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A Combined Model for Image Inpainting

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Abstract: *This paper present a combined method for image inpainting. Inpainting is the art of modifying an image in a visually plausible manner so that it seems reasonable to the human eye. There are numerous and very different approaches to tackle the inpainting problem, these are based upon one the following basic techniques: copy-and-paste texture synthesis, geometric partial differential equations (PDEs), coherence among neighboring pixels, and exemplar based inpainting. We combine these techniques in a variational model, and provide a working algorithm for image inpainting trying to approximate the minimum of the proposed energy functional and its also helpful for video inpainting of stationary back ground by considering the temporal coherence among frames. So obviously say that the combination of all terms of the proposed energy works better than taking each term separately.*

Keywords: *Image inpainting, texture synthesis, partial differential equations (PDEs), coherence, variational models.*

I. Introduction

Inpainting is the process of modifying an image in a form that is not detectable by an ordinary observer, and has become a fundamental area of research in image processing. Image inpainting consists in recovering the missing or corrupted parts of an image. In the digital world, inpainting refers to the application of sophisticated algorithms to replace lost or corrupted parts of the image data (mainly small regions or to remove little defects). Reconstruction of missing or damaged portions of images or videos is an ancient practice used extensively in art work restoration. Inpainting is also known as retouching, this activity consists of filling in the missing areas or modifying the damaged ones in a non-detectable way by an observer not familiar with the original images. Applications of image inpainting range from restoration of photographs, films and paintings, to removal of occlusions, such as text, subtitles, stamps and publicity from images. There are many objectives and applications of video inpainting. In photography and cinema, inpainting is used for film restoration; to reverse the deterioration. It is also used for removing red-eye, the stamped date from photographs and removing objects to creative effect. This technique can be used to replace the lost blocks in the coding and transmission of images, for example, in a streaming video. It can also be used to remove logos in videos. In addition, inpainting can also be used to produce special effects.

Inpainting problem can be expressed in the following way: given an image or video u with a masked region Ω, fill-in each pixel inside Ω with a value taken from Ωc. Inpainting is the great practical importance of restoring and modifying images and videos, but is also a result of using image inpainting to understand the validity of different image models [2]. Image inpainting algorithms are used to perform the task of filling in missing or destroyed or unwanted regions in images.

In the paper [2], the texture is modeled that the probability distribution of brightness values for one pixel given the brightness values of its spatial neighborhood is independent from the rest of the image. The neighborhood is a square window around the pixel and its size is a global parameter of the algorithm. One-pass greedy algorithm is used in the texture synthesis. That is, once a pixel is filled-in, its value remains unchanged. The texture synthesis problem is used to finding the correspondence map [3]. Diffusion with partial differential equations (PDEs) and variational formulations, are used for piecewise smooth images or when the gap is thinner than the surrounding objects [4] [5]. This algorithm performs inpainting by joining with geodesic curves the points of the level lines arriving at the boundary. Geometric diffusion method does not appear to affect the result; it appeared preferable to work with the Laplacian diffusion. Coherence in the mapping function which clearly improves the visual quality of the synthesis result. Both spatial and temporal coherence for video inpainting are imposed through a variation formulation globally optimized. Coherence appears also in the inpainting formulation by favoring the similarity of the overlapping region of patches corresponding to neighboring pixels.

The inpainting technique has been generalized to video sequences with occluding objects. The reconstruction of motion fields has been proposed in the field of video completion. Several video inpainting methods are used to minimize the energy [6] [7]. In case of large holes with complicated texture, previously used methods are not suitable to obtain good results. Instead of reconstructing the frame itself by means of inpainting, the reconstruction of the motion field allows for the subsequent restoration of the corrupted region even in difficult cases. This type of motion field reconstruction is called “motion inpainting” [8]. The similar method is used to continue the central motion field to the edges of the image sequence, where the field is lost due to camera shaking.

II. Earlier Related Works

2.1 Texture Synthesis Method

The texture synthesis process grows a new image outward from an initial seed, one pixel at a time. In this algorithm “grows” texture, pixel by pixel, outwards from an initial seed. If choosing a single pixel as the unit of synthesis so that the model could capture as much high frequency information as possible [2]. To proceed with synthesis, a probability table for the distribution is needed.

Texture synthesis is an alternative way to create textures. Because synthetic textures can be made of any size, visual repetition is avoided. Texture synthesis can also produce tolerable images by properly handling the boundary conditions. Potential applications of texture synthesis are also broad; some examples are image denoising, occlusion fill-in, and compression. The problem of texture synthesis can be stated as follows: let us define texture as some visual pattern on an infinite 2-D plane which has a stationary distribution. Given a finitesample from some texture, the aim is to synthesize other samples from the same texture. Without additional assumptions this problem is clearly ill-posed since a given texture sample could have been drawn from an infinite number of different textures. The usual assumption is that the sample is large enough that it captures the stationary of the texture and that the scale of the texture elements is known.

2.1.1 The Algorithm

In this, texture is modeled as a Markov Random Field (MRF). That is, assuming that the probability distribution of brightness values for a pixel given the brightness values of its spatial neighborhood is independent from the rest of the image. The neighborhood of a pixel is modeled as a square window and it is around that pixel. The size of the window is a parameter that specifies how stochastic the user believes this texture to be.

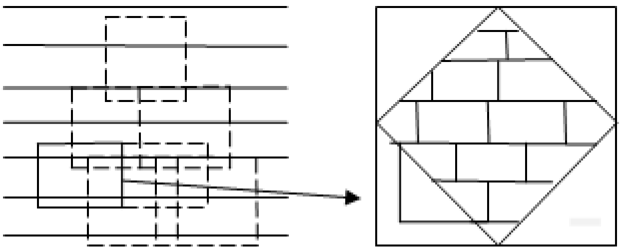

Fig 1: Efros and Leung’s algorithm overview

A sample texture image (left), a new image is being synthesized one pixel at a time (right).If the texture is presumed to be mainly regular at high spatial frequencies and mainly stochastic at low spatial frequencies, the size of the window should be on the scale of the biggest regular feature.

Synthesizing one pixel: A method of synthesizing a pixel when its neighborhood pixels are already known. This method can be used for synthesizing the single texture. The correct solution would be to consider the joint probability of all pixels together.

Synthesizing texture: A method of synthesizing a pixel when its neighborhood pixels are already known has been discussed earlier. Unfortunately, this method cannot be used for synthesizing the entire texture or even for hole-filling since for any pixel the values of only some of its neighborhood pixels will be known. The correct solution is to consider the joint probability of all pixels together but this is intractable for images of realistic size.

2.2 Geometric PDE

Diffusion with partial differential equations (PDEs) and variation formulations, which have been very successfully used, in particular for piecewise smooth images or when the gap is thinner than the surrounding objects [4] [5]. This algorithm performs inpainting by joining with geodesic curves the points of the level lines arriving at the boundary. Geometric diffusion method does not appear to affect the result, it is preferable to work with the Laplacian diffusion.

In the variational or "energy"-based models, nonlinear PDEs emerge as one derives formal Euler-Lagrange

equations or tries to locate local or global minima by the gradient descent method. Some PDEs can be used by the viscosity solution approach, while many others are used for additional theoretical investigation. Compared with other approaches, the variational PDE method has remarkable advantages in both theory and computation.

First, it allows one to directly handle and process visually important geometric features such as gradients, tangents, curvatures, and level sets. It can also effectively simulate several visually meaningful dynamic processes, such as linear and nonlinear diffusions and the information transport mechanism.

Second, in terms of computation, it can profoundly benefit from the existing wealth of literature on numerical analysis and computational PDEs. For example, various well-designed shock-capturing schemes in Computational Fluid.

Dynamics (CFD) can be conveniently adapted to edge computation in images.

Inpainting is an image interpolation problem, with broad applications in image processing and vision analysis. PDE-based image inpainting has become a very active area of research. The Total variation model for image inpainting is an effective method. But the interpolation of this model is limited to creating straight isophotes, not necessarily smoothly continued from the boundary and it does not always follow the Connectivity Principle. Some improvements have been made on it and use a fourth-order PDE method to inpaint missing data domain. In both smooth of inpainting and connectivity.

Image inpainting is first used to remove the crakes or patch the target region in image. A TV (total variation) inpainting model, introduced an euler's elastica curvature based inpainting model which can correctly propagate along curvature[7] . All above methods based on partial differential equation (PDE) which diffuses into the target region pixel by pixel. PDE diffuses according to image property, so linear structure is preserved well. But it smoothes image when diffuses, so if the target region is large, the result will be blurring. Exemplar-based model is used in texture synthesis[3]. It tries to replicate texture in image to fill the target region. This procedure can maintain all the tiny texture in image, while inpainting cannot implement this. The images processed by inpainting models lose texture. But exemplar-based model cannot preserve linear structure, so introduce an along isophotes exemplar-based inpainting model (AIEI) [10]. In this model, the crucial part is the filling priority which is determined by confidence term and data term.

2.3 Coherence

Coherence in the mapping function which obviously improves the visual quality of the synthesis results. Both spatial and temporal coherence for video inpainting are imposed through a variation formulation globally optimized. Coherence appears also in the inpainting formulation by favoring the comparison of the overlapping region of patches corresponding to neighboring pixels. Video inpainting aims at completing the corrupted areas of a video. For each frame, the reconstruction has to be spatially coherent with the rest of the image and temporally with respect to the reconstructions of adjacent frames.

There are many possible applications to the inpainting problem: movie post-production, product replacement, video stabilization, image restoration.

One of the techniques of texture or diffusion or coherence is used for inpainting of the images or videos. Energy function is not used and small patches are used for the mask and separate search engines database of images is used. The disadvantages of using each term separately is that,

- Diffusion methods are able to synthesize new information but they are not able to deal with texture.
- Texture patch-based methods treat texture correctly but are not good at creating new information. So thecombination of result is not produced.
- Energy function is not used to reduce the energy for Inpainting. So there is waste of energy during the process.
- With small patches, the algorithm is unable to inpaint correctly the blob of the images.

III. New Development: Combining Techniques

Combining the texture synthesis, coherence among neighboring pixels, exemplar based inpainting and geometric PDEs, image inpainting can be achieved that minimizes the energy functions. Inpainting is achieved by an iterative way. To generate a mapping function for the proposed system we adopt the scheme given by [1] that combine the three energy function d1,d2,and d3 of texture synthesis, coherence and geometric PDEs respectively.

So the energy function is

$$\boldsymbol{\varepsilon}(\boldsymbol{\psi}) = \alpha_1 \boldsymbol{\varepsilon}_1(\boldsymbol{\psi}) + \alpha_2 \boldsymbol{\varepsilon}_2(\boldsymbol{\psi}) + \alpha_3 \boldsymbol{\varepsilon}_3(\boldsymbol{\psi})$$

Where ψ is the correspondence map, α_1 , α_2 and α_3 represent weights, is $\varepsilon_1(\psi), \varepsilon_2(\psi)$ and $\varepsilon_3(\psi)$ are the energy corresponding to texture synthesis (self-similarity), propagation/diffusion with partial differential equation, and reinforces coherence.

In the reference paper[1] states that it would be easier to compute coherence terms and diffusion terms if whole image was already estimated. Therefore we perform an initialization step , where we inpainting image only using by pixel replacement. But for the following iteration it is not possible to apply exemplar based synthesis, because other two terms are based on pixel by pixel replacement at the same time. So there we use pruning technique inspired by label pruning[7]. We reduce the number of possible candidates for each pixel of after the initialization step has been performed. The number of candidates kept for each pixel is a fixed parameter set by the user. These candidates are simply the ones that had the highest similarity (smallest measure) to the pixel during the initialization step. In the sequel, we will denote C(P) as the pruning set (with N candidates) for the pixel .So the subsequent iterations are now much faster, and the visual quality does not deteriorate when N is high enough (higher than 200 in practice).

Improved Choice of the Weights and Practical Computation of the CorrespondenceMap: The final inpainting algorithm is an iterative method that at each iteration n and for each pixel p finds the best corresponding pixel
$\psi^n(p)$ by solving,

$$\psi^n(p)\ \epsilon\ \arg\min_{q\epsilon C(p)} \sum_{i=1,2,3} \alpha_i\, d_i(p, q, \psi^{n-1})$$

Let us discuss an improved choice of weights. The weights αi define the influence of each of the three terms on the result. They have to be defined depending upon the properties of each pixel of the image. For example, for a pixel situated in a textured area, the parameter α1should be larger than the two other ones, while if it ismlocated on a sharp contour, α2 should be the largest one. It is more difficult to interpret the influence of α3and its value will be given by a formula similar to the ones used for α1 and α2

$$\alpha_i(p) = e^{-\left(\frac{m_i}{\sigma}\right)}, i = 1,2,3$$

where

$$\sigma = \frac{m_1+m_2+m_3}{3}$$

$$m_i(\mathrm{p}) = \mathrm{q}\min_{i\epsilon\Omega c} d_i(\mathrm{p}, q_i, \psi)$$

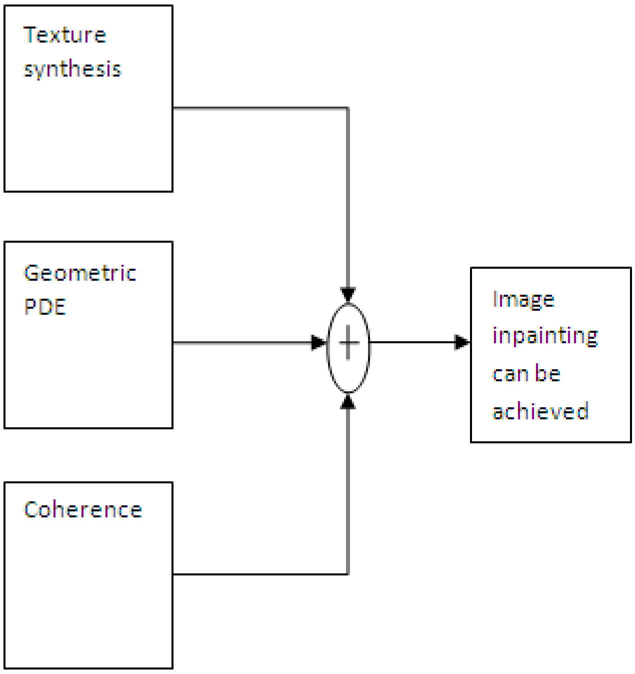

Fig 2: Block diagram for image inpainting

The algorithm must be applied to an image where there are no valid values inside the mask Ω: while this is standard procedure in texture synthesis for our diffusion and coherence terms it would be much easier to compute d3 if the whole image was already estimated. Therefore, we perform an initialization step where we fill-in using only the texture synthesis term. Searching for the best patch among all the patches of the image is extremely time consuming. Reducing the Computational Cost here we can use exemplar based texture synthesis. Because at initialization only texture synthesis is needed, then following iterations we go for combined energy functions, here also have to reduce the computational cost, we propose to use a method that we name pruning, inspired by the label pruning of [7]. We reduce the number of possible candidates for each pixel of Ω after the initialization step has been performed. The number of N candidates kept for each pixel is a fixed parameter set by the user. These candidates are simply the ones that had the highest similarity (smallest mea sure d1) to the pixel during the initialization step. In the sequel, we will denote as C(p) the pruning set (with N candidates) for the pixel P .

(a) input image. (b) inpainted image (c) output image.

Fig 3: Influence of the three terms.

IV. Conclusion

The three models or building blocks are common to all the most successful image and video inpainting algorithms. It is then combined into one energy functional. A working algorithm for image inpainting trying to approximate the minimum of the energy function and combination of different techniques inspired from label pruning, exemplar based patch synthesis to reduce computational cost are also provided and, thereby we can reduce the wastage of energy and time for execution . Literature shows that the combination of all three terms of the energy works better than taking each term separately. Performance analysis can only be done once it is implemented. When comparing other techniques, some papers are based upon all the three, but at most two, of the stated building blocks. When the image has not enough patches to copy from, either because the mask is too spread and the patch size is large, or because the mask is placed on a singular location on the image, then the results are reduced. This problem is common to all patch-based inpainting methods, and although the presence of a geometry term seems to help, it is clearly not enough. In this, trying to deal with these problems, as well as working on the speeding-up of the algorithm by optimizing the search in the patch space.

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