has a close relationship with mathematical physics students' physical psychology, electronics, and computer science. It is widely used in various fields such as scientific research, agricultural production, industrial production, military and national defense, aerospace, culture and entertainment, medical and health care, and traffic management [2]. With the advent of information society, the information people deal with is not only digital and symbolic information but also a large number of image information. Computer image processing technology is a new computer application field developed with the development of computer technology. It is a discipline gradually developed on the basis of achievements in image analysis and research. (is technology

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has been involved in all fields of people's life, study, and work. With the improvement of people's living and economic standards, they also have their own unique opinions on the pattern requirements in clothing. Using computer technology to identify clothing patterns, so as to improve clothing production efficiency to meet market demand, has become the current trend. In the process of clothing pattern generation, a certain database is designed to generate directly according to people's favorite needs. (erefore, the management and retrieval of clothing pattern database is the key [3]. (e traditional management of clothing images is in the form of documents. When users want to query a clothing image, they have to open the file one by one and browse manually to find the target image [4]. Although this manual retrieval method is still in use, with the rapid increase of the number of image files, this query method has been difficult to meet the retrieval requirements of large clothing image database. (e retrieval method based on keyword or descriptive text needs to specify the text features or keywords during query, which requires users to describe the text features with certain accuracy and standardization. (ere are two major problems in this method. One is that manual annotation of images needs to pay a lot of labor cost. Second, image manual annotation is subjective and imprecise, which cannot standardize and accurately describe the rich information contained in the image. Because there is no unified standard for image description, people have different understanding of image content. For example, there is no exact boundary between "big" and "big" of an object [5]. In addition, different language environments, different social conditions, and different nationalities will have different understanding of the same object, which will affect the consistency of image text description. With the passage of time, the things or concepts that people are interested in will also change. (e definition of text features of images in the early stage is difficult to adapt to various developments in the later stage. In order to improve the retrieval efficiency of clothing pattern database, a new clothing image database retrieval algorithm based on wavelet transform is designed in this paper. By collecting and preprocessing the data in the existing clothing pattern database, the wavelet transform method is introduced to design the retrieval scheme of the database and complete the retrieval of clothing image database. (e main technical route of this paper is as follows: Step 1: in Section 2, the process of image data acquisition in the clothing image database is carried out, where we characterize the color consistency vector of the clothing image, reflect the composition and distribution of the image color through the color histogram, quantify the visual features of the clothing image, aggregate them into a fixed size representation vector, and complete the clothing image data acquisition by using the FV model. Step 2: in the image data preprocessing in the clothing image database also carried out in Section 2, the size of the clothing image is adjusted by using the size transformation technology, and the clothing pattern is divided into four moments of the same size. On this basis, the clothing image is discretized with the help of Hu invariant moment to complete the clothing image data preprocessing. Step 3: progressing forward in Section 2, in the design of clothing image database retrieval algorithm based on wavelet transform, the generating function of wavelet transform is determined, and a cluster of functions is obtained through translation and expansion. (ewavelet filter is decomposed into basic modules, and then, the wavelet transform is studied step by step. (e clothing image data are regarded as a signal, split, predicted, and updated and input into the wavelet model. Complete the research of clothing image database retrieval. Step 4: experimental analysis is performed in Section 3. Step 5: conclusion is given in Section 4.

2. EXISTING SYSTEM:

We also compare our algorithm with state-of-the-art methods advanced by Michaeli and Irany , Levin et al. , Pan et al. and Xu et al. . The preferred method for evaluation and comparison of blur kernels consists of using the proposed method to find the blur kernel, and then using a single non-blind deblurring algorithm to test the kernel. In , the EPLL algorithm was used for non-blind deblurring. We find, however, that in textures the non-blind deconvolution method of (as used in) produces better results, both visually and in terms of objective metrics, in almost all cases. We, therefore, use the latter to compare the final results. It should be noted that in comparing with , the images were deblurred using existing software which yielded only the deblurred image, without having access to the estimated kernel.

3. LITURATURE SURVEY:

“Efficient Fractal Method for Texture Classification,”

This paper presents an alternative approach to classical box counting algorithm for fractal dimension estimation. Irrelevant data are eliminated from input sequences of the algorithm and a new fractal dimension, called efficient fractal dimension (EFD), which is based on the remaining sequences is calculated. The discriminating capacity and the time efficiency of EFD are evaluated in comparison with fractal dimension (FD) computed by box counting both theoretically and empirically. The results revealed that EFD is better than FD for texture identification and classification.

“Stochastic fractal models for image processing,”

Our study of fractal landscapes departs from the simplest but yet effective model of fractional Brownian motion and explores its two-dimensional (2-D) extensions. We focus on the ability to introduce anisotropy in this model, and we are also interested in considering its discrete-space counterparts. We then move towards other multifractional and multifractal models providing more degrees of freedom for fitting complex 2-D fields. We note that many of the models and processing are implemented in FracLab, a software MATLAB/Scilab toolbox for fractal processing of signals and images.

“Statistics of Natural Stochastic Textures and Their Application in Image Denoising,”

Natural stochastic textures (NSTs), characterized by their fine details, are prone to corruption by artifacts, introduced during the image acquisition process by the combined effect of blur and noise. While many successful algorithms exist for image restoration and enhancement, the restoration of natural textures and textured images based on suitable statistical models has yet to be further improved. We examine the statistical properties of NST using three image databases. We show that the Gaussian distribution is suitable for many NST, while other natural textures can be properly represented by a model that separates the image into two layers; one of these layers contains the structural elements of smooth areas and edges, while the other contains the statistically Gaussian textural details. Based on these statistical properties, an algorithm for the denoising of natural images containing NST is proposed, using patch-based fractional Brownian motion model and regularization by means of anisotropic diffusion. It is illustrated that this algorithm successfully recovers both missing textural details and structural attributes that characterize natural images. The algorithm is compared with classical as well as the state-of-the-art denoising algorithms.

“Fractional Brownian motions, fractional noises and applications,”

The basic feature of fBm’s is that the "span of interdependence" between their increments can be said to be infinite. By way of contrast, the study of random functions has been overwhelmingly devoted to sequences of independent random variables, to Markov processes, and to other random functions having the property that sufficiently distant samples of these functions are independent, or nearly so. Empirical studies of random chance phenomena often suggest, on the contrary, a strong interdependence between distant samples. One class of examples arose in economics. It is known that economic time series "typically" exhibit cycles of all orders of magnitude, the slowest cycles having periods of duration comparable to the total sample size. The sample spectra of such series show no sharp "pure period" but a spectral density with a sharp peak near frequencies close to the inverse of the sample size.

Mandelbrot, The fractal geometry of nature. Macmillan,

As technology has improved mathematically accurate, computer-drawn fractals have become more detailed. Early drawings were low-resolution black and white; later drawings were higher resolution and in color. Many examples were created by programmers working with Mandelbrot, primarily at IBM Research. These visualizations have added to persuasiveness of the books and their impact on the scientific community.

4. PROPOSED SYSTEM:

In order to provide a thorough benchmark testing of our algorithm, we provide also a comparison with Sun et al.'s natural image dataset . We use the results reported in and and perform our experiments according to the method reported in these papers. We observe (Fig. 17) that in natural image data, where there is ample edge information, the proposed algorithm is less effective. However, in NSTtype images, those are not dominated by edge structure, the advantages offered by our algorithm become most significant. We observe (Fig. 18) that, indeed, while the degraded images are blurred, the proposed algorithm yields better looking (sharper) images with restored textural content. We observe that state-of-the-art algorithms may not necessarily be suitable for texture processing. We further note that while the algorithm proposed by Michaeli and Irani , for instance, is considered to be better than Goldstein and Fattal's algorithm , in the case of textures, the latter performs better. Further, the non-blind deblurring algorithm of EPLL works better for images than the split-Bregman-based method of , but in textures, the latter, which is also much more efficient, produces better results.

ADVANTAGES:

- we show an anisotropic texture; here, our algorithm has an advantage due to the anisotropic texture model; while Goldstein and Fattal's result appears isotropic with edge type artifacts, our result appears more pleasing and similar to the ground truth.
- we observe a delicate texture that has been almost completely blurred. Nevertheless, our algorithm succeeds in reconstruction of detail, relative to the state-of-the-art algorithms by Levin at al. and Michaeli and Irani.
- In order to provide a thorough benchmark testing of our algorithm, we provide also a comparison with Sun et al.'s natural image dataset . We use the results reported in and and perform our experiments according to the method reported in these papers.
- We observe that in natural image data, where there is ample edge information, the proposed algorithm is less effective. However, in NSTtype images, those are not dominated by edge structure, the advantages offered by our algorithm become most significant.

DISADVANTAGES:

- Algorithms, is initiated several times with random support, due to the non-convexity of the phase retrieval problem.
- However, we find it suitable for our task since it provides a structured and optimization-based approach to signal retrieval.
- One of the disadvantages of this algorithm is its complexity, due to the use of the greedy local search method.
- However, since the blur kernels in our work are assumed to be of limited spatial support, we find the computational burden reasonable. The GESPAR algorithm is a general algorithm for phase retrieval of sparse signals. However, blur filters have other constraints not found in general signals.

5. MODULES:

BLIND DEBURRING :

Fractal texture models have been widely used in various inverse problems and enhancements applications . The basic fractal property of random signals is the selfsimilarity (or scale invariance), which indicates that a degraded fractal signal can be recovered from its lower scales. In a previous work, we proposed the fractional Brownian motion (fBm) as a suitable model for textured images. This model is Gaussian, and is therefore characterized by its second-order correlation and does not call for higher-order statistics that are required in the case of image features such as edges and contours. The equivalence of second-order statistics with the Fourier magnitude of a signal indicates that higher order statistics, whenever such exist, are encoded in the

Fourier phase of the signal, which complements the magnitude . In this work, we use the spectrum of fractal images for blind texture deblurring (blind deconvolution). The work relies on the knowledge that textures' inherent structure satisfies a known parametric power spectral density (PSD), or spectrum. Once this spectrum is estimated, a suitable inverse filter can be applied to a blurred image. The resulting image will have a PSD belonging only to the blur filter, inasmuch as the PSD content belonging to the texture has been whitened. Phase retrieval is then used to yield estimates of the blur filter, given its estimated PSD.

NATURAL STOCHASTIC TEXTURES:

We note that in , the L1/L2 ratio metric was used to select the best deblurred image. This metric reflects the sharpness of the deblurred image, under the assumption that the best image exhibits the sharpest edges. While this assumption is true for natural images, many stochastic textures do not contain sharp edges, and the existence of edges may be due to deblurring artifacts or incorrect kernel estimation. We, therefore, presented a supervised-learning-based method for prediction of the correct image, based on the SSIM metric. While this metric is not without flaws, it better represents textures as it takes into consideration the local statistics of images. In the case of natural images, objective metrics such as SSIM and PSNR may not necessarily correspond to visual assessment. This is in particular true in the case of natural textures. Visual assessment remains the preferred comparison method . However, to properly evaluate our method in many experiments we must resort to an objective metric. Throughout this section we mainly use the SSIM metric which we find to be more suitable for textures, but we also provide the PSNR values, as well as show the processed images for visual assessment. Due to the fact that textures are typically confined to segments of entire images, we perform experiments using images of size 256_256, a smaller dimension than is usually considered in blind-deblurring methods . Nevertheless, we observe satisfactory reconstruction results even in this moderate image size.

PREVIOUS STUDIES:

The purpose of this work is to deblur images blindly under arbitrary uniform blur, such as the blur that occurs with a handheld camera. This allows for a wide range of non-parametric blur kernels that occur under very limited constraints. The blur kernels considered in this work are uniform and do not vary spatially. There are studies which perform blind deblurring and assume a specific blur kernel (e.g. linear motion or Gaussian blur caused by a camera's point spread function) . The kernels found in these studies are parametric, for which estimation of a limited set of parameters is required. We, on the other hand, do not assume symmetry of any kind, such as symmetry that renders the blur filters to be zerophase. In deblurring images degraded by means of zero-phase blur filters, the phase information of the latent image can be estimated based on the degraded image . The most common approach to performing deconvolution is based on maximum a-posteriori (MAP) estimation of the latent image and the blur kernel, by iterative optimization . In the framework of this approach, prior models of the image.

ANISOTROPIC FRACTAL MODEL AND PARAMETER ESTIMATION:

In the fractal model, we assume that the textures are anisotropic and their PSD radial cross-sections obey a 1=f_(_)- type law, where _ (_) is a function of the angular spatial frequency. This is consistent with an anisotropic fractal model, in which the fractal behavior is allowed to change with the orientation, thus being suitable for anisotropic fractal surfaces. Estimation of the PSD is performed using angular projection of the image onto a certain orientation using the Radon transform that yields a 1D function. Then, its 1D spectrum, p (r), is estimated using a parametric function, mr□2H+1, to yield in turn the direction-dependent parameters m and H. This function corresponds to a fractional Gaussian noise (fGn) spectrum , the first order derivative of fBm. We find this model to be suitable in the case of 1D projections of NST. The two parameters are estimated from the blurred image(Appendix).

6. CONCLUSION

In order to solve the problems of low image data retrieval accuracy and slow retrieval speed in the existing image database retrieval algorithms, this paper designed a clothing image database retrieval algorithm based on wavelet transform. Moreover, the characterization of color consistency vector of clothing image is done, in which the color histogram reflects the composition and distribution of image color, which is aggregated into a fixed size representation vector, and the FV model is used to complete the collection of clothing image data. Furthermore, the size of clothing image is adjusted through the use of size transformation technology. In addition, with the aid of Hu invariant moment, the clothing image was discretized to complete the preprocessing of clothing image data. Determine the generating function of wavelet transform, decompose the wavelet filter into basic modules, and then study the wavelet transform step by step. (e clothing image data are regarded as a signal, split, predicted, and updated, input into the wavelet model, and complete the retrieval research of clothing image database. (e experimental results show that this method has certain retrieval advantages

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