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A HYBRID METHOD FOR OCCLUSION REMOVAL

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ABSTRACT

This work aims at the study and implementation of occlusion removal by reconstructing contour by anisotropic diffusion, which would be reliable since structural details are retained as far as possible. First, segment the image into structure and texture image. The sparse technique is used for decomposition of the image and reconstruction of the structure image. Texture image is reconstructed based on anisotropic diffusion. Finally, the structure and texture image is recombined and we get an image where occlusion is filled. The results are found better since the patches selected are from the source region, and also regularization is carried out during diffusion.

KEY WORDS: Occlusion, Inpainting, Sparse representation, reconstruction, Anisotropic diffusion.

1. INTRODUCTION

If we look around the nature, there are many objects which are obstructing the other. Since some objects may be hidden under another object, by removing these objects, we would be able to get a visually good scene. Viewers should perceptually identify the occlusion to be removed. Thus occlusion is a barrier which disturbs our vision. In order to get a better perception and clarity, we get rid of these occlusions. Removal of occlusion means filling this barrier in the image. In other words, occlusion removal fills the gap left behind in the image while removing the occluded part. We can fill the occluded gap using many ways [1,2,3,4,10]. Occlusion may also be removed for improving the aesthetic beauty of an image. Since the occlusion to be removed is defined by the user, the reconstruction process is purely based on human intention.

Bertalmio et al. in [1] proposed an algorithm on the base of PDE. The region of occlusion is selected by user. It fills the gap left behind by using surrounding pixels. The fill is completed on the base of isophote line .The algorithm works only for structure inpainting not for large texture regions. If we apply PDE for texture regions, it introduces some blur easily.

A. Criminsi et al. [2] proposed an algorithm based on combining texture synthesis and inpainting together. Algorithm defines confidence term and data term. The algorithm finds the best confident value and based on the confident value, algorithm fills the gap left behind the occlusion region. Propagation takes through this confidence and data term.

Inspired by the work proposed by Bertalmio et al. [1], Chan and Shen proposed TV algorithm for inpainting. Total variational (TV) inpainting model works based on the Euler Lagrange equation. The proposed model makes use of anisotropic diffusion which is based on contrast of the isophotes. The Curve Driven Diffusion (CDD) model is an extended version of TV model. The CDD model takes geometric information of isophotes. Even though the CDD model was proposed for large occlusion regions, it did not give satisfying results. The method worked well for small regions.

Some authors have proposed algorithm for occlusion removal by combining texture synthesis and inpainting. Bertalmio et.al and A Crimnisi et al. decompose the input image into textural and structural images. The texture image is preprocessed with texture synthesis and structure image is preprocessed with inpainting. When these preprocessed images are combined, the inpainted result is obtained.

Efros and Leung [3] proposed an algorithm for texture synthesis. After removing the occlusion, the gap left behind is filled recursively. The gap is filled inwardly from the occlusion boundary. Initially, a point is selected from the boundary ‘p’ and is filled with the value of ‘Q’ from the source region. After filling ‘P’, next point is selected and the procedure is repeated for the whole occlusion region. Elad et al. [4] proposed an algorithm based on decomposing image into structure and texture. Both these images are inpainted separately. Tolga Tasdizen et al. [5] proposed an algorithm based on surface reconstruction using anisotropic diffusion. Surface reconstruction is calculated by minimizing the weighted sum of data discrepancy and model smoothness term. The normals are processed separately from the surface. It preserves the geometric features.

Joachim Weickert[6] proposed an algorithm based on combining compression and diffusion together. Compression makes loss of data. Diffusion smoothens the data and reduces the rate of broken contours and edges. The proposed algorithm makes use of diffusion tensor and edge enhancing diffusion. Gabriele Becattini et al. [7] proposed an algorithm based on Anisotropic Contour Completion. Here, Dilation using elliptical structuring element is performed which helps to complete the contours in very small objects.

Maximilan Baust et al. [8] proposed an algorithm based on diffusion regularization. Here they find a new paradigm for regularization. The paper conveys both implicit and explicit methods of regularization. Simon Masnou and Jean Michel Morel [9] proposed an algorithm based on level lines based dis-occulsion. The paper deals with recovery of hidden parts in an occluded area. Kanizas theory of “amodal completion” is applied here.
In a previous paper, the image is reconstruct the by reconstructing the lost structure details by sparse method [10]. In this work, both structure and texture are preprocessed and then combined. Texture is preprocessed using anisotropic diffusion.

2. PROPOSED METHOD

The aim of this work is occlusion removal and reconstruction of the image. An image mainly consists of two parts, structure and texture. We decompose the image into structure and texture by morphological component analysis (MCA) decomposition method. They are processed separately. Structure image is processed using sparse inpainting method. Texture image is processed using anisotropic diffusion. Anisotropic diffusion is an edge enhancing function. The output of the anisotropic diffusion is regularized using regularization method to get an improved texture result. Inpainting retains the lost structure in various iterations. Anisotropic diffusion and regularization reconstructs the lost contour. Further we will reconstruct by recombining the results. We are also applying Texture synthesis over the combined image.

2.1 SPARSE REPRESENTATION.

A signal or image is said to be sparse if it contains very small number of non-zero values. A signal could be sparse in all domains some may be sparser in frequency domain, some more in time domain or vice versa. Sparsity solutions are a recently emerging technique and are used for many applications. By compressed sensing technique only 30% of the signals samples are needed to reconstruct the complete image. It is a recent method for signal recovery in applied mathematics, which uses L1 optimization technique.

2.2 SPARSE SIGNALS

For images, we know that in order to make a sparse signal we need to project the corresponding image into its bases. From this we get n measurements. The base matrix is known as the dictionary matrix. It is the combination of identity matrix and any of the transform base matrices. If signal is more sparse in curvelet domain, then the curvelet bases are selected`. Dictionary matrix contains many column entries, and these entries are known as atoms. The number of atoms is usually same as that of rows. If the number of atoms is greater than that of rows then the system is an under determined. It then becomes an optimization problem to determine the non-zero entries. In order to get sparsest solution, we go for an l_1 optimization method. If a signal x is reconstructed on the base of this equation, $y = \phi x$, here ϕ is the dictionary matrix , x is the original signal and y is the n measurements. In order to reconstruct the image we use the relationship $x = y^T \phi$.

2.3. Image inpainting

We first decompose the image into two, namely the structure and texture images. Structure image is processed using sparse inpainting. The occluded region is selected by using region of interest (ROI). Segmenting this region, we are creating a mask, which is used for subtracting it from the original image. First of all we project the image into structure and texture, $x_t = T_t \alpha_t$, where α_t is a sparse.

Similarly we use another transform to project the image, containing only structure as , $x_n = T_n \alpha_n$ where α_n is sparse. Sparsity of l_0 norm finding is hard so we are going for l_1 norm.

A sparse representation using dictionary and l_1 norm will be $\{\alpha_t^{opt}, \alpha_n^{opt}\} = \arg\min_{\{\alpha_t, \alpha_n\}} \| \alpha_t \|_1 + \| \alpha_n \|_2$ subject to

$$x = T_t \alpha_t + T_n \alpha_n \qquad (1)$$

This equation will provide inpainting with decomposition. The mask indicates the occlusion region. The mask will find the occluded part. So value of 0 will indicate the occlusion.

$$\{\alpha_t^{opt}, \alpha_n^{opt}\} = \arg\min_{\{\alpha_t, \alpha_n\}} \| \alpha_t \|_1 + \| \alpha_n \|_1 + \lambda \| K(x - T_t \alpha_t - T_n \alpha_n) \|_2^2 + \gamma TV(T_n \alpha_n)$$

2.4. Anisotropic diffusion

To the texture image which largely consists of edges or repetitive patterns, anisotropic diffusion is applied. It contains more number of contours than the structure image. However, the anisotropic diffusion enhances the edges and also connects the broken edges, where as isotropic diffusion dilates the edges. From the texture image we obtain the broken edges, and from that region we extract the surface normals from the gradients. This enables us to complete the path of the contour. After finding these paths, we diffuse them from both ends and enable to connect them.

We now discuss about the contour completion where we have to connect the broken contours. The broken part is an empty region in the texture image .We need to reconstruct the empty part using anisotropic diffusion, as anisotropic diffusion takes place along the edges or closed contours. If it is not closed, then intensity is to be distributed along the contour and diffused along the direction of the tangent. We define a deformable surface based on the base of region ϕ. If $\phi > 0$ it is inside, else it is outside. We have an energy function,

$$F(\phi, o) = \int_{\Omega} G(x, D) H(\phi(x)) dx$$

The energy function is used for finding energy in the corresponding surfaces. Using this we need to obtain the broken part and reconstruct it. The surface reconstruction energy is described in the basis of two terms. They are D and ϕ . D is the function of the data and ϕ is the level set model.

G is the accurate line sight model and H is the Heaviside model. In order to obtain the broken part we use gradient information of each and every contour. From this we calculate the gradient of the contour and also the structure tensors. Structure tensor defines the maximum contrast difference in an image. For the calculation of structure tensor,

$$S = G_p * P(\nabla U_\sigma) = G_p * (\nabla U_\sigma \otimes \nabla U_\sigma) = G_p * (\nabla U_\sigma \nabla U_\sigma^T)$$

$$U_\sigma = \begin{bmatrix} I_x^2 \; I_x I_y \\ I_x I_y \; I_y^2 \end{bmatrix}$$

G_p is the center of Gaussian . U_σ is a tensor matrix. P is a implicit surface normal. We have a Gaussian and the solution of Gaussian by heat equation, and the structure tensor is the solution of the heat equation, and the extension properties are performed by structure tensor. Contour is regularized and extended by using diffusion method. Contour is completed by using extended diffusion through this path and its tangent position. The reason going for tangent is to obtain the direction of the vector field. Anisotropic diffusion elongates the edges only through their tangent direction, and since initial conditions remain at non-occluded area, it facilitates completion of the edges.

2.5. REGULARIZATION

Our aim is to complete the broken contours in an image. The diffusion process smoothen the contour in various directions. In order to orient diffusion process, we apply a diffusion tensor matrix onto the gradient of the image. To determine the diffusion tensor fully, we need to collect the diffusion weighted image at every position. The diffusion tensor matrix D is taken as,

$$D = \begin{bmatrix} D_{xx} \; D_{xy} \; D_{xz} \\ D_{yx} \; D_{yy} \; D_{yz} \\ D_{zx} \; D_{zy} \; D_{zz} \end{bmatrix}$$

This will be used for calculating the gradient direction by $G \bullet *[tensor\, matrix]$. Here the diffusion function is adapted to the local image structure. So the process is again directed anisotropic diffusion. Now we apply the regularization process which consists of two oriented 1D heat flows, leading to 1D Gaussian smoothing process along ortho-normal directions.

Regularization process makes more uniform contours in the occluded area thus making it more accurate. It typically works by applying a penalty for complexity like, adding the coefficient of the model into the minimization. Regularization technique flattens the image variations and remove the noise and also provides a restriction on smoothness. Non-linear PDE preserves large global features like corners and contours and their use within variational frame work. Generally image is regularized step by step and as continuous sequence of smoother images. The regularization PDE consists of nonlinear filter that changes the image a little by little and removes its variations. The anisotropic diffusion is separately applied on the gradient of the contour. After that there is some synthetic discontinuities that may occur due to the missing of corresponding vectors. The regularization diffusion is formulated as

$$\partial v_i / \partial t = \nabla.(D \nabla V_i) \;\; (i = 1........6) \;.$$

The diffusion tensor matrix D is a 3×3 symmetric, semi definite smoothing tensor which is determined according to the regularization characteristics. And it is smoothened along its Eigen direction.

3. TEXTURE SYNTHESIS

Efros et.al proposed an algorithm based on texture synthesis for occlusion removal. We use this approach as the last step in our proposed algorithm. Here the process filled in recursively inwards from the occlusion boundary. We have an image 'I' and specify a region 'Ω' as occlusion in that image. We need to fill the 'Ω' using the known pixel from the 'I'. The pixel moves from known region to unknown region. The occluded part does not contain any known data. After occlusion removal, the image looks more natural without any discoloration artifacts. In order to complete the large occlusion we copied entire patch instead of a single pixel. We are selecting the similar patches from outside occlusion area and assigned a patch. During the occlusion filling using patches, overlapping of patches may occur, and this can be minimized by using minimum error boundary cut. The popular method of texture synthesis is explained in [3]. We adopt the concept from [3]. The process needs large computation time. It is difficult to find an appropriate patch to fill the occlusion. The selection of the patch is dependent on resolution in [3]. In our method we select the patch for filling the occluded region from the source region. Here the filling of occluded region is based on finding best priority patch. The patch is always nearer to the source region. It also improves the computational efficiency of our algorithm. Patch size is proportional to whole size of image and image content, otherwise patch size becomes a problem during occlusion filling.

4. EXPERIMENTAL RESULT

The proposed method gives better inpainting and reconstruction of contour of the occluded bungee image and its mask. Figure.1 it illustrates the complete process, where the original image is decomposed into structure and texture images. After that we process with anisotropic diffusion of the texture image and sparse inpainting of the structure image.

Bungee jumper image and the mask indicating occlusion are shown in Figure 1. The bungee jumper image is widely used in large area image inpainting problem. Figure 2 illustrates the proposed method. The figure 2a shows the combined image of structure and texture. The image is more sharpen because the iteration in the anisotropic diffusion is more than 50. Figure 2.b shows the occlusion free image and the iteration is only about 50. Figure 3 shows various results based on other method. An example of real image reconstructed by our proposed method is also given in figure 4.

The proposed method is the combination of sparse inpainting, anisotropic diffusion and texture synthesis. This is applied in famous bungee jumper image for occlusion removal. We can notice a blur effect on the PDE method. The total variation method fails to reconstruct structure and texture image. In texture synthesis and Criminsi method, some artifacts are present in the occlusion removed region. In our proposed method, a very faint ghost image is present at the location of the occlusion.

(a) Original image b) Mask indicating by occlusion.

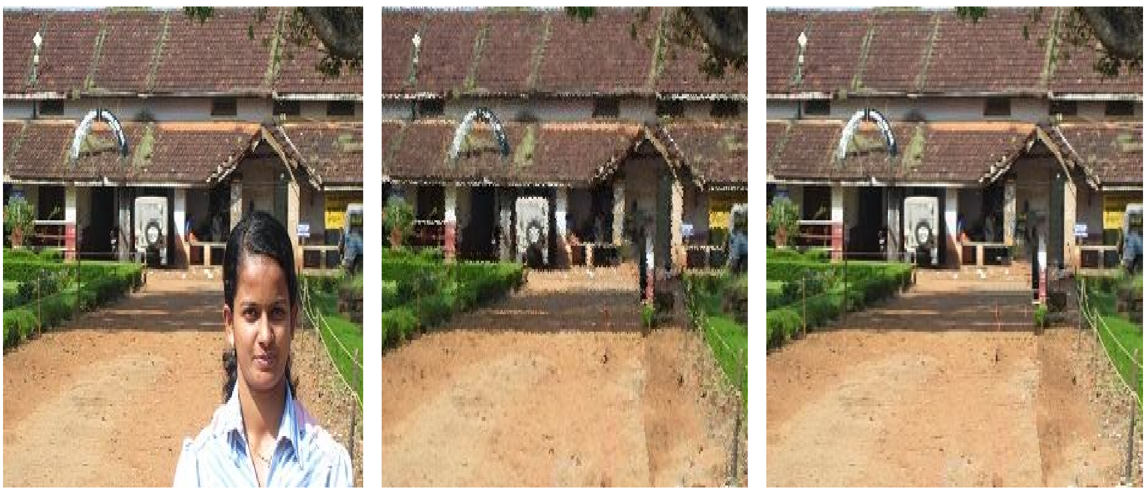
Figure1: Input Images

c)Structure and Texture image more than 50niterations d) Structure and Texture image with 50niterations

Figure 2: Proposed Method

e)PDE inpainting f) Criminsi[2] g) Texture Synthesis

Figure 3: Comparative Result of other methods.



h)Original image i) Structure and Texture image j) Structure and Texture image

Figure 4: Result of proposed method

Table.1.SUBJECTIVE EVALUATION CHART

Sl.No	Image1	Image2	Image3	Image4	Image5	Image6
1	E	E	VG	VG	VG	G
2	E	VG	VG	VG	VG	VG
3	E	VG	VG	G	G	VG
4	E	VG	E	G	G	VG
5	E	E	E	G	G	VG
6	E	G	E	G	G	VG
7	E	VG	E	VG	G	VG
8	E	VG	E	VG	G	VG
9	E	VG	E	VG	G	VG
10	E	VG	E	VG	G	VG
11	E	VG	E	VG	VG	VG
12	E	VG	E	VG	VG	VG
13	E	E	E	VG	VG	VG
14	E	E	VG	VG	VG	VG
15	E	VG	E	VG	VG	VG
16	E	VG	E	VG	VG	VG
17	E	VG	E	VG	VG	VG
18	E	VG	E	VG	VG	VG
19	E	VG	E	VG	VG	VG
20	E	VG	VG	VG	VG	G
21	E	VG	VG	VG	VG	G
22	VG	VG	VG	VG	VG	VG
23	VG	VG	VG	VG	VG	E
24	VG	VG	VG	G	VG	E
25	VG	VG	VG	VG	VG	E
26	VG	VG	VG	VG	VG	E
27	E	E	VG	VG	VG	E

Excellent (E) – 10 Very Good (VG) – 9 Good (G) - 8

Above graph is the representation of the subjective evaluation chart. The subjective evaluation chart contains the details about image and its quality as expressed by the subjects. We took 6 images and 27 subjects for the subjective evaluation using our proposed method. The individual results are given in Table.1 and a graph based on the table is shown in Figure.5.

GRAPH BASED ON SUBJECTIVE EVALUATION

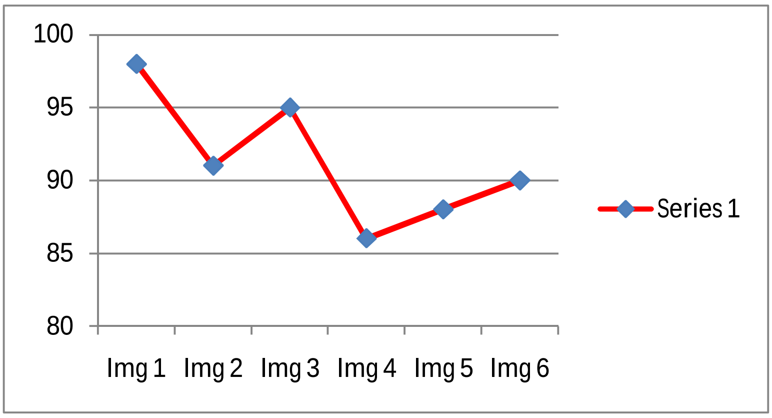


Figure.5. Subjective evaluation chart constructed (X axis- images, Y axes-scores).

4. CONCLUSION

By our experiments with the various methods and by our proposed method, we see that it works well for reconstructing contour in texture images and sparse reconstruction in structure images. The proposed method is similar to the previous work[10] and it decomposes the image into following two types; i.e., structure image is the apparent outlook of an image and texture is the repetitive patterns. The texture image is processed with anisotropic diffusion which supported by local gradient and surface normal information. From this the values are interpolated along the path generated. We then recombine the structure and texture together and reconstruct to produce an occlusion removed image, and visually better or compare with various previous inpainting results. A very faint ghost image boundary is the shortcoming of our method. However the results are visually better than previous methods. Our aim now is to extend the algorithm in videos for removing occlusions.

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