

REVIEW OF EXEMPLAR BASED IMAGE INPAINTING USING STRUCTURE TENSOR

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ABSTRACT

Image inpainting is a new area of research in the field of image processing which has gained wide popularity because of its large number of applications. Image inpainting technique has been widely used for reconstructing damaged old photographs and removing unwanted objects from images. In this paper, we present a review of Exemplar based Image Inpainting using Structure tensor. Image Inpainting deals with filling in the missing pixels of an image by using the information from the surrounding pixels. This problem can be modeled as a tensor completion problem. The missing pixels can be estimated by using tensor completion algorithms. Since the structure tensor contains not only intensity information in a local area but also the predominant directions of the gradient in a specified neighborhood of one pixel and the degree to which these directions are coherent. This method is effective in removing large objects from an image, ensuring accurate propagation of linear structures.

Keywords: Exemplar Based Image Inpainting, Image Reconstruction, Structure Tensors, And Tensor Completion.

I. INTRODUCTION

Image inpainting is the art behind reconstructing damaged parts of an image in a visually undetectable way. Inpainting has been used by restoration artist to restore old photographs. The increase in computing power and digital media storage gave rise to sophisticated algorithms for recovering the lost or corrupt portions of an image. Inpainting is used in a primitive form in certain image editing software. They expect the user to specify the area to be inpainted and also specify the sample that has to be put in its place. Digital image inpainting requires the user to specify the area to be inpainted, but fills it automatically using the information available in the surrounding area of the same image. The inpainting problem is also addressed under disocclusion, object removal, image editing etc. The propagation of the information into the inpainted area determines the success of the algorithm. The geometric and the photometric propagation which is generally called as structure and texture propagation poses a major challenge to inpainting algorithms. The algorithms found in literature can be classified as PDE based, convolution based, texture based exemplar based super resolution based DWT based pyramid based and so on, But these algorithms can be broadly classified as diffusion based and exemplar (non diffusion based). The diffusion based algorithms are isotropic (PDE) and anisotropic like convolution. The first category of methods, known as diffusion-based inpainting, introduces

smoothness priors via parametric models or partial differential equations (PDEs) to propagate (or diffuse) local structures from the exterior to the interior of the hole. Many variants of PDE use different models (linear, nonlinear, isotropic, or anisotropic) to favor the propagation in particular directions or to take into account the curvature of the structure present in a local neighborhood. These methods are naturally well suited for completing straight lines, curves, and for inpainting small regions. They, in general, avoid having unconnected edges that are perceptually annoying. However, they are not well suited for recovering the texture of large areas, which they tend to blur. The second category of method exploits image statistical and self similarity priors. The statistics of image textures are assumed to be stationary (in the case of random textures) or homogeneous. The texture to be synthesized is learned from similar regions in a texture sample or from the known part of the image. Learning is done by sampling, and by copying or stitching together patches (called exemplar) taken from the known part of the image. The corresponding methods are known as exemplar-based techniques. In order to understand the algorithms we need to understand the terms used in image inpainting literature. The original image is described as I , the area that has to be inpainted is denoted as Ω , the border of this region and the known region also known as source region is indicated by ϕ . This is shown in Figure



Fig1. Notation Diagram

Given an image and a region Ω inside it, the inpainting problem consists in modifying the image values of the pixels in Ω so that this region does not stand out with respect to its surroundings. The purpose of inpainting is to restore damaged portions of an image (e.g., an old photograph where folds and scratches have left image gaps) or to remove unwanted elements present in the image (e.g., a microphone appearing in a film frame). See Fig. 1. The region Ω is always given by the user, so the localization of Ω is not part of the inpainting problem. Almost all inpainting algorithms treat Ω as a hard constraint, whereas some methods allow some relaxing of the boundaries of Ω .

II. INTRODUCTION TO TENSORS

Tensors are geometric objects that describe linear relations between vectors, scalars, and other tensors. Operations that can be carried out on tensors include the dot product, the cross product, and linear maps. A tensor can be represented as a multi-dimensional array of numerical values. The order of a tensor is the dimensionality of the array needed to represent it, or equivalently, the number of indices needed to label a component of that array. For example, a linear map can be represented by a matrix and therefore is a 2nd-order tensor. A vector can be represented as a 1-dimensional array and is a 1st-order tensor. Scalars are single

numbers and are thus 0th-order tensors. Just as a scalar is described by a single number, and a vector with respect to a given basis is described by an array of one dimension, any tensor with respect to a basis is described by a multidimensional array. The numbers in the array are known as the scalar components of the tensor or simply its components. They are denoted by indices giving their position in the array, as subscripts and superscripts, after the symbolic name of the tensor. The total number of indices required to uniquely select each component is equal to the dimension of the array, and is called the order, degree or rank of the tensor. For example, the entries of an order 2 tensor T would be denoted T_{ij} , T_i^j , T_j^i , or T^{ij} , where i and j are indices running from 1 to the dimension of the related vector space. Tensors are the higher-order generalization of vectors and matrices. They have many applications in the physical, imaging and information sciences. Tensor decompositions give a concise representation of the underlying structure. Tensor decompositions serve as useful tools for data summarization in numerous applications, including chemometrics, psychometrics and higher order statistics.

III. TENSORS IN IMAGE PROCESSING

Tensors are widely used in the field of image processing. A video sequence can be represented by a third order tensor with dimensionality of height width time; . Color images can be expressed as third order tensors. Image inpainting is filling in the missing regions of an image. Filling in the missing regions of an image can be considered as tensor completion problem. Tensor completion, has become a new research focus area and received considerable attention in recent years. It can be treated as a natural generalization of matrix completion. Tensor completion is a procedure for filling in missing entries of a partially known tensor under a low-rank constraint. The information about the tensor is modeled as the image of the underlying tensor under a known linear mapping. One example of such a map is the sampling of a subset of the entries of the tensor. This problem is called the tensor completion problem; it is a missing value estimation problem. In computer graphics missing value estimations problem are known as inpainting problems and appear for images, videos, etc. The methods used for tensor completion are divided into local and global approaches. A local approach takes information from neighboring pixels of a missing element and estimates locally the unknown values on basis of some difference measure between the adjacent entries. In comparison, the global approach takes advantage of a global property of the data.

IV. LITERATURE SURVEY

Exemplar Based Image Inpainting is presented in [1][2]. The exemplar-based texture synthesis is useful to preserve, propagate and extend linear image structure. Exemplar-based texture algorithm reconstructs the damaged part of an image by finding patches in the rest of the image which are similar to the known parts of the image patch to be filled, and then copying the missing information over. This algorithm maintains the image isophotes of the known parts of a target patch. Filling order is important and is related with image quality. The algorithm first estimates the priority term of all the pixels on the boundary. It then finds the border pixel with the largest priority and copies the missing information by finding a similar patch from the source regions. The algorithm estimates border pixel priorities. Given a patch centered at the point p , the algorithm defines its priority term for each boundary pixel p as:

$$P(\vec{p}) = C(\vec{p})D(\vec{p})$$

$$C(\vec{q}) = \frac{\sum_{\vec{q} \in \Psi_p \cap (I-\Omega)} C(\vec{q})}{|\Psi_p|}$$

$$D(\vec{p}) = \frac{|\nabla I_p^\perp \cdot \vec{n}_p|}{\alpha}$$

The term $C(p)$ is referred to as the "confidence" term, and determines how confident the algorithm is about a patch. This confidence value is designed such that it gives high confidence values to patches which are almost filled; as the exemplar based patch matching has a high chance of finding the correct patch. As the image progresses from the border of the region into the center areas of the region, the confidence will decay, reflecting that the algorithm is less sure about the center areas of the inpainting region than the areas close to the border. The term $D(p)$ is referred to as the "data" term, which models the amount of structure information that this patch contains, and how relevant is this structure to our patch. This term helps strong linear image structure to be inpainted first, thus not to be overridden by patches with less structure. The results from this algorithm are better than PDE methods, which result in inevitable blurring of the inpainted region, this method uses texture synthesis, and therefore preserves texture information. The algorithm is sensitive to image structure, and propagates along strong image isophotes to preserve and extend the structure.

Paper [3] [4] proposes a technique similar to that in [1] with a modification in priority function

$$P(p) = \alpha R_c(p) + \beta D(p), 0 \leq \alpha, \beta \leq 1$$

where α and β are respectively the component weights for the confidence and data terms. Also $\alpha + \beta = 1$ and $R_c(p)$ is the regularized confidence term

$$R_c(p) = (1 - \omega)C(p) + \omega, 0 \leq \omega \leq 1$$

where ω is regularizing factor for controlling the curve smoothness. Using this confidence term the value of the confidence term is regularized to $[\omega, 1]$. In this way the new priority function will be able to resist the "dropping effect". [5] This paper presents a robust method for exemplar-based image inpainting based on structure tensor. In Criminisi's algorithm, the filling priority is the product of the data term $D(p)$ and the confidence term $C(p)$, which helps the algorithm retain not only structure information but also texture information. The data term contains isophote structure information. The confidence term measures the reliable information around the pixel p to be inpainted. But the result is not satisfactory to unexpected noise and extreme values. linear structure information is completed first when the value of $D(p)$ is large, than texture information. However, when the patch centered at the pixel p has too few pixels of the source region, the corresponding data term becomes not reliable. The value of confidence term drops too fast to zero while the value of data term is quite steady. To overcome this problem structure tensor is used in calculation of the data term $D(p)$. Since the

structure tensor contains not only intensity information in a local area but also the predominant directions of the gradient in a specified neighborhood of one pixel and the degree to which these directions are coherent. Structure tensor, also named the second-moment matrix, is a reliable tool in image processing and computer vision. Structure tensor contains the information on orientation and magnitude of the image structures and the information which measures the homogeneity of orientations within the neighborhood of a pixel. It has been used in many application fields such as optical flow estimation, corner detection, and texture analysis. Evaluation of the efficiency of the image inpainting algorithm is generally done with PSNR and SSIM. Structure tensor is adopted in the priority function. Structure tensor contains the transformation direction of the image and the size of transformation along these directions. Therefore, a patch along a strong geometric structure has a higher inpainting priority and would be completed prior to other patches to preserve the linear structure. Additionally, as seen in our experiments, the weighted sum of the priority can achieve better results than other traditional exemplar-based inpainting model. Paper [6] has proposed a method where the first term, called the confidence, is the same as above. The second term, called the data term, is different. The definition of this term is based on the structure tensor, and is given by:

$$J = \sum_{i=1}^n \nabla I_i \nabla I_i^T$$

$$J_{\sigma} = J * G_{\sigma}$$

$$G_{\sigma} = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

J is the sum of the scalar structure tensors of each image channel I_i (R,G,B). The structure tensor gives information of magnitudes and orientation of structures of the image, as the gradient information. Structure tensor field is more advantageous than a gradient field as the tensor can be smoothed without cancellation effects. The Gaussian convolution of the structure tensor provides more coherent local vector geometry. This smoothing improves the robustness to noise and local orientation singularities. Another benefit of using a structure tensor is that a structure coherence indicator can be deduced from its Eigen values. Based on the discrepancy of the Eigen values, this kind of measure indicates the degree of anisotropy of a local region. The local vector geometry is computed from the structure tensor. The structure tensors are computed in a hierarchic manner whereas the template matching is based on a K-nearest neighbor algorithm. The value K is adaptively set in function of the local texture information. For finding the best patch with K-nearest neighbor approach statistical parameter like local variance is calculated. [7] The algorithm proposed in this paper is based on Criminisi's algorithm. The idea is to start from where the structure is the strongest and from patches containing the highest number of known pixels, $C(p)$. The priority is then expressed as $P(p) = D(p) * C(p)$. The second step consists in searching for the best candidate in the remaining known image in decreasing priority order. $D(p)$ of the inpainting method is replaced with a more robust structure tensor. This term is defined by partial differential equation (PDE) regularization methods on multi-valued images and provides a more coherent local vector orientation. The priority computation has been further improved by exploiting the depth information, first by defining a 3D tensor product, secondly by constraining the side from where to start inpainting. The 3D tensor

allows the diffusion of structure not only along color but also along depth information. It is critical to jointly favor color structure as well as geometric structure. The depth information is used to drive the filling order, while enforcing the structure diffusion from similar candidate-patches. By using patch prioritization, selection and combination, the completion of distant synthesized views allows a consistent and realistic rendering of virtual view points. [8] This paper presents an improved Exemplar based Structure tensor inpainting method based on the exemplar-based image inpainting technique by modifying the distance function. The method is effective in removing large objects from an image, by propagation along linear structures. This paper introduces a structure tensor in calculation of the data term $D(p)$. The structure tensor contains not only intensity information in a local area but also the strong directions of the gradient in a specified neighborhood of one pixel and the degree to which these directions are coherent. This paper modifies the distance function by a term G representing image gradient as an additional similarity metric. Where G is the gradient value for each pixel in the two considering patches. Hence, the similarity function now depends on the difference between the patches according to two criteria, the difference in color and in gradient values. The gradient of an image measures how it is changing. It provides two pieces of information. The magnitude of the gradient measures how quickly the image is changing while the direction of the gradient measures the direction in which the image is changing the highest.

V. CONCLUSION

Exemplar based Image Inpainting using Structure tensor introduces structure tensor in calculation of the data term $D(p)$. Structure tensor, also called the second-moment matrix, is a reliable tool in image processing and computer vision. Structure tensor contains the information of the image structures such as magnitude and direction. This measures the homogeneity of orientations within the neighborhood of a pixel. Structure tensor is adopted in the priority function. Therefore, a patch along a strong geometric structure has a higher inpainting priority and would be completed prior to other patches to preserve the linear structure. Evaluation of the efficiency of the image inpainting algorithm is generally done with PSNR and SSIM.

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