International Journal of Scientific Engineering and Research (IJSER)
www.ijser.in
ISSN (Online): 2347-3878
Volume 1 Issue 2, October 2013

Robust Exemplar based Object Removal in Video

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Abstract***: Image completion or image inpainting is the technique that automatically completes or restores removed areas in an image. Exemplar-based image inpainting technique can be used to remove objects from an image and fill the hole area with matching background content. This paper presents an exemplar-based video inpainting mechanism that restores the area of the removal object, and the mechanism can be further employed to extract the back ground of videos. Firstly, video is converted in to frames and object tracking in each frame using normalized cross correlation. Exemplar-based inpainting methods iteratively search the source region and fill the missing or damaged region, i.e., target region, with the most similar patch in the source region. With segmentation map, the proposed methods automatically select the parameter values for the robust priority function and reduce the search region.***

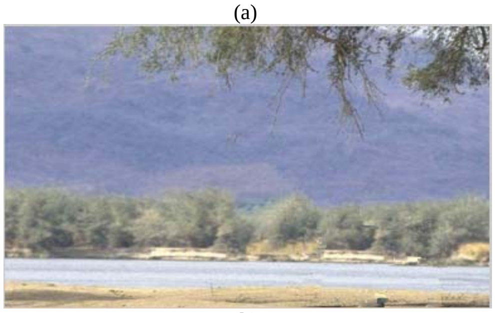
Keywords: 2D Normalized cross correlation; Exemplar-based inpainting; Segmentation map; Robust priority function

1. Introduction

Inpainting is mainly used for reconstructing lost or deteriorated parts in images and video. The term inpainting comes from art restoration, where it is also called retouching In photography and cinema, is used for film restoration, to reverse the deterioration, example cracks in photograph and scratches and dust spots in film. And it is also used for red eye correction, removing object to creative effect and removing stamped date from photographs. The technique can be used to replace the lost blocks in the coding and transmission of images.

Exemplar-based image inpainting is used for removing large objects from an image and fill that whole area with suitable background contents (shown in Figure 1). Image inpainting fills the missing or damaged region in an image utilizing spatial information of neighboring region. Exemplar-based inpainting iteratively synthesis the unknown region i.e target region, by most similar patch in the source region. According to the filling order, the method fills structures in the missing regions using gradient information of neighboring region. This method is an efficient approach to reconstructing large target regions. Exemplar based inpainting method, generally use a fixed patch size and search the whole region of the source region for matching neighborhood. But sometimes, the use of fixed patch size cannot give an efficient result; because exemplar based method assume that texture patterns in the source region are distinguishable with the appropriate patch size. If each patch size is not appropriate to fill the part of target region, texture and structure information cannot be assigned properly. For example, if the size of each patch is too large, structure can be incorrectly reconstructed. And also, if the patch is too small, it is too consuming to synthesize a large region that has similar texture patterns.

(a)



(b)

Figure 1: (a) Original image (b) The region corresponding to the foreground object in image has been manually selected and then automatically removed.

In this paper, we propose a robust video inpainting algorithm using region segmentation. First, video is converted in to number of frames and object tracking in each frame using normalized cross correlation. A segmentation map provides local texture similarity and dominant structure region. We adaptively choose weighting parameter values of the robust priority function for each segment. With boundary information of a segmented image map, the proposed method determines the suitable patch size and selects candidate source regions for reducing unnatural artefact. Dominant structures are filled using interpolated contours in the target region.

2. Related Work

Recently, several inpainting methods were proposed, in the case of image and video. Firstly, A.Criminisi [1] was proposed a method object removal in image by exemplar-based inpainting. Weiliang fan et al. [2] proposed a method a pixel missing patch inpainting method for remote sensing images. After that Somayeh Hesabi et al. [3] proposed a method for structure and texture image inpainting. Zhen Xie [4] proposed an adaptive matching algorithm for image inpainting. Seunghwan yoo and Rae-Hong Park[5] established a method for red-eye detection and correction using inpainting in digital photographs. And Lixin Yin et al.[6] introduced a method for an inpainting method for face images. K. Sangeetha et al. [7] proposed a method a novel

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www.ijser.in
ISSN (Online): 2347-3878
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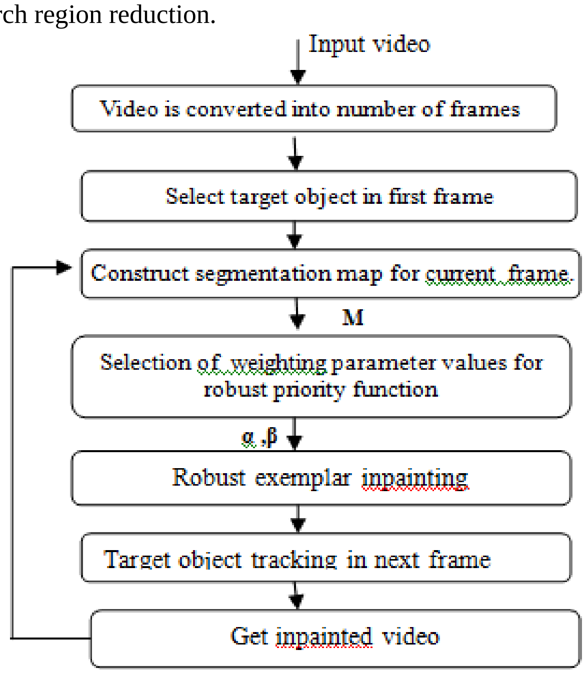
exemplar-based image inpainting algorithm for natural scene image completion with improved patch prioritizing. Timothy K. Shih *et al*.[8] proposed video motion interpolation for special effect applications. Aijuan Xia *et al*,[9] proposed exemplar-based object removal in video using GMM. The proposed method in this paper preserves dividing falsified video into several frames and the blind detection method based on zero-connectivity feature and fuzzy membership is applied to detect the forgery. This paper proposes the inpainting algorithm using region segmentation [10] is combined with a parameter selection method of the robust priority functions. The proposed method extended this exemplar-based inpainting method in the case of video.

3. Proposed Video Inpainting Method

Fig. 2 shows the block diagram of the proposed method. However, this makes more complications when a moving object is taken into consideration. When this technique is used for Video 'Object Detection' i.e. tracking of the interested object in each frame should be done. First, the proposed method convert video into number of frames and tracking objects in each frame using video motion detection algorithm.

Then, the proposed method constructs the segmentation map M in each frame, where target region T is manually selected. After that, determines parameter values of the robust priority function, it will largely affect the inpainting results. The difference of Gaussians (DoG) can be used for selecting appropriate parameter values. In the exemplar-based inpainting step, the proposed method computes the priority of target patches using Cheng et al.'s robust priority function and searches the best matching source patch using Criminisi et al.'s algorithm. For improving the efficiency of the proposed algorithm, we use adaptive patch size selection and search region reduction.



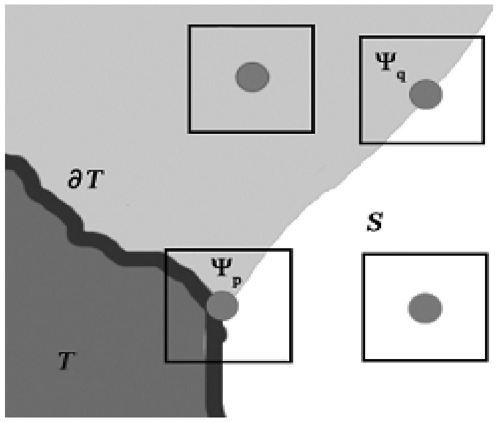


Figure 3: Notation diagram for exemplar based-inpainting [12]

Robust exemplar-based algorithm fills the target region T using patches in the source region S. First, the proposed method computes the priority of each target patch Ψp at the boundary ∂T of target region T and then searches the source patch $\Psi \hat{q}$ that is the most similar to the maximum priority patch $\Psi \hat{p}$. Here, Fig. 3 describes a notion diagram of an exemplar based inpainting, in which an image is divided into two regions S and T by boundary ∂T . To perform an efficient inpainting, the proposed method fills target region, T with adaptive source patches that have various sizes.

A. Target tracking

Firstly, video is converted into number of frames and apply inpainting technique for each frame. However, this makes more complications when a moving object is taken into consideration. When this technique is used for Video 'Object Detection' i.e. tracking of the interested object in each frame should be done user would always prefer marking selecting the object manually the object only one time. The algorithms should itself do the inpainting of the object in every frame of the video automatically. This can be done only by tracking the object in every frame starting from the first frame of selection. The object shall be detected in every frame thereafter and the position shall be tracked accordingly to further inpaint the area. Pattern matching and motion detection are the two techniques which shall be applied. The selected object shall be saved as template for tracking the same in the next frames. Motion detection shall be used to find the new position if the object is moved.

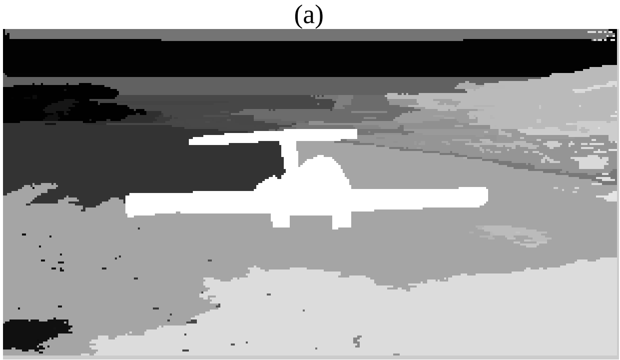
Implement pattern matching algorithm as follows:

- Reduce the size of image under test (IUT) and the target in order to ensure that the cross correlation is computed over lesser area thereby saving computation time.
- Calculate the normalized cross correlation in the frequency domain.
- Track the target based on the maximum correlation value.

B. Region Segmentation

We use a graph-based region segmentation algorithm [11]. An initial graph G = (V, E) is refined as a segmentation map M that provides significant structural information of I, where V represents initial vertex set and E denotes the corresponding set of edges. A segmentation map M is a set of properly refined regions through iterative merging process. In each merging step, components of vertices Ck and Ck+1 are merged into one segment if the difference between two components is smaller than internal difference of two components. 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.

(a)



(b)

Figure 4: Region segmentation result. (a) Original image. (b) Segmentation map of (a).

Figure. 3 shows examples of segmentation map M with an input image. Segmentation maps are labelled with gray-scale values [0, 255]. We update labels of an initial segmentation map to classify target region. We set the label of user-defined target region to 255 (white). Also, if there are source regions that have values of 255, we change the label to an unused gray-scale value. Figure 3(a) is an input image. Figure 3 (b) is final segmentation results of Figure 3(a), in which target regions have values of 255. Moreover, source regions are divided and represented as gray-scale values according to their local texture similarities.

C. Parameter selection of robust priority function

Criminisi et al. proposed the priority function P(p) that is defined as the product of confidence term C(p) and data term D(p) [1][13].

P (p) = C(p)D(p) (1)

where p is center pixel of a patch. P(p) can be rapidly decreased when the number of iterations increases due to dropping of the confidence term. The confidence term C(p) is expressed as

$$C(p) = \frac{\sum_{q \in \Psi p \cap S} C(q)}{|\Psi p|} \quad (2)$$

where $|\Psi p|$ represents the number of pixels in the patch and initial values of C(p) are defined as

$$C(p) = \begin{cases} 0 & \forall p \in T \\ 1 & \forall p \in S \end{cases} \quad (3)$$

The confidence is determined by the number of pixels that belong to S. It measures the amount of texture information of a target patch. After several iterations of the filling process, the confidence term induces the dropping effect because confidence values become close to zero. 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

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

is used to encourage the propagation of linear structure into the target region. A normalization value of 255 is chosen for 8-bit images. We compute directional similarity between the normal component of intensity gradient , $\nabla I_p^{\perp}$ where the superscript $\perp$ represents the normal component, and normal vector n_p at pixel p. With the data term, linear structures are synthesized first. However, due to 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

$$RP(p) = \alpha . Rc(p) + \beta . D(p), \quad 0 \le \alpha, \beta \le 1, \quad \alpha + \beta = 1 \quad (5)$$

with the regularized confidence term RC(p) expressed as

$$R_C(p) = (1 - \omega).C(p) + \omega \quad (6)$$

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www.ijser.in
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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 .However, according to the parameter setting of α and β, the inpainting algorithm shows visually varying results. Thus, selection of appropriate parameter values is one of the primary problems to obtain good inpainting results.

The proposed method uses DoG values to determine the weighting parameters. DoG is not only robust against noise components but also can enhance edge and detail of images. The data term D(p) in (5) has much influence in propagating structure components. For accurately propagating 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–β.

However, the use of parameter values does not guarantee that the same parameter values are applicable to other images. Thus, to obtain an appropriate inpainting result, we have to repeat the filling process with a large number of parameter value sets for each input image. Instead, we obtain good inpainting result with adaptive parameter selection.

D. Robust exemplar inpainting

Considering local texture similarity using a segmentation map, the proposed method fills efficiently the target region with patches in source regions. An image can be separated into several regions depending on texture similarity while dominant structures are identified as boundaries of adjacent segments. Using segmentation map M, an input image I can be separated into several regions, which is expressed as

$$I = \bigcup_{i=1}^{N} R_i \quad (7)$$

where R_i represents ith segment of I and N denotes the total number of segments. 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 neighbouring 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 $\hat{p}$ with the maximum priority and thus the most similar source patch , $\Psi\hat{q}$ where $\hat{q}$ is the center point of the patch. We search the candidate source region to find a patch with the minimum distance from the patch , $\Psi\hat{p}$ i.e.,

$$\Psi\hat{q} = \arg\min_{\Psi q \in s} d(\Psi\hat{p}, \Psi q) \quad (8)$$

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

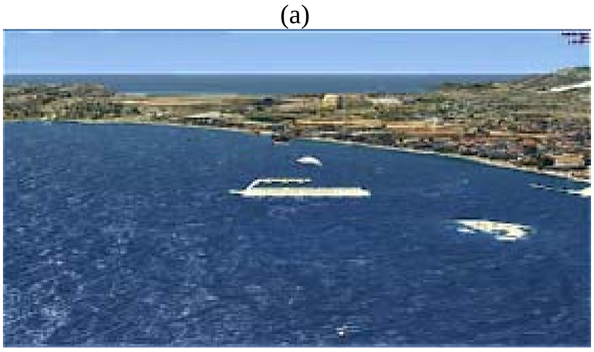
$$d(\Psi\hat{p}, \Psi q) = \sqrt{\frac{1}{N_p}\sum_{i}^{N_p}\left(\left\|C\hat{p}_i - Cq_i\right\|^2 + \left\|G\hat{p}_i - Gq_i\right\|^2 \right)} \quad (9)$$

where Np is the number of pixels in a patch and C is the color vector and G is the image gradient vector. A target patch $\Psi\hat{p}$ is updated by a selected source patch $\Psi\hat{q}$

$$\Psi\hat{p} = \begin{cases} \Psi\hat{q}(s), & \forall r \in \Psi\hat{p} \cap T \\ \dfrac{\Psi\hat{p}(r) + \Psi\hat{q}(s)}{2}, & \forall r \in \Psi\hat{p} \cap S \end{cases} \quad (10)$$

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 , $\Psi\hat{p}$ thus pixels in $\Psi\hat{p}$ that belong to source region and co-located pixels in $\Psi\hat{q}$ are overlapped. We fill overlapped region with the average of target and source pixels. Then, its confidence term and boundary ∂T are updated. A filling order is determined by the priority function. The data term is used to propagate linear structure. To show the robustness of the proposed method, we implement two priority functions that use each different data term. Criminisi et al.'s priority function uses direction of isophotes. Wu and Ruan proposed a priority function using variation of cross isophotes. In experiments, we test our proposed method with various test images. Figure 5 and Figure 6 shows the robustness of the proposed image inpainting method. Figure 5 shows the comparison of inpainting results by the proposed method and existing method.

(a)



(b)

(c)

Figure 5: Image inpainting result (a) Original image (b) result using [1] (c) Corresponding inpainting result of (a) Using our method.

We can apply this method to a variety of videos. Figure 6 shows the video inpainting result by the proposed method.

(a)

(b)

Figure 6: Video inapainting result. (a) Original video. (b) Video inpainting result of (a).

4. Conclusions

In this paper, we propose a robust exemplar-based inpainting method in video. Firstly, video is converted into number of frames and object tracking in each frame using normalized cross correlation. Then proposed method automatically select the parameter values of robust priority function and reduce the search region using segmentation map. The structure and texture information are used to determine candidate source regions. With this approach, we can reduce the number of iterations and error propagation caused by incorrect matching of source patch. Experimental results show the effectiveness of the proposed method with natural inpainting results.

5. Acknowledgment

Above all, I would like to thank God. Then I would like to begin by thanking Reeba R, my thesis supervisor and first person motivated me to work this subject.

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