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HOMOGENEOUS REGION SEGMENTED USING THE MEAN-SHIFT ALGORITHM FOR VIDEO INPAINTING

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***Abstract* - :** Here propose a new video inpainting method which applies to both static or free-moving camera videos. The method can be used for object removal, error concealment, and background reconstruction applications. To limit the computational time, a frame is inpainted by considering a small number of neighboring pictures which are grouped into a group of pictures (GoP). More specifically, to inpaint a frame, the method starts by aligning all the frames of the GoP. This is achieved by a region-based homography computation method which allows us to strengthen the spatial consistency of aligned frames. Then, from the stack of aligned frames, an energy function based on both spatial and temporal coherency terms is globally minimized. This energy function is efficient enough to provide high quality results even when the number of pictures in the GoP is rather small, e.g. 20 neighboring frames. This drastically reduces the algorithm complexity and makes the approach well suited for near real-time video editing applications as well as for loss concealment applications. Experiments with several challenging video sequences show that the proposed method provides visually pleasing results for object removal, error concealment, and background reconstruction context.

Key Terms : Video Inpainting, Mean-Shifting Algorithm, Homogeneous Region Segmented, Image Processing.

1. INTRODUCTION

The major issue of video inpainting methods is to fill in the missing part, also called hole, as faithfully as possible both in space and time. This can be achieved by extending still images inpainting methods, either by considering spatio-temporal similarities between patches by taken into account the motion information or by ensuring global space-time consistency thanks to the global minimization of an energy function.

These methods work quite well for videos captured by static cameras. However, they often fail with videos captured by free-moving cameras. One solution to deal with complex dynamic video sequences is to register frames and preferably those located near the frame to be inpainted.

The missing areas can then be filled in by using the most appropriate known pixels in the stack of aligned frames. In this kind of methods, the quality of the inpainting result significantly depends on the alignment quality. Two widely used alignment approaches are described in the literature, namely the dense and sparse motion-based alignment The dense approaches estimate the 2D or 3D motion vectors of each pixel or block in the video in order to infer the camera motion.

The 2D methods compute the motion vectors between consecutive frames in the video. The 3D methods estimate the global camera motion by using all frames in the video. This generally provides more accurate results but at the expense of a higher computational cost. Sparse-based methods yield a fast and robust alignment using the correspondence between sparse sets of key points in the frames.

These algorithms use the homography transformation which relates the pixel coordinates in the two images. Unfortunately, a single homography transformation is not sufficient to align a pair of images. To reduce the registration errors, a global minimization function is often used to find the best transformation for each pixel.

Homography based registration methods are used by various video editing approaches dealing with view changes and moving camera sequences proposed an efficient inpainting method, yielding compelling results even for large holes and high resolution videos. A brief description is given in the following. All the frames of the input video sequence are first aligned to the target frame using the homography-based registration.

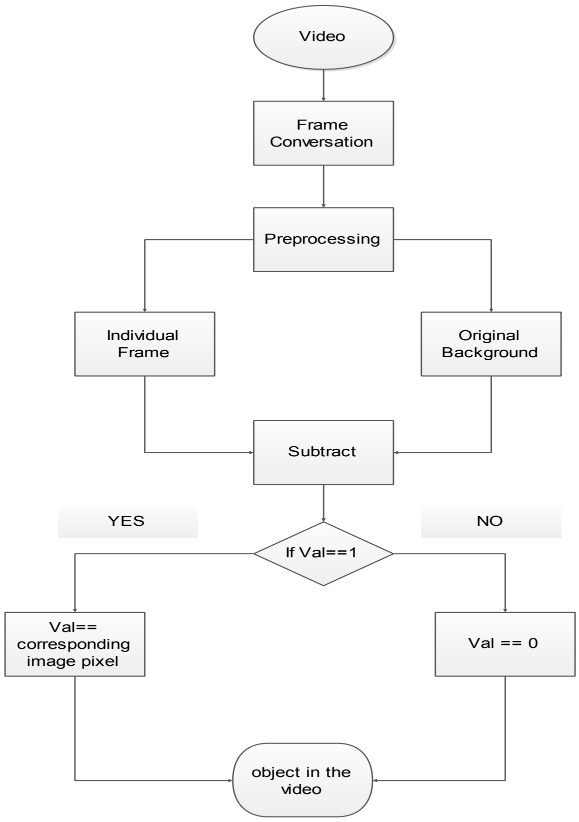
Each missing pixel is assigned to a collocated known pixel value extracted from the registered frames. To find the best one, a cost function is globally minimized. Such global minimization, which strives to find the best trade-off between different energy terms, significantly improves the space-time consistency.

These approaches are unfortunately time consuming even for low resolution sequences. Another drawback concerns the minimization process which is usually steered by an initialization term also named prediction term. the initialization is obtained by a simple spatial or temporal interpolation. This kind of interpolation lacks accuracy to be very helpful for inpainting.For instance, the predicted term in is a simple weighted interpolation of collocated pixels in the aligned frames. This approach assumes that there is, in the stack of aligned frames, at least one unoccluded pixel for each missing pixel in the current frame. This assumption turns out to be true when the temporal window is very large and when the displacement between frames is high.

2. PROPOSED METHOD

In Existing system Two widely used alignment approaches are used, namely the dense and sparse motion-based method is used. The dense approaches estimate the 2D or 3D motion vectors. The 2D methods compute the motion vectors between consecutive frames in the video. The 3D methods estimate the global camera motion by using all frames in the video. This generally provides more accurate results but at the expense of a higher computational cost. Sparse-based methods yield a fast and robust alignment. relates the pixel coordinates in the two images.

In Proposed System a single homography transformation is not sufficient to align a pair of images. The image inpainting problem can be formalized using either a local or global optimization framework. Inwardly propagated from the boundaries of the missing region. A well-known algorithm of this category is the examplar-based inpainting algorithm. Homography transformation between two images is in general not enough to find a good alignment. This condition is unfortunately not sufficient to force each planar region in the images to be registered in a similar manner.



System Architecture Design

Here using video inpaniting Frames Registration,MRF based registration.Hence, most Region-Based Registration methods search for each pixel the best homography transformation that minimizes a predefined energy function.

A homogeneous region segmented using the mean-shift algorithm.Inpainting is then performed using a predefined energy cost which is globally minimized.

MRF-based approaches often provide better inpainting quality compared to greedy examplar-based methods.Highly depends on the quality of both the registration and the segmentation methods, which need to be very accurate to provide reasonable inpainting results.

3. MODULES AND DESCRIPTION

Here using 4 modules Registration and hole filling ,Region-Based Registration , Mean shift algorithm and Poisson blending .

3.1.Registration and hole filling

It consists in aligning the neighboring source frames *Is* with the target frame *It* . An efficient registration method is required . Since alignment errors can propagate an undermine the spatial and temporal coherency of the inpainted areas. Registration method should be fast enough to provide a reduced complexity.Video inpainting methods is to fill in the missing part, also called hole .The approach more robust to noise and illumination variations.

***3.2.Region-Based Registration Approach*:**

The proposed method aims at being well suited for various viewpoint changes and motion characteristics, while being fast enough to be reasonably considered as a preprocessing step in video editing algorithms. The proposed region-based registration approach is motivated by the recent registration approach proposed. Assuming that the image pair is composed of two dominant planes, perform the alignment by using only two homography transformations. First, SIFT features are extracted and clustered into two groups based on their spatial positions in the image.

Two homography transformations that map each feature group are computed. These two homography transformations are then linearly combined.The weight of the linear combination controls on a pixel-basis the contribution of each homography and depends on the spatial proximity of the closest feature points.The key idea is that neighboring pixels with similar features have to be aligned using the same homography transformation. This constraint is also used in MRF-based homographies methods thanks to the smoothness term but the spatial consistency is limited to the chosen neighborhood (i.e. 4-neighbors are usually used).

To ensure a higher spatial consistency, we use a spatial segmentation to determine homogeneous regions. Assuming that a plane is homogeneous in terms of color, such regions may correspond to the actual planes of the scene. For this purpose, the mean-shift algorithm, which is a fast and automatic segmentation tool, requiring only few parameters such as the minimum size of a region, is used.

3.3. Mean shift algorithm:

For each data point, mean shift defines a window around it and computes the mean of data point. Then it shifts the center of window to the mean and repeats the algorithm till it convergens.

Mean shift is a nonparametric iterative algorithm or a nonparametric density gradient estimation using a generalized kernel approach

Mean shift is the most powerful clustering technique. Mean shift is used for image segmentation, clustering, visual tracking, space analysis, mode seeking . Mean shift segmentation is an advanced and vertisale technique for clustering based segmentation

The mean shift vector computed with kernel *G*is proportional to the normalized density gradient estimate obtained with the kernel *K*

The mean shift algorithm seeks a *mode*or local maximum of density of a given distribution

Mean shift can be sumedup like this

- For each point *xi*
- Choose a search window
- Compute the mean shift vector *m(xit)*
- Repeat till convergence
- Shadow of the Kernel K is kernel H if

$$m(x) - x = \frac{\sum_{s \in S} K(s-x)w(s)s}{\sum_{s \in S} K(s-x)w(s)} - x,$$

is in the gradient direction at x of the density estimateusingH

$$q(x) = \sum_{s \in S} H(s-x)w(s).$$

Mean Shift Segmentation

For each *i= 1…n* run the mean shift procedurefor *xi*and store the convergence point in *zi*.

Identify clusters *{Cp} p=1…m*of convergence pointsby linking together all *zi*which are closer than 0,5from each other in the joint domain.

For each *i= 1…n* assign*Li= {p | zi∊Cp}.*

Optional: Eliminate spatial regions smaller than

M pixels.

***3.4.Poisson blending*:**

Poisson image blending is a popular tool for seamless image Cloning. In our approach, we apply the Poisson blending to the inpainted result. Interestingly, the Poisson blending allows to strengthen the temporal consistency and to increase the robustness of the proposed approach as well.

Indeed, once the blending has been performed, we replace the current image by the blended and inpainted image into the GoP, as illustrated by Figure 1. The subsequent image will be then inpainted by taking into account the previous blended and inpainted frames.The quality of the inpainted image is improved when the Poisson blending is applied.

4. CONCLUSION

Here propose a novel video inpainting method. In a first step, neighboring frames are registered with a region-based homography. Each plane in the scene is assimilated to a homogeneous region segmented using the mean-shift algorithm. Inpainting is then performed using a predefined energy cost which is globally minimized. A spatial inpainting is used to guide this minimization leading to improve the quality of the inpainted areas. The proposed approach has a reduced complexity compared to existing methods. Missing areas are filled in by considering a sliding window of 20 frames. Unlike Granados et al.'s method [13], in which three optimization steps are involved (homography computation, inpainting and illumination handling), our approach uses only two global optimization methods and uses as mentioned previously a reduced number of frames. Experiments show that the proposed approach provides high quality inpainting results. Future work will focus on inpainting both background and moving objects in the videos.

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