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A EFFECTIVE WAY TO MODIFY VIDEO FOR DELETING FORGROUND OBJECT FROM BACKGROUND USING EXEMPLAR BASED INPAINTING METHOD

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ABSTRACT
A surveillance video for analyzing doubtful action in CCTV footage can be observed by military, police, Intelligance Bureau daily but some footage must be kept private and it's content not getting viral for maintaining peace in society for this purpose reconstructing that footage is good option to avoid any misuse with that footage so we have implemented inpainting method to modify that video for deleting forground object from background , here we have use Exemplar based inpainting method which is used in Image Inpainting this method is combination of PDE based and Texture Synthesis based method in this process we have taken a video afterwards we have made conversion from video to frames then bineriwise morphology is applied for extracting forground object from background then available patches is inpainting by Exemplar based method then video is getting modified

KEYWORDS: Image Inpainting, Video Inpainting, Morphology, Exemplar Based Inpainting

1.INTRODUCTION
Embedded text in associate in nursing passing video sequence provides valuable information. Texts generally appear as logos, subtitles, captions or banners among the video sequence. Such information embedded texts area unit usually largely found among the news and totally different common place and in cricket broadcastings that text might necessary components of a video. There got to be the need to erase the unwanted text from the video .The various in painting are discussed here to recover the missing pixel in an image.Inpainting is the process of reconstructing lost or deteriorated parts of images and videos. For instance, in the museum world, in the case of a valuable painting, this task would be carried out by a skilled art conservator or art restorer. In the digital world inpainting   also   known   as image   interpolation or video   interpolationrefers   to   the   application   of sophisticated algorithms to replace lost or corrupted parts of the image data mainly small regions or to remove small defects the global picture determines how to fill in the gap. The purpose of inpainting is to restore the unity of the work.The filling of lost information is essential in image processing with applications as well as image coding and wireless image transmission, special effects and image restorationis to fill-in these regions with available information from their environment [1].

Fig.1 Person removal by using Video Inpainting

TYPES OF INPAINTING
Inpainting can be done in various applications but mainly over images and videos

1.1 Image Inpainting

The region of unwanted information in the bounded variation image is removed by using image inpainting A comparative study on this all inpainting techniques includes image processing over each image toreconstruct missing partsor removal of unwanted parts from that image.
The Three types of Image Inpainting are as follows:

1) Partial Differential Equation (PDE) based 2) Texture Synthesis based 3) Exemplar based Inpainting.

1.1.1 Partial Differential Equation (PDE) based

Bertalmioetal [2] have proposed a digital image inpainting algorithm based on Partial Differential Equation (PDE) in which the direction of the lines of equal luminescence is maintained by evaluating the direction of the largest spatial change obtained by computing a gradient vector and rotating this vector by 90 radians. Bertalmioetal took the ideas from computational fluid dynamics (CFD) to continue the isophote lines into the region to be in painted [3]. It treats the image intensity as a stream function and the laplacian of the image as vorticity of the fluid which is continued into the region to be in painted by vector fields defined by stream function .PDE based algorithm is an iterative algorithm. The basic idea behind the algorithm is to propagate both the geometric information (gradient direction) and the photometric information (gray-scale values) of theimage that is available at the boundary of the occluded area into the area to be filled in (Ω). This is done by formulating a partial differential equation which propagates the information (laplacian of image) in the direction of minimal change using 'isophote lines' (the lines of equal gray value) [4],[5].This method is thus based directly on the Navier Strokes Equations for CFD. The PDE technique for inpainting produces good results if the region to be filled in is small but if the missed regions are large ,the efficiency of this algorithm decreases as it takes a long time to fill in large missing areas and the results produced will also be unsatisfactory. Inspired by the work of Bertalmio at.al, Chan &Shenforthput Total Variational (TV) in painting algorithm based on second order partial differential equation [6], [7], [8]. This algorithm uses Euler-Lagrange model as well as anisotropic diffusion based on the intensity of the isophotes. This algorithm performs quite well for noise removal applications and for filling in small regions. But the weak point of this model is that it neither greats texture patterns nor connects the broken edges. The TV model was then extended to the Curvature Driven Model (CDM) which also included the geometric information of the isophotes in order to handle the curved structures in a better way thus allowing this inpainting technique to proceed over large areas [9]. Although CDM connects the broken edges but also results in some blur. Then Telea [10] proposed a Fast Marching Method (FMM) which in-paints the near pixels to known areas first and also maintains a narrow band of pixels which distinguishes the unknown pixels from the known pixels. The drawback of this method is that it produces a post inpainting blur which becomes noticeable when the area to be in painted is larger than ten pixels .This method computes the smoothness of an image and is considered as a PDE method which is simpler as well as faster to implement as compared to other PDE based techniques. PDE being an iterative method is very time consuming, requires difficult implementation process and is not applicable to large textured areas, the results for which are often blocky. PDE based technique has numerous applications such as restoration, image segmentation etc. Partial Differential Equation (PDE) based algorithms focuses on maintaining the geometric structure of the area to be inpainted.

1.1.2 Texture Synthesis Based Inpainting:
PDE based techniques are well suited for filling in small gaps, text overlays etc. but PDE technique usually fails if applied to areas containing regular patterns or to a textured area. This failure is because of the following reason:

   1. Mostly high intensity gradients are present in textures which may be interpreted wrongly as edges and falsely transported into the region to b in painted.

   2. In case of PDE based in painting, the information used is only the boundary condition that is present within a narrow band around the region to be in painted. Thus, it is impossible to recognize structures, textured areas or regular patterns from such an insignificant amount of information. Texture synthesis based algorithms are based on the concept of synthesizing artificial texture from an (typically small) initial seed, striving to preserve the

appearance structure and color) in a way that the synthesized texture Markov Random Field (MRF) is utilized for modeling the local distribution for pixel is local pixel distribution after which a new texture is created by inquiring existing texture and retrieving informationfrom similar neighbourhoods. Their difference mainly lies in the way continuity is maintained between the already existing pixels and the in painting domain (hole). This pixel based texture synthesis performs very well on set of selected images. Synthesis based approaches are well suited for only a selected set of images where completing the missing region with homogenous textures results in nature completion. Since the filling- in of the in painting domain is done pixel by pixel, this scheme is very slow

　　　　　a) Input Image　　　　　　　　　　　　　*b)Texture Synthesis*
Fig.2 Example of texture synthesis (a) Input Corrupted Image (b) In-painted output using texture synthesis

1.1.3 Exemplar Based Inpainting:

As natural images (paintings) are composed of both structures and textures (regions with regular patterns), more complex inpainting techniques are required for faithfully reconstructing the corrupted regions. Because of this distinguishing feature of natural images, a technique that is designed strictly for texture synthesis will not provide satisfactory results
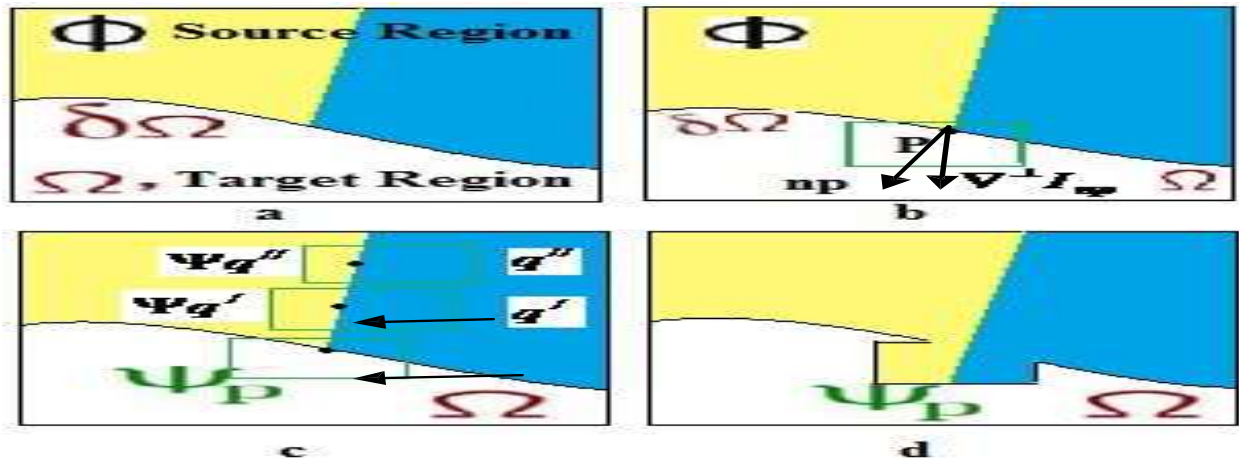

Fig.3- Criminisi et.al Exemplar based Texture synthesis Algorithm.(a)Original image with target region (Ω) , its source region ϕ and boundary d Ω. (b) Area to be synthesized delimited by the patch ψpcentred at point p.(c) Most likely candidate patches (ψq/ ,ψq// lying in the source region ϕ . (d)Best matching patch among candidate patches copied to the position occupied by ψp, thereby achieving partial fill-in in target region Ω.

Exemplar based in painting inspired by local region growing techniques that grow texture using one patch or one pixel at a time perform well for a wide range of images and are able to produce reasonably better quality results by combining texture synthesis with isophote (lines of equal gray value) driven inpainting methods. Exemplar based methods have proved to be very effective for reconstructing large target regions. The basic idea behind Exemplar based image interpolation is the use of a set of image exemplars/ blocks that are derived either from the same image that needs to be in painted or from other images that are related to the representative images. Exemplar based approach consists of two basic steps:

Firstly, priority assignment is done. Each pixel p belonging to the patch ψp has a patch priority given by the product of the confidence term C(p) and the data term D(p) . The confidence term tells us about the number of existing pixels in this patch.The data term tells us about the strength of the isophote that hits the boundary and is important since it maintainsthe structure of an edge at the target patch and focuses on the linear structure to be synthesized first

VIDEO INPAINTING

The process of removing and reconstructing the specific area in video is known as video Inpainting. Most of the automatic techniques of video Inpainting are computationally intensive and unable to repair large holes.To overcome this problem, exemplar based video Inpainting method is extended by incorporating the Sparsity of natural image patches using background registration technique.VideoInpainting refers to a field of Computer Visionthat aims to remove objects or restore missing or tainted regions present in a video sequence by utilizing a technique of patch Sparsity to fill-in the missing parts of video sequence taken from a static camera using background registration method. The overriding objective is to generate an inpainted area that is merged seamlessly into the video so that visual coherence is maintained throughout and no distortion in the affected area is observable to the human eye when the video is played as a sequence. Inpainting technique is the modification of the images in an undetectable form Video is considered to be the display of sequence of framed images. Normally twenty five frames per second are considered as a video. Less than twenty five frames per second will not be considered as a video since the display of those will appear as a flash of still image for the human eye. The main difference between the video and image inpainting methods using texture synthesis is in the size and characteristics of the region to be inpainted. For texture synthesis the region can be much larger with the main focus being the filling in of two-dimensional repeating patterns that have some associated stochasticity Removing unwanted objects or art effects from videos is a common task in professional video and movie productions. For instance, when filming in public locations, it is often necessary to remove walking people and other objects that accidentally occlude the scene. Objects may also have to be erased from a video sequence due to copyright issues. In other cases, the film crew needs to be in a scene for technical reasons, and needs to be removed in post-processing. Bertalmio [13] is the first pioneer to video inpainting. The author repaired a video using image inpainting frame by frame. A user-provided mask specifies the portions of the input image to be retouched and the algorithm treats the input image as three separate channels (R, G and B).For each channel, it fills in the areas to be inpainted by propagating information from the outside of the masked region along level lines (isophotes). Isophote directions are obtained by computing at each pixel along the inpainting contour a discredited gradient vector and by rotating the resulting vector by 90 degrees. This intends to propagate information while preserving edges to handle the missing region with composite textures and structures, patch priority is defined to encourage the filling-in of patches on the structure. Wexler [14] defined an optimal function to search the best matching patch in a foreground and use the found patch to repair the moving foreground. This algorithm filled the video frame patch by patch. Space-time completion of video (Wexler, Shechtman, &Irani,2007), Wexler et al. consider video inpainting as a global optimization problem, which inherently leads to slow running time due to its complexity. Video inpainting meant for repairing damaged video was analysed in [15] which involves gamut of different techniques which made the process very complicated. These works combine motion layer estimation and segmentation with warping andregion filling-in.Finally, there is a very interesting paper by Patwardhan [16] et al.(Patwardhan, Sapiro, &Bertalmio, 2007), which proposes a pipeline for video inpainting. However, the pipeline is so simple that it failed to perform well in many cases. [17] zhang uses a motion layer segmentation algorithm to separate a video sequences to several layers according to the amount of motion. Each separate layer is completed by applying motion compensation and image completion algorithms. Except for the layer with objects to be removed, all of the remaining layers are combined in order to restore the final video. However, temporal consistency among inpainted areas between adjacent frames was not taken care of in [17].

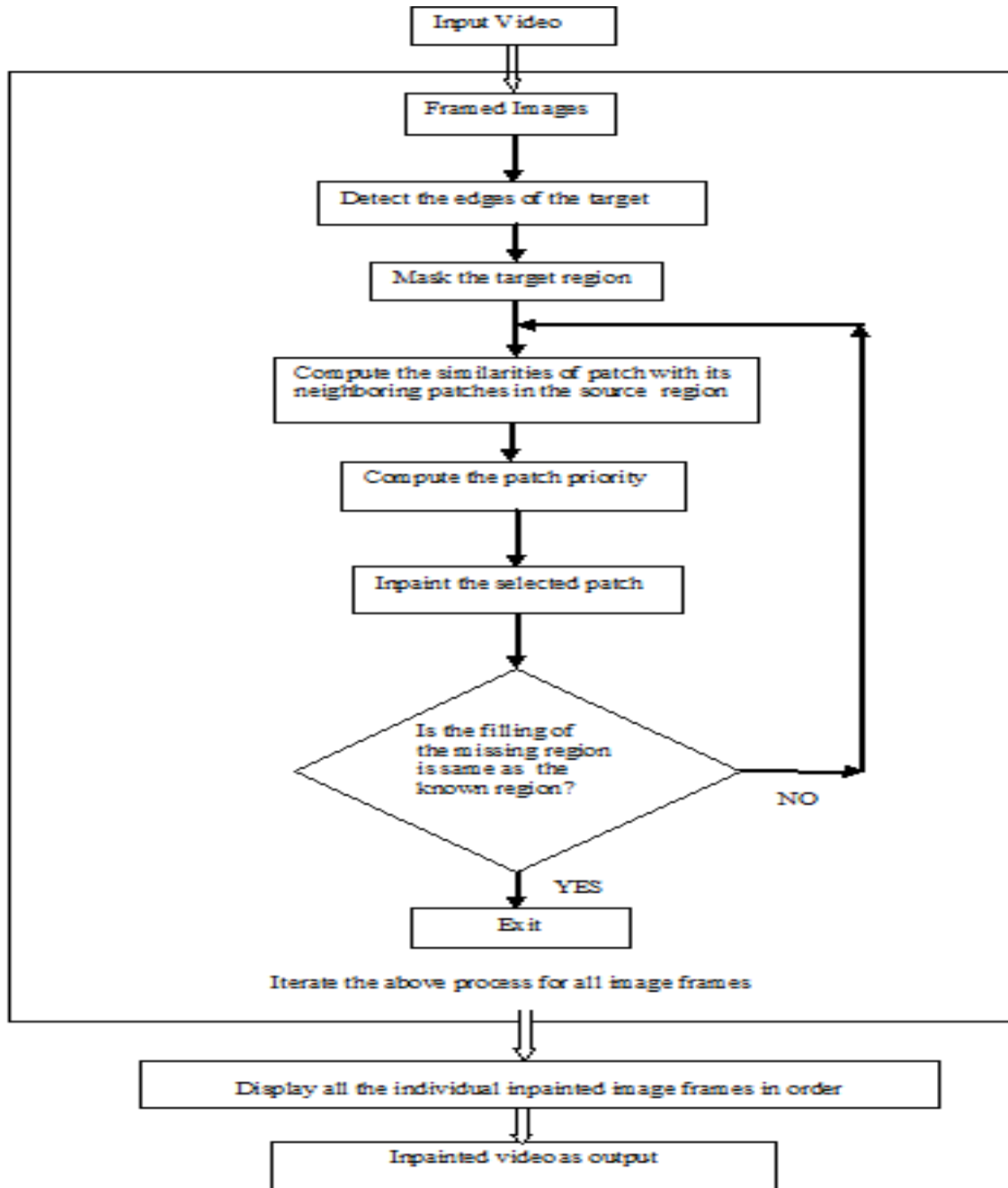**RESULT OF VIDEO INPAINTING USING EXEMPLAR BASED METHOD**

Fig.4 Algorithm for Video Inpainting

in this algorithm we have implementing a video inpainting method by uploaded a video in matlab tool after that converted into equivalent frames after that morphological operation is performed into all frames for extracting forground object from background after extracting object patch is created in each frame this patch is filled by exemplar based inpainting algorithm.

Methodology of Exemplar Method

- *Initialize the target region-*
  This is generally performed separately from the inpainting process and requires the use of an additional image processing tool. This is performed by marking the target region in some special colour. Without any loss of generality, let us consider that the colour that the target region will be marked in is green (i.e. R = 0, G = 255, B = 0).

- *Find the boundary of the target region.*

- *Select a patch from the region to be inpainted*
  The patch size should be a bit larger than the largest distinguishable texture element in the image. We have used a default patch size of 9 x 9 which can be changed with the knowledge of the largest texture element in the image. We denote the patch by ψp.

- *Find a patch from the image which best matches the selected patch, ψ_P*
  This matching can be done using a suitable error metric. We use the Mean Squared Error (please refer eq. 1) to find the best matching patch.

$$MSE = \sum \frac{(fx,y - gx,y)2}{N} \quad \text{......................................(1)}$$

where fx,y represents the element of the patch ψp and gx,y represents the elements of the patch for which MSE is to be calculated. N is the total number of elements in the patch.

- *Update the image information according to the patch found in the previous step*.

As mentioned earlier, the result does depend considerably on the third step wherein a patch is selected to be inpainted. The result that we obtain would almost always depend on the selection order and thus there have been approaches that try to define this selection order so that the result is improved.

In Criminisi"s algorithm, the priority function used for selecting the best patch from the target region was defined in a multiplicative form (please refer eq. 2).

$$P(p) = C(p) \times D(p) \quad \text{......................................(2)}$$

where C(p) represents the confidence term for the patch and D(p) the data term for the patch. These terms are defined in equations 3 and 4 respectively.

$$C(p) = \frac{\sum q \in \varphi p \cap \emptyset \ C(q)}{|\varphi p|} \quad \text{......................................(3)}$$

$$D(p) = \frac{|\nabla Ip.np|}{\gamma} \quad \text{......................................(4)}$$

where |ψP| is the area of the patch ψP and γ is the normalization factor (equal to 255 for a normal grey level image), nP is a unit vector orthogonal to the front δΩ at the point p and represents the perpendicular isophote at point p. The value of nP is found by finding the gradient for the source region. The source region represents a matrix with all ones on the points that are not in the target region and zeros otherwise (i.e. for the points in Ω). Isophote can be determined using the gradient of the image. Cheng et al. [16] discovered that the confidence term that was defined in Criminisi"s algorithm decreases exponentially and thus the multiplicative definition of the priority term.

Also, the authors proposed the addition of weights to different components in the definition of priority term so that a balance between confidence and data term could be maintained. Thus the modified priority term can now be represented as (please refer eq. 5)

$$P(p) = \propto \times Rc(p) + \beta \times D(p), 0 \leq \propto, \beta \leq 1 \quad \text{.........(5)}$$

where α and β are respectively the component weights for the confidence and data terms. Also α + β = 1 and Rc(p) is the regularized confidence term (please refer eq. 6).

$$Rc(p) = (1 - \omega) \times C(p) + \omega, 0 \le \omega \le 1………….(6)$$

where ω is regularizing factor for controlling the curve smoothness. Using this confidence term the value of the confidence term is regularized to [ω,1]. In this way the new priority function will be able to resist the "dropping effect". Now, as we have the priorities for the patches on the fill front, we can find the patch with maximum priority and select it as the patch that is to be inpainted. Let us call it ψ_p. The next step in the inpainting process is to find the patch with the maximum similarity with the selected patch. In the earlier approaches, the metric used for finding the similarity was the mean squared error.

To verify the effectiveness of the proposed variance approach and the improvement in speed, we performed tests on several videos and compared the so-obtained results with the conventional approaches.. In most of the experiments, the patch size was set to 9 x 9. We will state appropriately wherever a different patch size was taken by us and the reasons for the difference

A. Comparison with Criminisi's approach

Now we present the comparison of our approach with the one presented by Criminisi et al. in [18]. The Animated Video in Figure 5 (a) was given as input to the inpainting process that used our approach as well as to our implementation of the Criminisi"s approach. The results using Criminisi"s approach were not that promising whereas our algorithm achieved better results. The difference in the results occurred while searching for the best exemplar patch. In Criminisi"s approach, nothing is described about which patch to select if we get two patches with same minimum error. During our implementation of Criminisi"s algorithm, we assumed that we would choose the patch that was found earlier and got the results as shown. Using our approach, however, the best exemplar process was well defined and therefore it selected a better patch as shown in Figure 5.
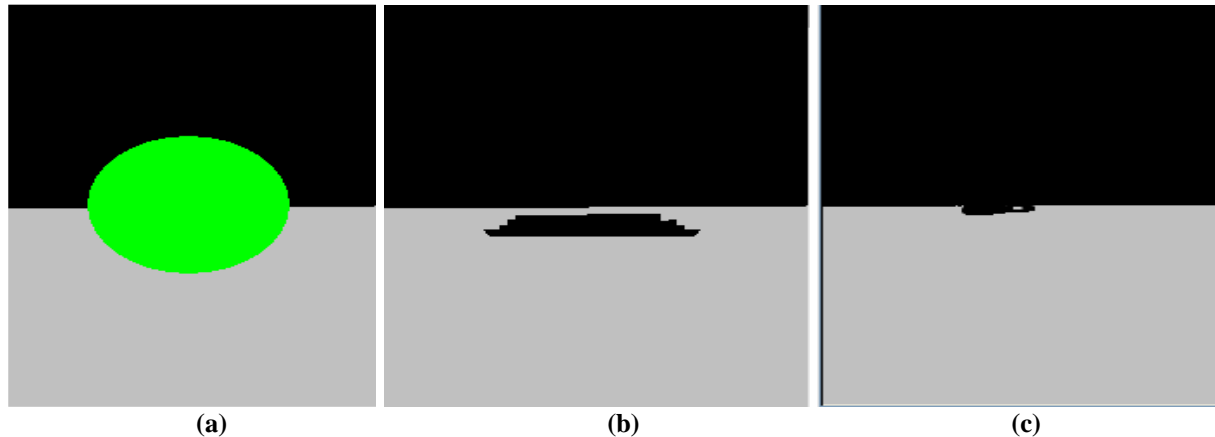

(a) **(b)** **(c)**

Figure 5. Comparison with Criminisi"s approach. (a) Animated Video to be inpainted (b) Result using of Criminisi"s approach. (c) Result using our algorithm

Thus the total time using our algorithm obviously depends on how much area is selected to be inpainted. In addition to this, the time would be less if the user selects small but spatially disconnected regions rather than if he selects the same percentage of target region continuously. This is so because we have taken into consideration the number of continuous green (color of the target region) pixels to remove the possibility of finding regions with no available patches.

B. **Comparison on the basis of time with Criminisi's aproach**
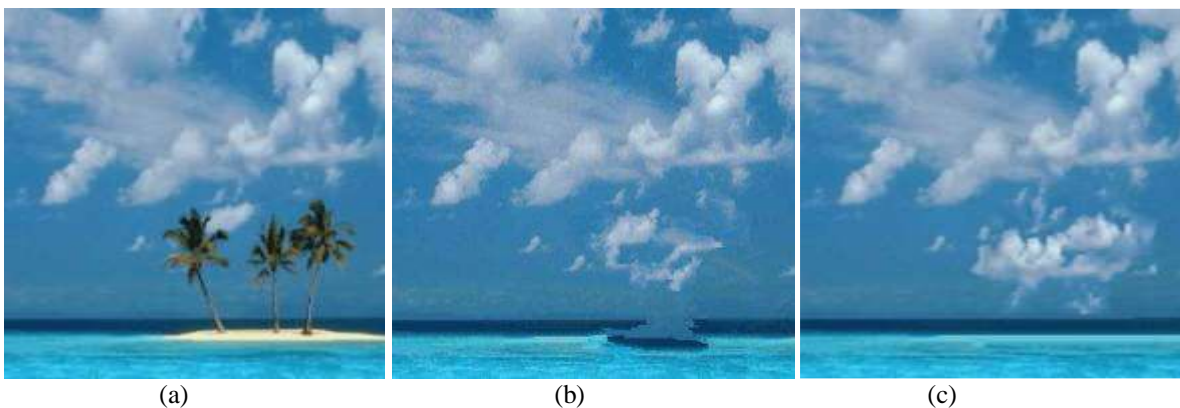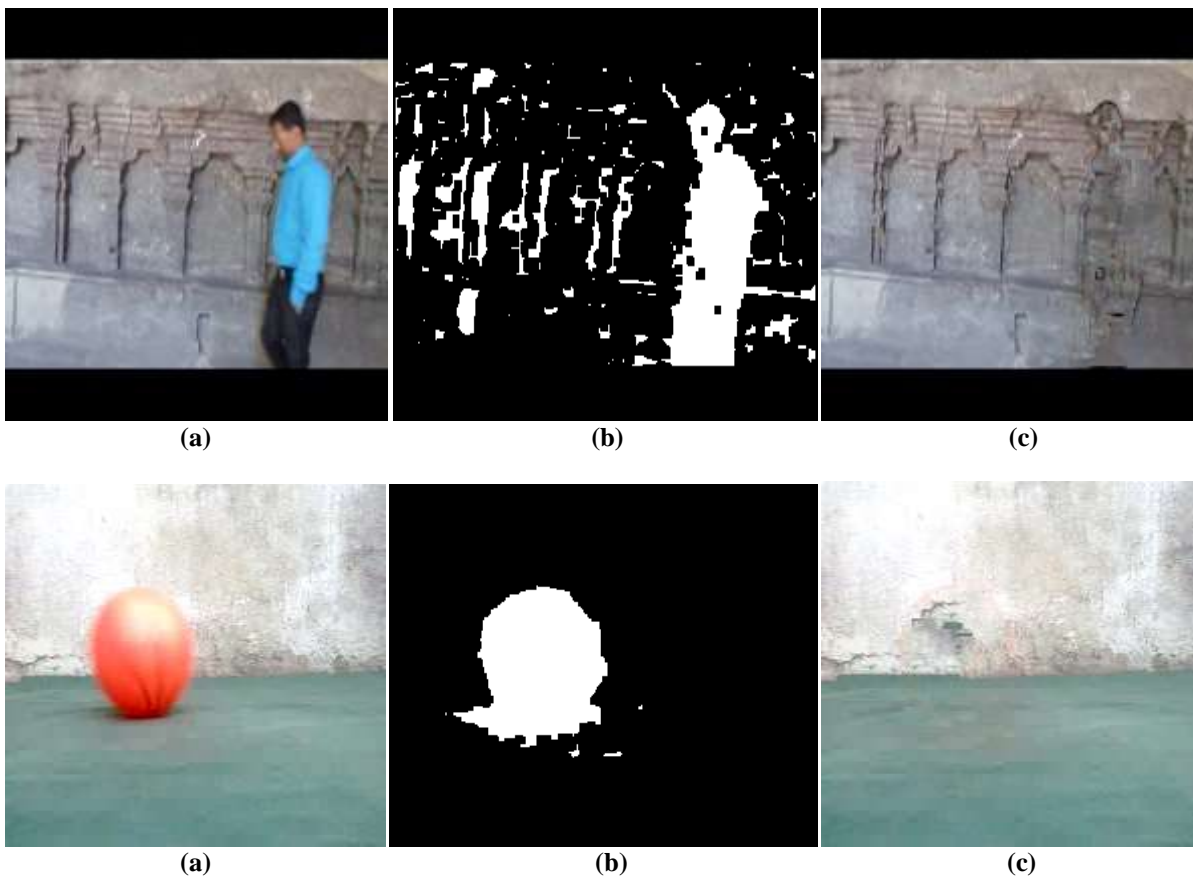

(a)   (b)   (c)

Fig. 6- Comparison with Criminisi's approach on benchmark data. (a) Video to be inpainted (b) Result using our algorithm. (c) Result using our implementation of Criminisi's approach.

C. **Video Inpainting Results using Exemplar based Method using different examples**

(a)   **(b)**   **(c)**

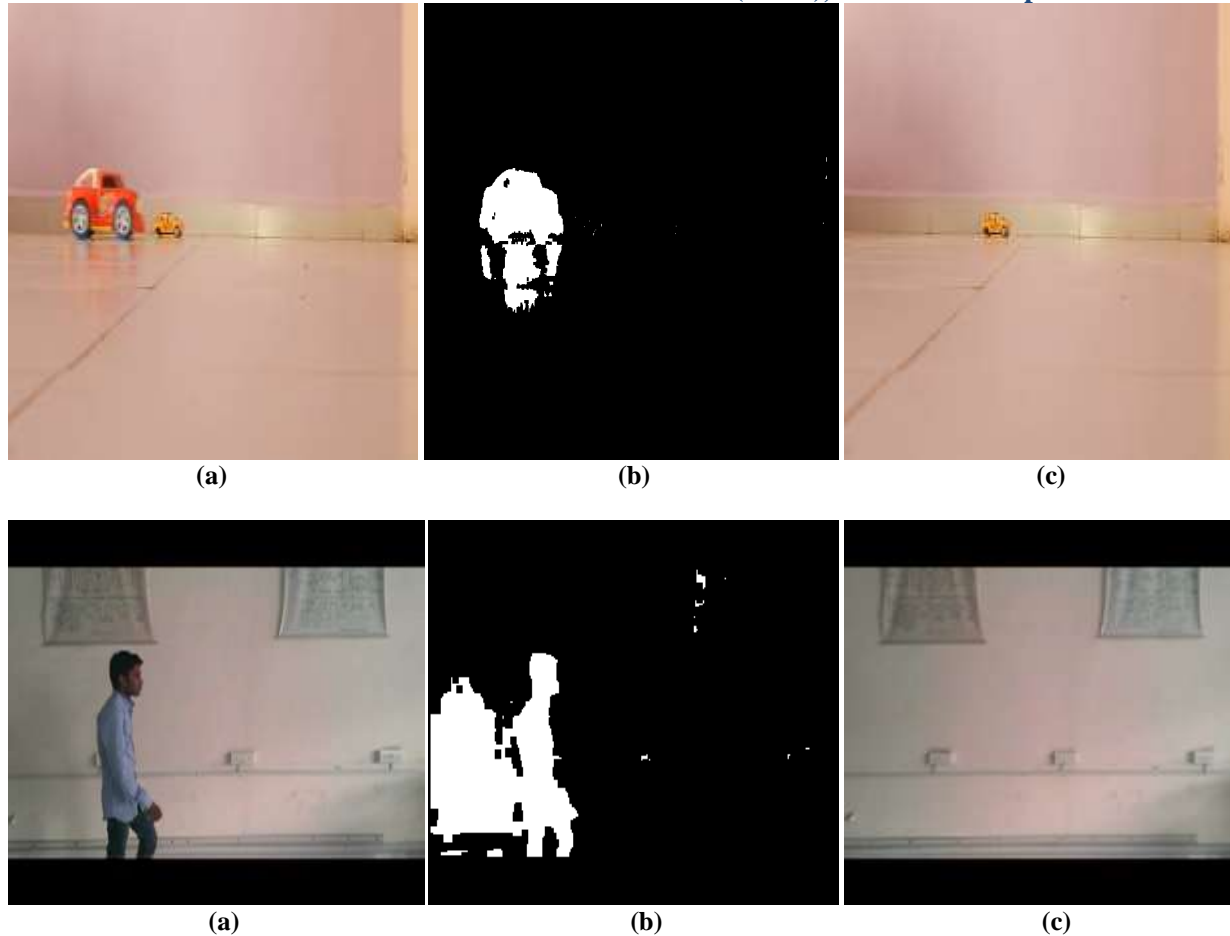**(a)**   **(b)**   **(c)**

Fig. 7- Different examples for Video Inpainting. (a) Video to be inpainted (b) Mask Images (c) Result using our implementation of Exemplar based Inpainting Method.

Here we have taken different examples our approach is to extract moving forground object in stationary background in each example forground object size is different some forground is small size e.g. Volleyball and other was Human so whenever video is getting captured by camera then it is uploading in matlab tool then this video is converted back into it's equivalent frames then moving forground object tracking and extraction is implemented by using bineriwise morphology operation then each frame consist of patches each patch size is different because of movement is getting changed by human body but in case of fixed size object e.g. moving volleyball video it consist same size of patch so it's result is better than other results for patches is masked by 9×9 mask then selected mask is filled by Exemplar based inpainting Method and successfully forground object is inpainted by this algorithm.

Following (Table 1) is a brief comparison of time taken using our approach and our implementation of Criminisi"s approach. Thus the total time using our algorithm obviously depends on how much area is selected to be inpainted. In addition to this, the time would be less if the user selects small but spatially disconnected regions rather than if he selects the same percentage of target region continuously. This is so because we have taken into consideration the number of continuous green (color of the target region) pixels to remove the possibility of finding regions with no available patches.

Table1. Comparison with Crminisi's Algorithm

Serial No.	Image Size (in pixels)	Percentage area to be removed	Time taken (in milliseconds)	
			Criminisi's	*Our Algorithm*
1	124032	0.81	11223	2283
2	60492	2.80	11546	4042
3	120000	5.00	53971	27319
4	60492	14.62	61286	52378

CONCLUSION

We present an algorithm that can remove moving objects from the Video in a way that it seems reasonable to the human eye. It can also restore old videos (e.g. removal of scratches). Our approach is an exemplar based inpainting method along with a priority term that defines the filling order in the Video Frames. In this algorithm, pixels maintain a confidence value and are chosen based on their priority that is calculated using confidence and data term. The approach defines a way of differentiating between patches that have the same minimum mean squared error with the selected patch. This approach is capable of propagating both linear structures and two dimensional textures into the target region. This technique can be used to fill small scratches in the Video frames as well as to remove larger objects from them. It is also computationally efficient and works well with larger images.We are looking forward to improving the algorithm so that the computational complexity is further improved.

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