

Image Inpainting Via Video Frames

Mr. Shailendra Kumane¹ Prof. Kanchan Doke²

^{1,2}Department of Computer Engineering

^{1,2}Bharati Vidyapeeth College of Engineering, Navi Mumbai

Abstract— Image inpainting technique is the process to reconstruct or filling-in missing or damage parts of image or video in a way that is undetectable to the casual observer. We have specifically address the problem of de fencing of image from fenced image or video as there are fences or barricades at public places due to various reasons like security, which hindered our capability to capture scene of interest. Our proposed approach consists of three steps; initially we will detect a fence using image matting approach. After detecting the fence we will determine the relative motion of pixel, in our approach we have exploit the fact that region invisible in one frame might be visible in other frame and we have model image to be inpainted or frame as Markov Random Field for efficient repainting. The last step in our approach is inpainting of missing (fence covered) region using primal dual total variation algorithm. In this paper we have provided brief overview of various task and techniques use for image inpainting.

Key words: Video Frames, Image Inpainting

I. INTRODUCTION

Image Inpainting technique is the process to reconstruct or filling in missing or damage parts of image or video in a way that is undetectable to the casual observer [1]. The process of inpainting can be viewed as an intelligent interpolation of adjacent pixels in the regions surrounding the areas to be recovered. It has been long problem for painting restoration it has gained importance in growth of digital photography market, since it allow users to remove disturbing element from their pictures or repairs damages such as visible dust on sensors of the camera or scratches in an old digitalize photograph [4].

Tourists and amateur photographers are often face problems in capturing their images or videos by a fence or occlusion that limits accessibility to the scene of interest [3]. It would be so much nice if a post-processing tool existed that can efficiently get rid of fences in the input image or video of occlusion artifacts. Reconstruction of missing parts or scratches of digital images is an important field used extensively in artwork restoration. Removing or repairing the imperfections of a digital images or videos is a very active and attractive field of research belonging to the image inpainting technique. Image inpainting has a wide range of applications, such as removing scratches in old photographic image, removing text and logos or creating cartoon and artistic effects [1].

Natural images are composed of structures and texture [5]. The structures constitute primal sketches on image like edges, corner etc. The textures are image region with homogenous patterns or feature statistics including flat patterns. The image restoration is mainly done by filling missing regions with the new information coming from surrounding pixels. In order to product image in perceptually plausible manner, an inpainting technique must attempt to continue the isophotes as smoothly as possible inside the missing regions [1][5]. The isophotes are line of

equal grey value. The contextual constraints are necessary in the interpretation of visual information. A scene in image is in spatial and visual context of the object in it. The objects are recognized in the context of object features at low level representation. The object features are identified based on the context of primitives at even lower level and primitives are extracted in the context of image pixels.

The most fundamental inpainting approach is the diffusion based approach, in which 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 well founded on the theory of partial differential equation (PDE) and variational method. The second category of approaches is the exemplar-based inpainting algorithm. This approach propagates the image information from the known region into the missing region at the patch level. Most inpainting methods work as follows. As a first step the user manually selects the portions of the image that will be restored. This is usually done as a separate step and involves the use of other image processing tools. Then image restoration is done automatically, by filling these regions in with new information coming from the surrounding pixels or from the whole image [5]. Markov Random Field (MRF) has been widely employed to solve image analysis problem at all level. MRF provides a convenient and consistent way of processing context dependent entities like image pixels and correlated features. This is achieved through characterizing mutual influences among entities using conditional MRF distributions. The practical use of MRF is largely ascribed to a theorem stating equivalence between MRF and Gibbs distributions [3].

Our work is mainly focuses on getting defended the image from fence image or video. Our aim is to produce a post processing tool for de fencing image from fenced video or image because today people often hindered in capturing pleasant image or video and capturing memories at their landmark. We have exploit the fact that user span the camera to cover entire scene while capturing the video. In this paper section 2 contains our propose work in brief and section 3 contains image modeling using Markov Random Field. Section 4 and 5 contains brief introduction to fence detection and calculation of relative motion of pixels .The section 6 contains brief context to image inpainting.



Fig. 1: Fenced Images

II. PROPOSE SYSTEM

Our work is mainly related to obtaining de fence image from fence video or image because due to various reasons such as security in public places, fences in the stadium we cannot capture scene of our interest. Our propose system is mainly divided into three tasks. The first task is detecting the fence we use learning base image matting algorithm for detecting the fence in robust manner. The most of works in the image inpainting propagate the texture or structures from neighbor region to the target region. We have decided to take advantage of the fact that user usually span his camera for capturing the entire scene. So region or part which is invisible in one frame is visible in the other frame of the video. We have considered fence as static part in the video frame and background as moving part. We have exploited the relative motion of pixel in successive frame for tracking of missing region. We have model the target frame as Markov Random Field distribution for efficient and robust inpainting the missing regions. We have proposes the primal dual total variation algorithm for inpainting the missing region in way that those missing region will not visible to casual observer.

The image to be de fence or frames in fence video can be specified in term of set of sites. Let S index a discrete set of m sites

$$S = \{1, 2, \dots, m\} \quad (1)$$

In which $1, 2, \dots, m$ are indices. A site often represents a point or region in an Euclidean space such as image pixel or image feature such as corner, line segment or a surface patch. A set of sites can be categories in term of regularity. A site on a lattice is considered to be especially regular. A rectangular lattice for 2D image of size $n \times n$ can be denoted by

$$S = \{(i, j) | 1 \leq i, j \leq n\} \quad (2)$$

MRF provides a convenient and consistent way of processing context dependent entities like image pixels and correlated features. MRF tell us how to model a prior probability of contextual dependent pattern, such as textures and object features. We model de fence image as a Markov Random field. We seek to derive the maximum a posterior estimate of the reconstructed image given multiple frames from captured video of scene occluded by frame. Normally we treat sites in MRF as Un- ordered. For an $n \times n$ image pixel (i, j) can be conveniently re-indexed by a single number k where k takes on values in $\{1, 2 \dots m\}$ with $m = n \times n$. The interrelation between sites is maintained by neighborhood system. The sites in S are related to one another via a neighborhood system. The neighborhood system for S is defined as

$$N = \{N_i | \forall i \in S\} \quad (3)$$

Where, N_i is the set of sites neighboring i . The neighboring relationship has following properties:

- 1) A site is not neighboring to itself : $i \in N_i$
- 2) The Neighbor relation is mutual :
 $i \in N_i \leftrightarrow i' \in N_i$ (4)

For regular lattice S , the neighbor of i is define as a set of site within radius of \sqrt{r} from i .

$$N_i = \{i' \in S | [dist(pixel_{i'}, pixel_i)]^2 \leq r, i' \neq i\} \quad (5)$$

Where $dist(A, B)$ denotes the Euclidean distance between A and B and r takes an integer value.

When ordering of an element is specified neighbor set can be determine more explicitly. For Example $S = \{1, \dots$

, $m\}$ is ordered set of sites and its element are index. When site in regular rectangular lattice

$$S = \{(i, j) | 1 \leq i, j \leq n\} \quad (6)$$

Corresponds to the pixel of an $n \times n$ image in 2D plane the internal site (i, j) has four neighbor as

$$N_{i,j} = \{(i-1, j), (i+1, j), (i, j-1), (i, j+1)\} \quad (7)$$

For irregular site S the neighbor N_i of i is defined in the same way as to comprise nearby sites within the radius \sqrt{r}

$$N_i = \{i' \in S | [dist(feature_{i'}, feature_i)]^2 \leq r, i' \neq i\} \quad (8)$$

III. MARKOV RANDOM FIELD

Let $F = \{F_1, \dots, F_m\}$ be a family of random variable define on set S , in which each random variable F_i takes value f_i . The family F is called a random variable. We use notation $F_i = f_i$ to denote the event that F_i takes the value f_i to denote the event that F_i takes the value f_i and the notation

$$F_1 = f_1, \dots, f_m$$

to denote joint event. For simplicity, a joint event is abbreviated as $F = f$ where

$$F_1 = \{f_1, \dots, f_m\}$$

is a configuration of F . The probability that random variable F_i takes the value f_i is denote as

$$P(F_i = f_i)$$

F is said to be a Markov Random Field on S with respect to neighborhood system N if and only if the following two conditions are satisfied

$$P(f) > 0, \forall f \in F \quad (\text{Positivity}) \quad (9)$$

$$P(f_i | f_{S-\{i\}}) = P(f_i | f_{N_i}) \quad (\text{Markovianity}) \quad (10)$$

Where

$$f_{N_i} = \{f_{i'} | i' \in N_i\} \quad (11)$$

is a set of sites neighboring i . The markovianity depicts the local characteristics of F . MRF tells us how to model apriori probability of contextual dependent patterns such as textures and object features. The practical use of MRF model is largely ascribe to a theorem stating equivalence between MRF and Gibbs distribution. A set of random variable said to be in Gibbs random field on S with respect to N if and only if its configuration obey Gibbs distribution. Gibbs distribution takes following form

$$P(f) = Z^{-1} \times e^{-(1/T)U(f)} \quad (12)$$

Where Z is the partition function and second term is the clique potential function. The $P(f)$ measures the probability of the occurrence of particular configuration or pattern f .

IV. DETECTING THE FENCE

The significant amount of work has been done in literature of fence or barricades detection in images. Traditional texture filling tools such as Criminisi et al. [8] require users to manually mask out unwanted image regions. There is a rich body of work on lattice detection has been done in the literature [10][11]. Hays et al who first developed an automatic deformed lattice detection algorithm for real image without pre-segmentation, is based on looking for neighbors of randomly selected interest point in the image. Park et al [10] developed a deformed lattice detector with a Markov Random Field using an efficient inference engine called Mean Shift Belief propagation; they show 72%

improvement over Hays method. The fences and barricade can be classified as near regular texture [3]. The color of the fence is generally different from the background so some techniques use image segmentation approach such as graph cut to locate the fence pixels.



Fig. 2: Fence Detection with Scribbles

However, all algorithms discussed so far ignore the foreground/background characteristics of the repeating pattern we want to find [3]. One of the prominent techniques for detecting the fence is image matting, in this approach fence is consider as the foreground, we have use this approach for detecting fence. Accurate separating a foreground object from background involves determining both full and partial pixel coverage known as pull matting. This problem was mathematically established by Porter and Duff [3]. They introduce the alpha channel as the mean to control the linear interpolation of foreground and background color for antialiasing purpose when rendering foreground over an arbitrary surface. Our approach requires users to put scribble as show in figure 2 and this scribble observation is fed as input to the algorithm called learning base digital matting [3] whose output the gray scale intensity image representing the alpha met.

V. DETECTING RELATIVE MOTION OF PIXELS

The motion detection is very important problem in video coding and computer vision. There is a vast literature on motion detection. The major approach to computing displacement vector for corresponding pixel in two time consecutive image frame can be classified as using gradient-base methods, correspondence of motion tokens or block matching [6]. The gradient base methods are based on some relationship among image spatial and temporal derivatives.

Horn and Schunck work to allow gradual changes in moving objects appearance and for flow discontinuities at object boundaries. Broad classes of gradient base methods are all pixel recursive algorithm. In general gradient methods are analytically tractable and they often make use of iterative solution. The method can give dense displacement i.e displacement vector for pixel. However because method require derivative there usage limited to short range like at most 2 to 3 pixels. Another class of motion detection algorithm is correspondence of motion tokens where important image features are extracted and track over consecutive image frame. Various type of token can be used, such as isolated points, edges, and blobs. In the block matching methods, blocks in the previous frame are match with corresponding block in the current frame via criteria such as minimizing mean square error or by maximizing a cross relation. Jain and Jain proposed a mean

square error block matching algorithm for estimating inter frame displacement.

We use a video captured by a camera panning the scene containing a fence and obtain a “de-fenced” image. We have taken the advantage of the fact that user pan his camera while capturing the video to cover entire scene or Objects in scene can move with respect to static camera. We assume that fence is static and only background is shifted with respect to static scene. The part of scene hidden in one frame is visible in the other frame. So we have found the relative motion of the pixels between frames. We then use the implementation of the affine SHIFT. We assume that the region R' at $t = t_2$ has resulted from the region R at $t = t_1$ via affine shape deformation

$$p \rightarrow Mp + d \quad (13)$$

Where,

$$Mp + d = \begin{bmatrix} s_x \cos \theta_x & -s_y \cos \theta_y \\ s_x \sin \theta_x & s_y \sin \theta_y \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} d_x \\ d_y \end{bmatrix} \quad (14)$$

The vector $d = (d_x, d_y)$ account for special translation, whereas the 2×2 real matrix M account for rotations and scaling. That is S_x and S_y are scaling ratios in X, Y direction and θ_x and θ_y are corresponding rotation angle. This type of region deformation occurs in moving image sequence. For example, when objects rotate relative to the camera, the region R also rotates. When objects move closer or further from camera the region R get scale. Displacements by d can be cause by translation of object parallel to the image plane as well as by rotation.

VI. IMAGE INPAINTING

Image inpainting, also known as image completion, is the problem of finding missing parts of an image using only the available content and some regularization constraints. Traditional approaches to inpainting try to find a good continuation of the surroundings of the holes, effectively propagating lines inside.



Fig. 3: De fencing image using Image Inpainting

The most fundamental approach is diffusion base approach in which missing region is filled by diffusing image information from known region to the missing region at the pixel level. These algorithms are well founded on theory of partial differential equations and variational method. The diffusion base algorithms have achieved convincingly excellent result for filling non texture and

relatively small region. The second approach is exemplar base inpainting algorithm. This algorithm propagates image information from known regions into missing regions at the patch level. This idea is stem from the texture synthesis in which texture is synthesized by sampling the best match patch from the known region. The image to be inpainted can be model as a Markov Random Field distribution; will help us to effectively fill the missing regions. We have proposed primal dual total variation for image inpainting [2]. The total variation has been introduce in computer vision by Rudin, Oshel and Fatemi as a regularizing criteria for solving inverse problem. It has proved to be quite efficient for regularizing image without smoothing boundaries of the object.

VII. CONCLUSIONS

In this paper we have review the image inpainting system for obtaining de fence image from fence video or image. We have taken the advantage of different frames of video spans entire scene. We have discussed the modeling of image using Markov random Field. We have briefly discussed our proposed work contains three main steps for image inpainting like fence detection, calculating relative motion of pixel in frame and image inpainting. Further future work is mainly focused on the efficient and reliable inpainting using primal dual total variation algorithm.

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