A METHOD FOR EXEMPLAR BASED INPAINTING BY COMBINING
GRAPH BASED SEGMENTATION AND EXPECTATION
MAXIMIZATION ALGORITHM

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Abstract- Image inpainting is a process of restoring lost, damaged or selected portion of an image based on the neighboring information. The inpainted result should be such that, when viewed by any ordinary observer should feel a visually pleasing flow of data in and around the hole (selected region). Image Inpainting algorithm have a number of applications such as rebuilding of damaged photographs & films, removal of stamped date from photographs, removal of unwanted objects, red eye correction etc. This paper proposes a method for image inpainting using DEMA (Diffused Expectation Maximization Algorithm) and GBS (Graph Based Segmentation). Here an Exemplar-based in-painting algorithm is adopted, which iteratively search the neighboring region (source region) and fill the missing region (target region), with the most suited patches from the source region. Here the proposed method uses segmentation map along with diffused expectation maximization algorithm to improve the performance of inpainting. In Graph Based Segmentation method the spatial information in the source region is utilized. This method selects the parameter values of the robust priority function and thereby determines the most suited patch size and reduces the search region. The number of segments obtained from GBS is used in DEMA thereby we get a DEMA segmented image which is once again graph based segmented in order to get the parameter value of the DEMA segmented image. This parameter value along with the segmented image is passed through an exemplar based inpainting algorithm forming a better inpainted image. Certain parameters to evaluate the performance of the proposed algorithm is also done. Experimental results with a number of test images shows the effectiveness of the proposed method.

Index Terms- Diffused Expectation Maximization, Exemplar Based Inpainting, Garph Based Segmentation, Inpainting.

I. INTRODUCTION

Image inpainting is an art of restoring lost, deteriorated, broken or selected portion of an image utilizing the spatial information of the neighboring region, in such a way so that there should be a visually pleasing flow of data in and around the hole(target region). Image Inpainting is also known as modification or manipulation of an image. In image inpainting we would like to create an original image but this is completely unfeasible without the prior knowledge of the image. Inpainting technique has found a number of applications in many fields such as restoration of lost part of an image, object removal in digital photos, red eye correction, image coding and transmission, image compression and super resolution etc. With the tremendous increase in the use of the digitization of old photos, digital cameras, inpainting has become widespread technique. Nowadays, the image inpainting technology is a hotspot in computer graphics. Conventionally, inpainting is carried out by professional artist and is usually a time consuming process as each and every pixel is manually restored. In case of digital images we only have the image we are working on available to us and thus we are filling in a hole that encompasses an entire object and we know that, it is impossible to replace that entire object based on the present information. Therefore our aim is to create a visually pleasing continuation of the data around the hole in such a way that it is not detectable by an ordinary observer.

The term digital image inpainting was coined by Bertalmio et al.[1]. This paper is based on Partial Differential Equations (PDE), where it smoothens the complete isophote lines , arriving at the border of the inner region ,the two drawbacks related to this method are that they only perform well on small inpainting regions and they are not able to fill in texture [2]. Diffusion based Inpainting was the first digital Inpainting approach. In this method, the missing region is filled by diffusion of the image information from known region into the missing region at the pixel level. Basically these algorithms are based on theory of variational method and Partial Differential equation .The diffusion based Inpainting algorithm produces superb results or filling the non-textured or concentrates on smaller missing region. The main drawback of the diffusion process is that it introduces some blurriness, which becomes noticeable while filling larger regions. The PDE based in painting models are more suitable for filling small, non-textured target region. Instead of using a heuristic approach, Rothet al. propose an algorithm - called Fields of Experts (FoE) [3] which is based on probability theory. The authors use a model - which is trained on an image database - to describe the continuity of image. The underlying theory of the FoE algorithm is Bayesian inference, which makes it possible to calculate the prior of the image. The prior is the undamaged version of the input image and it is estimated with the observed (damaged) image. The prior is calculated with the usage of Markov Random Fields (MRF). The basic
II. PROPOSED METHOD

Initially a segmentation map M is constructed using an input image I[9]. On this input image the target region Ω is selected manually, it is the missing region or the region which is to be removed. The target region is filled by the information of the known region φ called the source region ie. the neighboring regions of the target region, ∂Ω be the boundary between the source and the target region called as decision boundary. Figure 2 shows the input image with target region, source region and the boundary.

The parameter values of the robust priority function is determined for this difference of Gaussian (DoG) is used. The target region and the number of segments found from graph based segmentation is used by the EMA to form a segmented image. This is followed by graph based segmentation to find the parameter value of the segmented image, which in turn is used by the robust exemplar inpainting algorithm to form inpainted image[10]. The proposed method computes the priority of the target patches using robust priority function and finds the best matching source patch using Criminisi algorithm [2]. In order to obtain a better efficiency, adaptive patch size selection and search region reduction is used. Fig: 1 shows the block diagram of the proposed inpainting.

A. Graph Based Segmentation

Graph-based image segmentation techniques generally represent the problem in terms of a graph $G = (V, E)$ where each node $v_i \in V$ corresponds a pixel in the image, and the edges in $E$ connect certain pairs of neighboring pixels[6]. A weight is associated with each edge based on some property of the pixels. Let $G = (V,E)$ be an undirected graph with vertices $v_i \in V$, which represents set of elements to be segmented, and $\text{edges}(v_i, v_j) \in E$ corresponding to pairs of neighboring vertices. Each edge $(v_i, v_j) \in E$ has a corresponding weight $w((v_i, v_j))$, which is a non-negative measure of the dissimilarity between

\begin{figure}
\centering
\includegraphics[width=0.5\textwidth]{image1.png}
\caption{Block diagram of the proposed Inpainting Algorithm}
\end{figure}

\begin{figure}
\centering
\includegraphics[width=0.5\textwidth]{image2.png}
\caption{shows the input image with target region, source region and the boundary.}
\end{figure}
neighboring elements $v_i$ and $v_j$. In the case of image segmentation, the elements in $V$ are pixels and the weight of an edge is some measure of the dissimilarity between the two pixels connected by that edge. In the graph-based approach, a segmentation $S$ is a partition of $V$ into components such that each component (or region) $C \in S$ corresponds to a connected component in a graph $G' = (V,E')$, where $E' \subseteq E$. In other words, any segmentation is induced by a subset of the edges in $E$. There are different ways to measure the quality of a segmentation but in general we want the elements in a component to be similar, and elements in different components to be dissimilar. This means that edges $\psi$ between two vertices in the same component should have relatively low weights, and edges between vertices in different components should have higher weights.

A segmentation map is a set of properly refined regions through iterative merging process. In each merging step, components of vertices $C_k$ and $C_{k+1}$ are merged into one segment if the difference between two components is smaller than internal difference of two components. [8] First, the segmentation algorithm is used to produce an initial segmentation map. Next, we merge segments in $T$ of the initial segmentation map into one segment and then assign a new label that indicates the target region. The segmentation map in the robust exemplar-based inpainting method performs two functions: as an indicator of $T$ and as selection criteria of patch size and candidate source regions.

**B. Parameter Selection Of Robust Priority Function**

Let $P(p)$ denotes the priority function which is a product of confidence term $C(p)$ and data term $D(p)$[2] where $p$ is the center pixel of a patch.

$$P(p) = C(p)D(p) \tag{1}$$

The confidence term $C(p)$ is expressed as

$$C(p) = \frac{\sum_{p' \in \psi} C(p')}{|\psi|} \tag{2}$$

Where represents the number of pixels in the patch and initial values of $C(p)$ are

$$C(p) = \begin{cases} \ 0 & \forall p \notin \psi \\ \ 1 & \forall p \in \psi \end{cases} \tag{3}$$

The confidence term is determined by the number of pixels that belong to $\psi$. The confidence term is determined by the number of pixels that belong to $\psi$. Using the priority function, we can determine the filling order of the target region, which is important to reconstruct structural information. The data term $D(p)$, which is defined as

$$D(p) = \frac{|\nabla p \cdot n_p|}{255} \tag{4}$$

A normalization value of 255 is chosen for 8-bit images. We compute directional similarity between the normal component of intensity gradient where the superscript $\perp$ represents the normal component, and normal vector $n_p$ at pixel $p$. Using the data term, linear structures are synthesized first. However, due to influence the dropping effect, structural information cannot be adequately assigned to the target region when the confidence is rapidly dropped. Cheng et al. proposed the robust priority function to avoid the dropping effect, which is defined as

$$R(p) = \alpha \cdot R_c(p) + \beta \cdot D(p), \quad 0 \leq \alpha, \beta \leq 1, \alpha + \beta = 1 \tag{5}$$

With the regularized confidence term $R_c(p)$ expressed as

$$R_c(p) = (1 - \omega) \cdot C(p) + \omega \tag{6}$$

where $\omega$ is set to 0.7 and fixed weighting parameters $\alpha$ and $\beta$ are manually selected by users in Cheng et al.’s algorithm[7]. However, the selection of $\alpha$ and $\beta$ in the inpainting algorithm shows visually varying results. Thus, selection of appropriate parameter values is one of the primary objective to obtain good inpainting results. The proposed method uses difference of Gaussian values to determine the weighting parameters where, DoG is not only robust against noise components but also can enhance edge and detail of images. The data term $D(p)$ in equation (5) has much influence in propagating structure components. For the accurate propagation of the structure components, we adaptively choose a coefficient $\beta$ of data term of the robust priority function according to the local image features. Thus, we set $\beta$ to the average values of the normalized absolute DoG values in each segment, where absolute DoG values are divided by the maximum absolute DoG value for normalization, and $\alpha$ is set to $1 - \beta$.

**C. Diffused Expectation Maximization Algorithm**

Diffused Expectation maximisation is an algorithm for image segmentation[9]. This method models an image as a finite mixture, in which each mixture component corresponds to a region class and uses a maximum likelihood approach to estimate the parameters of each class, via the expectation maximisation algorithm, coupled with anisotropic diffusion on classes, in order to account for the spatial dependencies among pixels. EM algorithm is an iterative optimization technique which is operated locally. Estimation step: for given parameter values we can compute the expected values of the latent variable. Maximization step: updates the parameters of our model based on the latent variable calculated using ML method.

**III. EM ALGORITHM FOR GMM**

Consider a Gaussian mixture model, our goal is to maximize the likelihood function with respect to the
parameters comprising the means and covariances of the components and the mixing coefficients.

1. Initialize the means, covariance and mixing coefficients, and evaluate the initial value of the log likelihood.

2. E step. Evaluate the responsibilities using the current parameter values.

   \[ \gamma_j(x) = \frac{n_i \cdot N(\mathbf{x} | \mu_i, \Sigma_i)}{\sum_{i=1}^{k} n_i \cdot N(\mathbf{x} | \mu_i, \Sigma_i)} \]  

(7)

3. M step. Re-estimate the parameters using the current responsibilities.

   \[ l_j = \frac{\sum_{i=1}^{k} \gamma_j(x_i) \mathbf{x}_i}{\sum_{i=1}^{k} \gamma_j(x_i)} \]  

(8)

\[ \Sigma_j = \frac{\sum_{i=1}^{k} \gamma_j(x_i) (\mathbf{x}_i - \mu_j)(\mathbf{x}_i - \mu_j)^T}{\sum_{i=1}^{k} \gamma_j(x_i)} \]  

(9)

\[ n_j = \frac{1}{N} \sum_{i=1}^{N} \gamma_j(x_i) \]  

(10)

4. Evaluate log likelihood

\[ \ln P(x | \mu, \Sigma) = \sum_{i=1}^{N} \ln \left( \sum_{i=1}^{k} n_i \cdot N(\mathbf{x}_i | \mu_i, \Sigma_i) \right) \]  

(11)

If there is no convergence return to step 2

D. GRAPH BASED SEGMENTATION

This step is same as that of the A, the only difference is that the GBS of the Expectation Maximized Segmented image is taken. The input to GBS is the segmented image from C and the target region. Once the graph based segmentation is done, selection of the weighting parameters of the robust priority function is carried out. The beta value obtained from this step is used in robust exemplar based inpainting to obtain a perfect inpainted image.

E. ROBUST EXEMPLAR BASED INPAINTING

Using segmentation map M, an input image I can be separated into several regions, which is expressed as

\[ \bigcup_{i=1}^{N} R_i = I \]  

(12)

number of segments. A chosen target patch \( p^* \) belongs to at least one segment \( R_i \). In the proposed method, we simply define selection rules for suitable patch size and candidate search region with segmentation result. First, the patch size is adaptively selected as follows. When the current patch is located on the segment boundaries, a default window size(9x9) is used. On the other hand, when the current patch belongs to a single segment \( R_i \), we increase the size of the patch while \( p^* \subset R_i \). In our experiments, we set the maximum window size of patches to 17x17 to achieve high quality results. Next, to prevent undesirable source patch selection, we restrict search region using adjacent segments. We assume that an image is grouped according to texture similarity, thus search area is restricted to adjacent neighboring regions. The proposed method searches corresponding candidate source regions that contain target region. With this approach, we can reduce the computation time and error propagation. We find pixel \( p^* \) with the maximum priority and thus the most similar source patch \( q^* \), where \( q^* \) is the center point of the patch. We search the candidate source region to find a patch with the minimum distance from the patch \( p^* \), i.e.,

\[ \psi_q = \arg \min_{\psi_q} d(\psi_p, \psi_q) \]  

(13)

Distance of \( (\psi_p, \psi_q) \) is defined as the sum of squared differences, which is expressed as

\[ d(\psi_p, \psi_q) = \sqrt{\frac{1}{N^p} \sum_{p \in N^p} (C_p - C_q)^2} \]  

(14)

where \( N^p \) is the number of pixels in a patch and \( C \) is the color vector and \( G \) is the image gradient vector. A target patch \( \psi = p^* \) is updated by a selected source patch \( \psi = q^* \).

\[ \psi_p(r) = \psi_q(s) \quad r \in C \quad \text{and} \quad C \subset \Omega \]  

\[ \psi_q(s) = \psi_q'(s) + \psi_q''(s) \]  

(15)

where \( r \) and \( s \) are pixels in the target patch and co-located pixel in the source patch, respectively. The proposed method updates whole pixels in the target patch \( p^* \), thus pixels in \( p^* \) that belong to source region and neighboring pixels in \( q^* \) are overlapped. We fill overlapped region with average of target and source pixels. Then, its confidence term and boundary \( \partial \Omega \) are updated. Following the region update rule, segment labels are introduced in the target segment. Therefore, we can infer the suitable patch size and candidate source region for the target region after a number of iterations. Propagation of segments affects the performance of the proposed algorithm because the proposed adaptive patch size and candidate selection rules depend on segments that belong to the target patch. However, segment information is not correct all the time. Incorrectly propagated segments cause error propagation. Thus, to reduce error propagation in the proposed method, we use a curve connection method in [10]. We link broken boundary lines along \( \partial \Omega \) to achieve perceptually good continuation.

III. EXPERIMENTAL RESULTS

Here the proposed method has been tested with various test images. Fig 3: shows the input image, here the target is the elephant shown in green, which is to be removed and has to be filled with the information from the neighboring region and the third one shows the segmentation map. Fig 4 shows the values of \( \beta \) with respect to different region of the image. Fig 5: shows the Expected Maximization segmented output. Fig 6 and 7 shows the confidence term and the data term during the initial stage of inpainting.Fig 8 shows the inpainted result. Fig 9:
A Method for Exemplar Based Inpainting by Combining Graph Based Segmentation and Expectation Maximization Algorithm

Fig 3: Original image, target region in green, segmentation map

Fig 4: Values of $\beta$ w.r.t different region

Fig 5: EM Segmented Image

Fig 6: Data term and Confidence term during initial stage of inpainting

Fig 7: Inpainted image

Fig 8: Inpainted output from [10]

Fig 9: Original image, target region in green, segmentation map

Fig 10: Values of $\beta$ w.r.t different region

Fig 11: EM Segmented Image

Fig 12: Data term confidence term during initial stage of inpainting
CONCLUSIONS

This paper combines the advantages of texture synthesis and structure synthesis, and proposes an exemplar based inpainting algorithm using region segmentation and expectation maximization algorithm to form an inpainted image. The structure and texture information are used to determine appropriate patch size and candidate source regions and to automatically select robust parameter values. With this approach we can reduce the number of iterations and error propagation caused by incorrect matching of source patch. From figure 8 and 9 it is clear that the output image obtained from the proposed algorithm is better compared to [11] visually.

REFERENCES

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