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New Similarity Measure for Exemplar Based in Painting

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Abstract: In this paper we intend to illustrate a utility and application of Kriging approximations in image processing problem designated by inpainting or filling in. We also review three state of the art infilling algorithms that deal with higher order PDE, Total Variation and exemplar-based approach. The computer model, a simple idea, we propose addresses this problem in deterministic way, and thus a response from a model lacks random error, i.e., repeated runs for the same input parameters gives the same response from the model. In its simple sense, Kriginng problem is related to the more general problem of predicting output from a computer model at untried inputs. Hence it lends it self for solving inpainting problem. Experimental results show that the proposed model yields qualitative results that are comparable to the existing complex approaches. The proposed method is very effective and simple to fill small gaps.

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I. INTRODUCTION

Very interesting and young area of research in the field of image processing is image inpainting, where the underlying goal is to reconstruct the missing regions within an image in such a way that it is visually plausible to an observer. In most cases, the missing region (called the target region) is filled in using information from the rest of the image (called the source region). Much of the traditional work in inpainting focused on filling in missing regions through the diffusion of local information [1, 2, 3, 4]. One of the main issues with such techniques is that it is restricted to using the information in the vicinity of target region.. Therefore, in many situations where the local information does not characterize the missing information, the resulting reconstructed information in the missing region will not be visually consistent with the rest of the image. Newer approaches have focused on the concept of exemplar-based synthesis [5, 6, 7]. In these techniques, a best match sample from the source region is found and copied directly into the target region. This approach yields decent results in situations where information of interest is not available locally but away from the target region. The main drawback is that the non-local information

is used in a very limited way. By using only the best match sample, the method runs the risk of choosing a sample that is corrupted, or not a perfect match. However, an image

with redundant content could have several samples that could be combined to form a more robust estimate of the missing

information. We will elaborate these methods in the next section.

The main contribution of this paper is, a novel approach, interpolation based inpainting using the concept of Kriging approximation. In this framework, the relative contribution of each sample pixel is determined for the reconstruction of a target pixel. This is accomplished by using a weighted similarity functions and their aggregation to form the missing information.

II. Formal Definition of the problem

The problem of image Inpainting can be loosely defined as follows: given an image I with missing regions (*e.g* see Figure 2), come out with an algorithm which fills the missing parts in such a way that a

visually plausible outcome is obtained at the end(Figure 3). Ideally, we would like any image inpainting algorithm, in addition to the afore mentioned structural aspects like boundary data and smoothness of the interior objects, to be able to handle related problem of texture synthesis as well. According to that problem, given a small texture as input, we are then asked to generate an arbitrarily large output texture, which maintains the visual characteristics of the input. It is exactly due to all of the above requirements that image completion is, in general, a very challenging problem. Nevertheless, it can be very useful in many areas, *e.g* it can be important for computer graphics applications, image editing, film post-production, image restoration, etc. It has thus attracted a considerable amount of research over the last years.

Figure 1 Figure 2

Figure3(inpainted image)

Roughly speaking, there have been three main approaches so far, for dealing with the image completion problem
• statistical-based methods,
• PDE-based methods,
•and exemplar-based methods.

Statistical-based methods: These methods are mainly used for the case of texture synthesis. Typically, what these methods do is that, given an input texture, they try to describe it by extracting some statistics
through the use of compact parametric statistical models. *E.g* Portilla and Simoncelli [1] use joint statistics of wavelet coefficients for that purpose, while Heeger and Bergen [2] make use of color histograms at multiple resolutions for the analysis of the textures. Then, in order to synthesize a new texture, these methods typically start with an output image containing pure noise, and keep perturbing that image until its statistics match the estimated statistics of the input texture. Besides the synthesis of still images,
parametric statistical models have been also proposed for the case of image sequences. *E.g* Soatto et al.[3] have proposed the so-called *dynamic texture* model. A parametric representation for image sequences had been previously presented by Szummer and Picard [4] as well.

PDE-based methods: These methods, on the other hand, try to fill the missing region of an image through a diffusion process, by smoothly propagating information from the boundary towards the interior of the missing region. According to these techniques, the diffusion process is simulated by solving a
partial differential equation (PDE), which is typically non-linear and of high order. This class of methods has been first introduced by Bertalmio et al. in [5], in which case the authors were trying to fill a hole in an image by propagating image Laplacians in the isophote direction. Their algorithm was trying to mimic the behavior of professional restorators in image restoration. In another case, the partial differential equations,
that have been employed for the image filling process, were related to the Navier-Stokes equations in fluid dynamics [6], while Ballester et al. [7] have derived their own partial differential equations by formulating the image completion problem in a variational framework. Furthermore, recently, Bertalmio et al. [8] have proposed to decompose an image into two components. The first component is representing structure and is filled by using a PDE based method, while the second component represents texture and is filled
by use of a texture synthesis method. Finally, Chan and Shen [9] have used an elastica based variational model for filling the missing part of an image. However, the main disadvantage of almost all PDE based methods is that they are mostly suitable for
image inpainting situations. This term usually refers to the case where the missing part of the image consists of thin, elongated regions. Furthermore, PDE-based methods implicitly assume that the content of the missing region is smooth and non-textured. For this reason, when these methods are applied to images where the missing regions are large and textured, they usually over-smooth the image and introduce
blurring artifacts. On the contrary, we would like our method to be able to handle images that contain possibly large missing parts. In addition to that, we would also like our method to be able to fill arbitrarily complex natural images, *i.e* images containing texture, structure or even a combination of both. We discuss this in the next topic.

Besides this, a general framework for combining of variational methods and wavelet analysis is developed by Julia A. Dobrosotskaya[10] . This frame work utilizes the variational formulation that allows us to build the properties of the inpainted image directly into the analytical machinery and exploits the efficient wavelet representation to capture and preserve sharp features in the image while it evolves in accordance with the variational laws.

Exemplar-based methods: Finally, the last class of methods consists of the so-called *exemplar-based* techniques, which actually have been the most successful techniques up to now. These methods try to fill the unknown region simply by copying content from the observed part of the image. Starting with the seminal work of Efros and Leung in [11], these methods have been mainly used for the purpose of texture synthesis.
Recently Jia *et al.* [12] have presented a technique for filling image regions based on a texture-segmentation step and a tensor-voting algorithm for the smooth linking of structures across holes. Their approach has a clear advantage in that it is designed to connect curved structures by the explicit

generation of subjective contours, over which textural structures are propagated. On the other hand, their algorithm requires (i) an expensive segmentation step, and (ii) a hard decision about what constitutes a boundary between two textures.

Finally, Zalesny *et al.* [13] describe an algorithm for the parallel synthesis of composite textures. They devise a special purpose solution for synthesizing the interface between two “knitted” textures.

Recent exemplar-based methods also place emphasis on the order by which the image synthesis proceeds, using a confidence map for this purpose [14]. However, two are the main handicaps of related existing techniques. First, the confidence map is computed based on heuristics and ad hoc principles, that may not apply in the general case, and second, once an observed patch has been assigned to a missing block of pixels, that block cannot change its assigned patch thereafter. This last fact reveals the greediness of these techniques, which may again lead to visual inconsistencies.

To over come these issues related to visual inconsistent results, fundamentally due to greedy patch assignments, Nikos Komodakis,[15] in their work, developed a discrete labeling problem with a well defined global objective function which corresponds to the energy of a discrete Markov Random Field (MRF). For efficiently optimizing this MRF, a novel optimization scheme, called Priority-BP, is proposed. Priority-BP carries two very important extensions over the standard Belief Propagation (BP) algorithm: “priority-based message scheduling” and “dynamic label

pruning”. To solve this problem, a novel optimization scheme, Priority-BP, is developed. This BP version carries two very important extensions over standard BP: priority-based message scheduling and dynamic label pruning. This optimization scheme does not rely on any image-specific prior knowledge and can thus be applied to all kinds of images. Furthermore, it is generic (*i.e* applicable to any MRF energy) and thus copes with main limitation of BP.

Implementation details.

In its own respect, DACE [16] offers us with a ‘surrogate computer model’ feature for any computer experiment. This endows us with Kriging approximation model for data from computer experiment. Here, a computer experiment is a collection of pairs of input and responses from runs of a computer model. Both the input and the response from the computer model are likely to be high dimensional.

In our problem, the input is an image.

Let the given image is of 2D denoted as

$I_{m \times n}$ with m * n total number of pixels. The pixel locations are represented as (x_i, y_i), what we call as design sites, for i=0 to m*n and pixel color or intensity value p_i at that location as response. It is imperative to assume that the mean and variance of the pixel values of the image satisfy the normalization conditions i.e. $\mu[p_i]=0$ and $V[p_i]=1$. Assume that, out of all m*n pixels, the response of only N pixels is known and response of M pixels is not known. It is trivial to observe that N+M=m*n.

Let S denote the set of all pixels for which the response is known. And let the set Y denote the corresponding responses.

The set of pixels for which the response is not known is denoted as Z. It is very simple to observe that Z stands for inpaint region (target region), and S acts as source region.

Then we shall extract the mask that encompasses pixel locations corresponding to pixel locations covered by the set Z. Let M denote the mask. In our implementation the contour(rectangle) of the target region is modeled as a pair of diagonally opposite image locations. In our experiment, these points are interactively selected by the user via a simple drawing interface. Now, our problem turns out to be, given N design sites we shall predict the responses at all M locations covered by Z. The first step towards the solution is about building the DACE model for the given N design site data. In fact, this task involves choosing appropriate correlation and regression model. In our experiment we opt to choose exp as correlation model.

Step 1: The actual DACE model is constructed by
[dmodel, perf] = ...
dacefit(S, Y, regr, corr, theta0, lob, upb).

In our implementation expg correlation model is used along with all possible three regression model parameters. Now let us understand the other parameters.

theta0 : If lob and upb are not present, then theta0 should hold the correlation function parameters, ɵ. Otherwise theta0 should hold initial guess on ϴ.

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lob,upb: Optional parameters. If present, then they should be vectors of the same
length as theta0 and should hold respectively lower and upper bounds on ϴ . If they are not present, then ϴ is given by the values in theta0.

dmodel: refers to the DACE model and
perf: gives Information about the optimization.

Step 2: Using the model from step 1 we predict the responses at new sites by calling

[y, dy, mse] = predictor(x, dmodel), where y refers to Predicted response, dy Optional result and mse is MSE.
Step 3: Reconstruct the approximated image.

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IV. RESULTS

Here we apply our algorithm to two images. The first experiment is on a gray level image and second one is on color image.

Result set I: On color Image

Figure 4: Input color Image

Figure 5: Mask

Input Image YX = predicted image

Figure 6: with 2

Input Image YX = predicted image

Figure 7 with 1

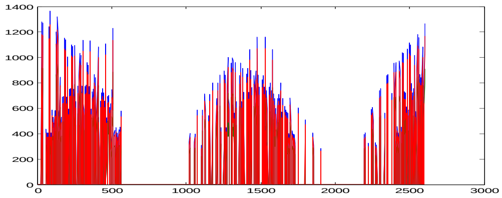


Figure 8

Result Set II: on gray Level Image

Figure 8:Gray Scale Image

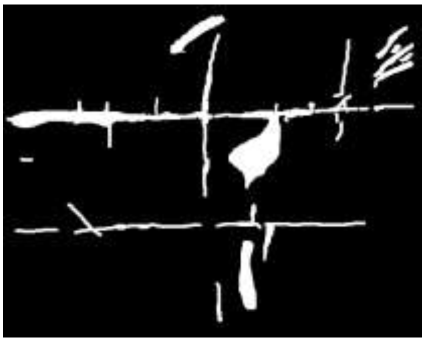
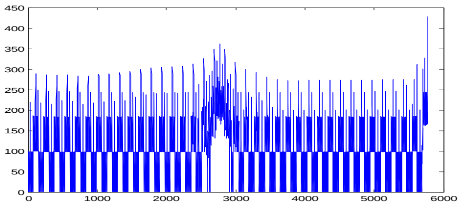


Figure 9: Mask

Figure 10

Predicted Image



Conclusion and Future work: This paper has presented a surrogate interpolation method for image inpinting with visually tolerable results. The computational time is substantially reduced. In our next attempt we are contemplating up on applying approximation tools and algorithms related to Banach Spaces.

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