Volume 6, Issue 2, February 2016 ISSN: 2277 128X

International Journal of Advanced Research in Computer Science and Software Engineering

Research Paper

Available online at: www.ijarcsse.com

Image in Painting Using Related Frames in Video

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Abstract— Image inpainting involved filling-in of removed, damage or unwanted region of image. One of the main approaches of existing image inpainting algorithms in completing the missing information is to follow a two stage process. A structure completion step, to complete the boundaries of regions in the hole area, followed by texture completion process using advanced texture synthesis methods. Now day's tourism is booming all over the world. It is often seen that public places are covered by fences for security reason. So tourist often faces the problem in capturing seen of their interest. This situation demands robust post processing tool which get rid of fence. We have addressed the problem of removing fence from images or video using image inpainting. We have divided the system in three modules: First is the detecting the fence, we follow the semi-automated approach that is require user to put scribble as input to image matting algorithm use for detecting fence. Second module is about detecting relative motion of feature of image among different frame. We have exploited the fact that part of image covered in one frame of video is visible in other frame of video. Third module is inpainting of fence part of image. We have cho sen primal dual total variation for inpainting. We have express inpainting as optimization problem. We have model image to be inpainted or frame as Markov Random Field for efficient repainting. In this paper we have provided brief overview of various task and techniques use for image inpainting

Keywords— Image inpainting; fence detection; relative motion; image matting; primal dual; markov random field (MRF)

I. INTRODUCTION

Digital inpainting is the technique of filling in the missing region of image or video using information from surrounding area. 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. Some of the early nomenclature referred small region filling as inpainting and large area inpainting as image or video completion, but now days there is no such distinction are commonly referred Digital image and video inpainting algorithm. The process of inpainting can be viewed as an intelligent interpolation of adjacent pixels in the regions surrounding the areas to be recovered. Image inpainting has wide range of application such as restoration, error recovery, multimedia editing and video privacy protection.

The goal of the image inpainting is to produce a missing region of image in perceptually plausible manner so inpainted region is undetectable to normal observer. 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. Basically images are composed of structures and textures. The structures are primal sketches on image like edges and corner. The textures are image region with homogenous pattern or feature statistic including flat pattern. 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.

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].

As tourist industries are growing rapidly, tourists are often facing a problem in capturing in their video because of fence or occlusion that limits their accessibility to scene of interest. We have particularly address the problem of reconstructing fenced or occluded images. We have divided the system into three modules namely 1. Fence detection using image matting 2. Estimation of relative motion of feature among different frame in video 3. Image inpainting using primal dual total variation.

II. RELATED WORK

Our work is mainly focused on getting de fence 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. In this section, we will focus on different techniques for inpainting. There are different approaches to image inpainting are available. We can classify them into several categories as follow: Texture Synthesis base Inpainting, PDE Based Inpainting, Exemplar Based Inpainting, Hybrid Inpainting, Semi-automatic and Fast Inpainting

2.1. Texture Synthesis Base Inpainting

This is one of the earliest methods of image inpainting. These algorithms are used to complete the missing region using neighbourhood of similar pixels. Markov Random Field is use to model the local distribution of pixel and new texture is synthesized from exiting texture and finding all similar neighbourhood. Their differences are mainly in how continuity is maintained between inpainted hole and existing pixels.

Various texture synthesis methods differentiate among themselves in their ability to create textures with different statistical characteristics and to generate textures under gradient, color or intensity variations. Then later, this technique was extended to fast synthesizing algorithm. This technique works by stitching together small patches of existing images referred to as image quilting. Heeger and Bergen developed a texture synthesis algorithm which can produce matching texture given target texture. Their idea is based on texture discrimination capabilities of Human visual System [0]. Fang et.al proposed a fast multi resolution texture synthesis method in which image is analyzed by a patch based method using Principal component Analysis and Vector Quantization was to boost matching process of texture inside hole region [0].

2.2 PDE base Inpainting

These algorithms pave the way for modern digital Inpainting. Borrowing the idea of the manual inpainting the iterative process propagates linear structure like edge into surrounding area called Isophotes into the missing r egion. Partial differential equation base algorithm is proposed by Bertalmio et.al [09]. This is an iterative algorithm. The main idea behind this algorithm is to continue geometric and photometric information that arrives at the border of the occluded area into area itself. This is done by propagating the information in the direction of minimal change using isophote line. This algorithm will produce good results if missed regions are small one. But when the missed regions are large this algorithm will take so long time and it will not produce good results. Chan and shen [00] proposed the total variation Inpainting model. This model uses Euler-Lagrange equation and anisotropic diffusion based on the strength of the isophotes. This model performs reasonably well for small regions and noise removal applications. But the drawback of this method is that this method neither connects broken edges nor greats texture patterns. These algorithms were focused on maintaining the structure of the Inpainting area. And hence these algorithms produce blurred resulting image. Another drawback of these algorithms is that the large textured regions are not well reproduced.

2.3 Exemplar Base Inpainting

This approach propagates the image information from known region to into missing region at patch level. These have proved to be very effective inpainting algorithm. Exemplar base algorithm basically consists of two steps 1. The priority assignment 2. Selection of best matching patch.

Chriminisi et.al [00] proposed an algorithm which combines the use of texture synthesis and isophotes driven inpainting , capable of handling large area. The region filling is determined by priority base mechanism, point which lies on edges have high priority and other pixels. The neighbourhood or filled patch surrounding the highest priority pixel is then filled by finding the best matching patch in the known regions. Cheng [13] generalized the priority function for the family of algorithms given in [12] to provide a more robust performance. Wong [14] developed a weighted similarity function.

That function uses several source patches to reconstruct the target patch instead of using a single source patch. Fang [20] developed a rapid image Inpainting system which consists of a multi-resolution training process and a patch-based image synthesis process. Xu [19] proposed two novel concepts of scarcity at the patch level for modeling the patch priority and patch representation. Compared with the diffusion-based approaches, the exemplar-based approaches achieve impressive results in recovering textures and repetitive structures no matter whether they are applied into the large regions or not.

2.4 Hybrid Inpainting

The hybrid approaches combine both texture synthesis and PDE based Inpainting for completing the holes. The main idea behind these approaches is that it decomposed the image into two separate parts, Structure region and texture regions. The corresponding decomposed regions are filled by edge propagating algorithms and texture synthesis techniques. Hybrid inpainting technique is also called as Image Completion. It is used for filling large target regions. These algorithms are computationally intensive unless the fill region is small.

2.5 Semi-automatic and Fast inpainting

These algorithm found the favoured with researchers. These algorithm works with user assistant. Semi- automated image inpainting use guide lines from user for structure completion. Jain et.al. [0] proposed a semi -automatic structure propagation algorithm follows two-step process. In the first step user manually specifies important missing information in the hole by sketching boundaries from known region to unknown region. And in the second step the missing patches are formulated by using user specified curve line. This is an optimization problem. Simple dynamic programming can be used to find optimal solution.

III. PROPOSE SYSTEM

Tourist and amateur photographers are often facing a problem in capturing their scene of interest due fences and barricades in public places. The situation has been exacerbated by growing concerns of security at public places, due to this problem we need post processing tool to get rid of fence. Our work is mainly related to obtaining de fence image from fence image or video. Our proposed system is mainly divided into tree task

1. Fence Detection
2. Detecting relative motion of pixels in video frame
3. Inpainting using Primal-dual inpainting algorithm

The first task is detecting the fence from different frames in input video. We have used learning base an image matting algorithm for detecting the fence in robust manner. It is common for user to pan the camera while capturing video of scene in order to cover entire landscape. The most work in image inpainting propagate texture and structures from neighbour region to the missing or target region. We have decided to take an advantage of fact that region or part of scene which is invisible in one frame of video is visible in other frame. So we have exploited motion clue in video frame to perform de fencing. We have considered fence as static part in video frame and background as moving part. We have model targeted frames as Markov Random field. We have used a Primal dual total variation for inpainting, it provide an optimal solution for targeted problem. Our proposed solution robustly finds a fence in frames and fills fence region such way that those inpainted region will not visible to casual observer.

3.1. Markov Random Field

Markov random field theory provides a convenient and consistent way for modelling context dependent entities such as image pixel and correlated feature. MRF can find mutual influence among entities using conditional MRF distribution. MRF tell us how to model a prior probability context dependent pattern such as texture and object features. The image to be de fence or fence in fence video can be specified in term of set of sites. Let S index a discrete set of m sites.

$$S = \{ 1, 2, \dots , m\}$$

In which 1, 2… m are indices. A site is often represents a point or region in a Euclidian 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 regularities.

A site on a lattice is considered to be especially regular. A rectangular lattice for 2D image of size n × n can be denoted by

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

Normally we treat sites in MRF as Un- ordered. For an n × n image pixel (i, j) can be conveniently re-indexed by a single number k where k takes on values in {1, 2… m} with m = n × n. The interrelation between sites is maintained by neighbourhood system. The sites in S are related to one another via a neighbourhood system. The neighbourhood system for S is defined as

$$N = \{ N_i \, | \forall i \ \in S \}$$

Where, Ni is the set of sites neighbouring i. The neighbouring relationship has following properties:

1. A site is not neighbouring to itself: i Є Ni
2. The Neighbor relation is mutual:

$$i \ \in N_{i'} \ \leftrightarrow \ i' \ \in N_i$$

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

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

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 $\mathrm{S} = \ \{1, \dots ,\mathrm{m}\}$ is ordered set of sites and its element are index. When site in regular rectangular lattice

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

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

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

For irregular site S the neighbour Ni of i is defined in the same way as to comprise nearby sites within the radius √r

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

Let *F = {F1, ..., Fm }* be a family of random variable define on set S, in which each random variable *Fi* takes value *fi* . The family *F* is called a random variable. We use notation *Fi= fi* to denote the event that *Fi* takes the value *fi* to denote the event that *Fi* takes the value *fi* and the notation

$F_1 = f_i, \ldots, F_m = f_m$

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

$f = \{ f_1, \ldots, f_m \}$

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

$P(F_i = f_i)$

F is said to be a MRF on *S* with respect to neighbor system *N* if and only if following two conditions are satisfied.

$P(f) > 0, \ \forall f \in F \qquad (Positivity)$

$P(f_i \mid f_{s-\{i\}}) = P(f_i \mid f_{N_i}) \qquad (Markovianity)$

Where,

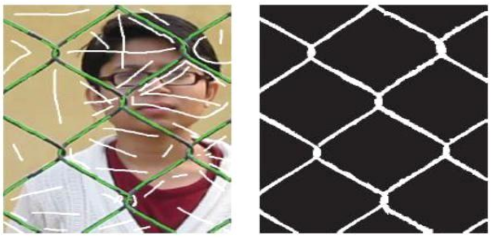
$f_{N_i} = \{ f_{i'} \mid i' \in N_i \}$

The practical use of MRF model is largely ascribe to a theorem stating equivalence between MRF and Gibbs distribution. A set of Random variable is 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

$P(f) = Z^{-1} \text{ X } e^{-\left(\frac{1}{T}\right)U(f)}$

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

IV. DETECTING FENCE WITH IMAGE MATTING



(a) (b)

Figure 1. Fence detection with scribbles by user

We use semi-automated option for detecting the fence. Our approach require user to mark scribble on image for fence detection as an input. We have considered fence as foreground object, so we have taken the advantage of work in image matting techniques which label some objects in images as foreground and background object. We have propose to use learning base image matting algorithm which give better result for detecting fence from fence frames from video. Matting consists of two main tasks: alpha matte's estimation and foreground (and background) color computation. Given an image *I* for which the complete set of image is denoted by

$\Omega = \{1, \ldots, n\}$

where n is total number of pixels and given a set of label pixel $\Omega l \subset \Omega$ for which we know the α value, alpha matting estimation is define as computing α values of set of unlabelled pixel $\Omega u = \Omega - \Omega l$. Here set of label pixels Ωl is composed of two subsets: Ω_l^f labelled as defined foreground and for which we know α is 1and Ω_l^b label as definite background and for which know α is 0.

We consider the alpha matte estimation as learning problem. We treat each pixel i $\in \Omega$ as data point denoted by $xi \in R^d$. xi can be set as Ii or other feature extracted for pixel i. We have set $xi = Ii$ which is scale value grey image (d=1) or vector composed of the RGB color component for color image (d=3). The learning problem can be formulated as follow. Given a data point set $X \subseteq R^d$, $X = \{ xi \} i\in \Omega l$ and the alpha values$\{\alpha i\}$ $i\in Xl$ of label data point $X_l = \{ x_i \}_{i \in \Omega l}$ our goal is to compute the accurate alpha values $\{\alpha_i\}_{i \in X_u}$ of unlabelled data points $\Omega u = \Omega - \Omega l$ through learning method.

There are two learning approaches for images matting

1. Local Learning
2. Global Learning

It is normally found that global learning method provides better result than local learning base method.

V. SIFT

People often pan their camera to capture entire scene of interest usually covered by fence in many public place, so there exist relative motion between scene and camera or there may be moving object with respect to static camera. We have exploited this fact because part if image or frame covered in in frame, visible in other frame. Hence to take advantage of fact we needs estimate the relative motion of pixels in different frame. We have used affine SIFT (Scale invariant feature transform) for estimating relative motion of pixels in frames.

SIFT is an algorithm in computer vision to detect to describe local feature in image. SIFT key points of object are first extracted from set of reference images and stored in a memory. An object in new image is recognized by individually comparing each feature from new image to previous stored in memory and finding candidate matching feature based on Euclidean distance of their feature vector. From full set of matches' subset of key point that agrees on the object and its location, scale, and orientation in new image are identified to filter out good matches. The determination of consistent cluster is performing rapidly by using efficient hash table implementation. Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and subsequently outliers are discarded.

We assume that the region R' at t = t2 has resulted from the region R at t = t1 via affine shape deformation

$$p \rightarrow Mp + d$$

Where,

$$Mp + d = \begin{bmatrix} S_x COS\ \theta_x & -S_y COS\ \theta_y \\ S_x SIN\ \theta_x & S_y SIN\ \theta_y \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} d_x \\ d_y \end{bmatrix}$$

The vector d = $(d_x\ d_y)$ account for special translation, whereas the 2 × 2 real matrix M account for rotations and scaling. 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 INPAITING WITH PRIMAL DUAL TOTAL VARIATION

We have used the primal dual total variation base technique for image inpainting. A popular variation model in reconstructing blocky image corrupted with Gaussian noise is the Rudin-Osher-Fatemi (ROF) model

$$\min_{u \in BV(\Omega)} \frac{1}{2} \int_{\Omega} (u - u_0)^2\, dx + \alpha \int_{\Omega} |\nabla_u|\, dx$$

Where Ω is connected bounded domain in R^d with Lipschitz continuous boundary $\partial\ \Omega$ and $\alpha > 0$ is regularization parameter. Chan and Shen proposed a restricted version of ROF model for inpainting non texture type of images.

$$\min_{u \in BV(E \cup D)} \frac{1}{2} \int_{E} (u - u_0)^2\, dx + \alpha \int_{E \cup D} |\nabla_u|\, dx$$

Where E is fix closed domain outside the inpainting domain D and | . | denotes an Euclidean norm.

In the discrete setting, we concatenate the n x n image matrix u to image vector $v \in R^N, N = n^2$. Let $[\nabla_v]_l = [(\nabla_x v)_l, (\nabla_y v)_{l+n}]^T, 1 \le l \le n$ Where ∇_x and ∇_y are approximated by forward differences. The inpainting domain is D, and $E = \{i \in \{1, \ldots, N\} | i \notin D\}$. A discretized version of the total variation image inpainting model above is

$$\min_{v \in R^N} \frac{1}{2} \|v - v^0\| + \alpha \sum_{l=1}^{N} \|\nabla v\|_l$$

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 modelling 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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