



A Method for Exemplar Based Inpainting By Combining Graph Based Segmentation and Diffused Expectation Maximization Algorithm

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ABSTRACT: Image inpainting is a method of restoring lost, deteriorated, damaged or selected portion of an image by making use of the neighboring information. Inpainting should be such that, the inpainted image when viewed by any casual observer should feel a visually pleasing continuous flow of data in and around the inpainted region. This paper proposes a method for image inpainting using DEMA (Diffused Expectation Maximization Algorithm) and GBS (Graph Based Segmentation) and compares it with the inpainting using GBS only. Here an Exemplar-based in-painting method 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. The proposed method uses graph based segmentation 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.

KEYWORDS: Diffused Expectation Maximization, Graph Based Segmentation, Exemplar Based Inpainting, Inpainting

I. INTRODUCTION

Image inpainting is an art of restoring lost, deteriorated 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). Here we use information from a single input image thereby filling in a hole that encompasses an entire object. It is impossible to replace that entire object based on the present information. Considering this as the aim of the inpainting algorithm, it not only fills the hole but also create a visually pleasing continuation of data in and around the hole in such a way that it is not detectable by a casual observer. Inpainting technique has found a number of applications such as restoration of old films, object removal in digital photos, red eye correction, super resolution, compression, image coding and transmission. With the tremendous increase in the use of digital cameras and the digitization of old photos, inpainting has become a widespread technique. Conventionally, inpainting is carried out by professional artist and is usually a time consuming process, as each and every pixel is manually reconstructed. Therefore our aim is to create a visually pleasing continuation of data around the hole in such a way that it is not detectable by an ordinary observer.



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

II. RELATED WORK

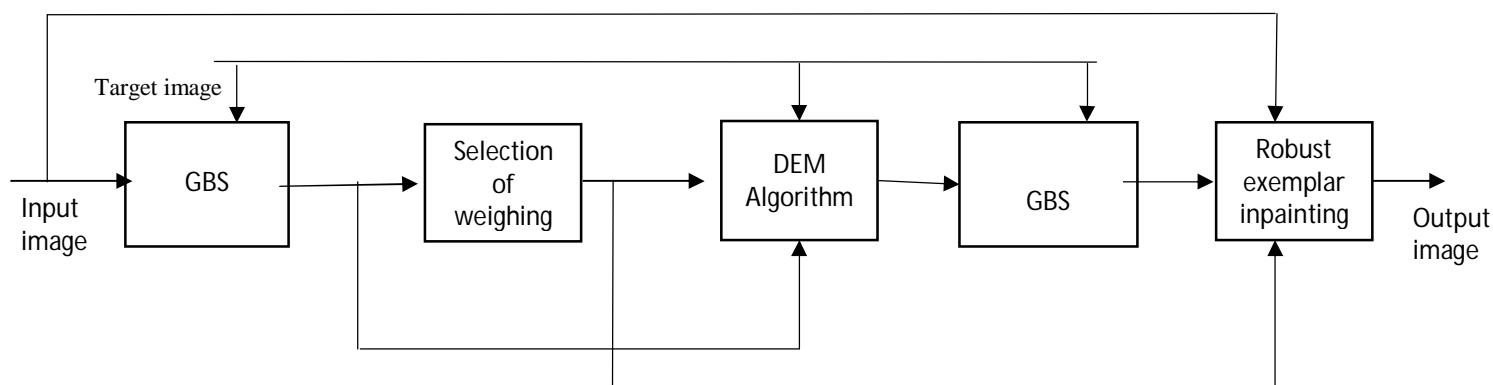
Diffusion based inpainting and Exemplar based inpainting are the two main methods used in inpainting. In case of diffusion based inpainting, which was the first digital Inpainting approach, where the missing region is filled by diffusing the image information from the known region into the missing region at the pixel level. These algorithms are based on theory of variational method and Partial Differential equation (PDE). The diffusion based Inpainting algorithm produces good results by filling the non-textured or relatively smaller missing region. The main disadvantages of the diffusion process is that it introduces some blur, which will be noticeable while filling larger regions. All the PDE based inpainting models are more suitable for completing small, non-textured target region. The second category of Inpainting is exemplar- based Inpainting algorithm. This method of Inpainting is an efficient approach in reconstructing large target regions. Exemplar-based Inpainting approach iteratively synthesizes the target region by most suited patch from the source region [1]. These algorithms also overcome the drawbacks of PDE based inpainting and removes smooth effect of the diffusion based Inpainting algorithm. Inpainting work as follows, In the first step of Inpainting method the user manually selects the portions of the image that need be restored or reconstructed. The image restoration is done automatically, by filling these regions with information from the surrounding pixels or from the whole image. The proposed algorithm for Inpainting uses the information from the surrounding portions of image to inpaint the selected region.

Now a days, exemplar-based algorithms have been proposed to use adaptive patch size in order to improve the quality of filling results. Zhou and Zheng proposed an adaptive-size patch based inpainting algorithm using gradient angle histogram [2], solved the optimization problem to determine the optimal size of each patch. Liu et al. proposed an adaptive inpainting method using local similarity and adaptive patch size [3], where it searched pre-selected source area to avoid incorrect matching and selected appropriate patch size using local similarity and gradient magnitude. Holtzman-Gazit and Yavneh proposed an adaptive inpainting algorithm using scale consistency measurement [4]. They tested several patch sizes to obtain a best matching result. Drori et al. proposed a fragment-based inpainting algorithm [5], where fragments as circular patches around target region are defined and the adaptive sizes reflecting structure components are computed.

In this paper we propose a method for image inpainting using Graph Based Segmentation (GBS) and Diffused Expectation Maximization Algorithm (DEAM). Here the segmentation map provides local texture similarity and dominant structure region and then we adaptively choose weighting parameter values of the robust priority function for each segment. With boundary information of a segmented image map, it determines the suitable patch size and selects candidate source regions for reducing unnatural artifact. Then a curve connection method is used [6] for visually plausible filling result. Dominant structures are filled using interpolated contours in the target region followed by parameter selection by robust priority function [7]. The proposed method improves robustness of inpainting results, which is influenced by priority functions. This paper is an extended version of [8] where DEMA (Diffused Expectation Maximization Algorithm) and GBS (Graph Based Segmentation) are combined thereby getting the advantages of those two methods. Detailed analysis, intermediate processes of the proposed method, and extensive experimental results are supplemented.

III. PROPOSED ALGORITHM

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 region which is to be removed. The target region is filled by using the information of the known region ϕ called the source region, $\partial\Omega$ 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.



Fig.2: shows the input image with target region, source region and the boundary

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 neighbouring 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 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 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. [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.

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

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.

$$P(p) = C(p)D(p) \quad (1)$$

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

$$C(P) = \frac{\sum_{q \in \psi_p \cap s} C(p)}{|\psi_p|} \quad (2)$$

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

$$C(P) = \begin{cases} 0 & \forall p \in \psi \\ 1 & \forall p \in \phi \end{cases} \quad (3)$$

The confidence term is determined by the number of pixels that belong to ϕ . The confidence term is determined by the number of pixels that belong to ψ . 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

$$D(p) = \frac{|\nabla I_p^\perp \cdot n_p|}{255} \quad (4)$$

A normalization value of 255 is chosen for 8-bit images. We compute directional similarity between the normal component of intensity gradient ∇I_p^\perp 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

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

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

$$R_c(p) = (1 - \omega) \cdot C(p) + \omega \quad (6)$$

where ω is set to 0.7 and fixed weighting parameters α and β are manually selected by users in Cheng et al.'s algorithm[7]. However, the selection of α and β 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 β of data term of the robust priority function according to the local image features. Thus, we set β 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 α 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. DEM 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.

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

DEM 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.

Estimation: repeat for t iterations until $|\log L^{(t+1)} - \log L^{(t)}| < 2$:

E-step: with fixed parameters $\alpha_k^{(t)}, \mu_k^{(t)}, \sigma_k^{(t)}$ compute the labelling probabilities at each site i as:

$$h_{ik}^{(t)} = \frac{\alpha_k^{(t)} p(f_i | k, \mu_k^{(t)}, \sigma_k^{(t)})}{\sum_k \alpha_k^{(t)} p(f_i | k, \mu_k^{(t)}, \sigma_k^{(t)})} \quad (7)$$

D-step: propagate h_{ik} by m iterations of the discrete form of anisotropic diffusion

$$h_{ik}^{(t+1)} = h_{ik}^{(t)} + \lambda \nabla \cdot (g(\nabla h_{ik}^{(t)}) \nabla h_{ik}^{(t)}) \quad (8)$$

and set $\tilde{h}_{ik}^{(t)} = h_{ik}^{(t+1)}$

M-step: with $\tilde{h}_{ik}^{(t)}$ fixed, calculate the parameters that maximize log L:

$$\alpha_k^{(t+1)} = \frac{1}{N} \sum_i \tilde{h}_{ik}^{(t)}, \mu_k^{(t+1)} = \frac{\sum_i \tilde{h}_{ik}^{(t)} f_i}{\sum_i \tilde{h}_{ik}^{(t)}}, \sigma_k^{(t+1)} \quad (9)$$

$$\frac{\sum_i \tilde{h}_{ik}^{(t)} [f_i - \mu_k^{(t)}]^2}{\sum_i \tilde{h}_{ik}^{(t)}}$$

and calculate $\log L^{(t+1)}$.

D. Graph Based Segmentation

This step is same as that of the A, the only difference is that the, here 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

$$\bigcup_{i=1}^N R_i = I \quad (10)$$

number of segments. A chosen target patch $\psi \hat{\mathbf{p}}$ 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(9×9) 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 $\psi \hat{\mathbf{p}} \subset \psi R_i$. In our experiments, we set the maximum window size of patches to 17×17 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 $\hat{\mathbf{p}}$ with the maximum priority and thus the most similar source patch $\psi \hat{\mathbf{q}}$, where $\hat{\mathbf{q}}$ is the center point of the patch. We search the candidate source region to find a patch with the minimum distance from the patch $\psi \hat{\mathbf{p}}$, i.e.,

$$\psi_q = \arg \min_{\psi_q \in S} d(\psi_p, \psi_q) \quad (11)$$

Distance $d(\psi \hat{\mathbf{p}}, \psi \hat{\mathbf{q}})$ is defined as the sum of squared differences, which is expressed as

$$d(\psi_p, \psi_q) = \sqrt{\frac{1}{N_p} \sum_i^{N_p} (||C_p - C_q||^2 + ||G_p - G_q||^2)} \quad (12)$$

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

where N_p is the number of pixels in a patch and \mathbf{C} is the color vector and \mathbf{G} is the image gradient vector. A target patch $\hat{\mathbf{p}}(r)$ is updated by a selected source patch $\hat{\mathbf{q}}(s)$.

$$\hat{\mathbf{p}}(r) = \hat{\mathbf{q}}(s), \forall r \in \psi_p \quad \text{T}$$

$$= \frac{\psi_p(r) + \psi_q(s)}{2}, \forall r \in \psi_p \quad \text{S} \quad (13)$$

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 $\hat{\mathbf{p}}$, thus pixels in $\hat{\mathbf{p}}$ that belong to source region and neighboring pixels in $\hat{\mathbf{q}}$ 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.

IV. SIMULATION RESULTS

Here the proposed method has been tested with various input 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 9 shows the EM segmented image Fig 14 Shows the confidence term, data term and the inpainting region. Fig 10 : shows the inpainted result.



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

Figure 4: shows the values of β with respect to different region of the image. Fig 5: shows the Expected Maximization segmented output.

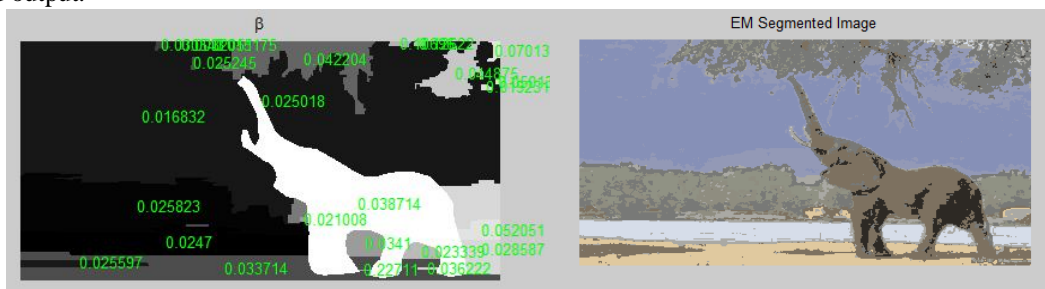


Fig 4: Values of β w.r.t different region

Fig 5: EM Segmented Image

Figure 6 shows the inpainted result. Figure 7: shows the output for paper [10]. From these two images it is clear that the inpainted image from the proposed method is better than the inpainted image from [10].

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015



Fig 6: Inpainted image



Fig.7: Inpainted output from [10]

Figure 8: shows the input image ,here the target is deer 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 8: Original image, target region in green, segmentation map

Figure 9: shows the DEM segmented image. Figure 10: shows the inpainted image

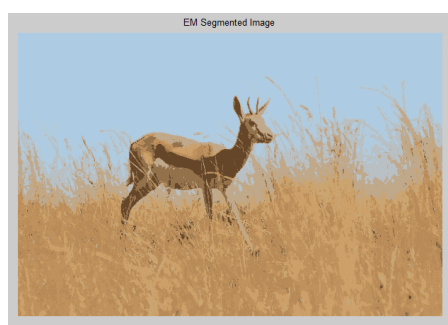


Fig 9:DEM Segmented Image



Fig 10:Inpainted output

V. PERFORMANCE EVALUATION

The performance evaluation is performed by calculating the following

Root Mean Square Error(RMSE)

The Root Mean Square Error (RMSE) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power. The RMSE of a model prediction with respect to the estimated variable X_{model} is defined as the square root of the mean squared error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{model,i})^2}{n}}$$

where X_{obs} is observed values and X_{model} is modelled values at time/place i



International Journal of Innovative Research in Computer and Communication Engineering

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Vol. 3, Issue 6, June 2015

Peak Signal to Noise Ratio (PSNR)

PSNR is the measure of peak error. It is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity. A higher value of PSNR is good because it means the signal to noise ratio is higher.

$$PSNR = 10 * \log_{10} \frac{(\text{Peak})^2}{MSE}$$

Structural Similarity (SSIM) Index

The structural similarity (SSIM) index is a method for measuring the similarity between two images. The difference with respect to other techniques mentioned previously such as MSE or PSNR is that these approaches estimate perceived errors; on the other hand, SSIM considers image degradation as perceived change in structural information. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene.

The SSIM metric is calculated on various windows of an image. The measure between two windows x and y of common size $N \times N$ is:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

The following table shows the performance evaluation corresponding to various input images.

GBS			GBS and DEMA			
Image	RMSE	PSNR	SSIM	RMSE	PSNR	SSIM
Elephant	4.15	28.35	.75	3.78	34.12	.86
Deer	5.45	26.12	.78	4.57	33.12	.90

From the table we could conclude that Exemplar based Inpainting Algorithm using Graph-based Segmentation and Diffused Expectation Maximized Algorithm is an efficient method of reconstructing lost and missing parts of an image

VI. CONCLUSIONS

This paper combines the advantages of texture synthesis and structure synthesis, and proposes an exemplar based inpainting algorithm using region segmentation and diffused 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 [10] visually. Experimental results and performance evaluation shows the effectiveness of the proposed method.

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ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 6, June 2015

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BIOGRAPHY

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