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Spatio-Temporal Image Inpainting for Video Applications

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Abstract: Video inpainting or completion is a vital video improvement technique used to repair or edit digital videos. This paper describes a framework for temporally consistent video completion. The proposed method allows to remove dynamic objects or restore missing or tainted regions presented in a video sequence by utilizing spatial and temporal information from neighboring scenes. Masking algorithm is used for detection of scratches or damaged portions in video frames. The algorithm iteratively performs the following operations: achieve frame; update the scene model; update positions of moving objects; replace parts of the frame occupied by the objects marked for remove by using a background model. In this paper, we extend an image inpainting algorithm based texture and structure reconstruction by incorporating an improved strategy for video. Our algorithm is able to deal with a variety of challenging situations which naturally arise in video inpainting, such as the correct reconstruction of dynamic textures, multiple moving objects and moving background. Experimental comparisons to state-of-the-art video completion methods demonstrate the effectiveness of the proposed approach. It is shown that the proposed spatio-temporal image inpainting method allows restoring a missing blocks and removing a text from the scenes on videos.

Keywords: Inpainting, Patching, Masking, Spatio-temporal, Restoring of missing pixels, Video, Dynamic textures.

1 Introduction

Video inpainting refers to a field of computer vision that aims to remove objects or restore missing or tainted regions presented in a video sequence. Video signals often contain static images which may hide some useful information. There are a lot of examples of such images like different channel logos, date, time or subtitles that are superimposed on the video with further coding. In addition, there are other factors like distorted video blocks caused by

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lossy compression performed by a video coder and media data transmission artifacts. In some cases there may be unwanted objects on the video sequence. Here, the term object refers to a connected region of pixels. The example of such object can be a moving car or person, the defect caused by a scratch on the film or the entire background scene.

The task of video repairing is related to the problem of image inpainting. The only difference is the necessity to maintain temporal continuity in addition to spatial continuity.

Most of image reconstruction methods can be divided into the following three groups: based on solution of partial differential equations in partial derivatives (PDE) [1 – 4]; based on orthogonal transformations [5 – 8]; based on texture synthesis [9 – 12]. The same distinction is made between local and nonlocal methods of processing. The methods of local processing are used to calculate the missing pixel values using information in the local area adjacent to the restored pixel. The methods of non-local processing in most of cases are based on the principle of texture synthesis and use information to restore pixels in all images.

The first work in video inpainting has used information from neighboring frames for recovering procedure. This approach is justified in removing the defects of the film [1]. Many types of defects appear only in one frame, and absent in its neighbors. The virtue of this method is its simplicity. But it is not suitable to delete an object that is presented in several successive frames.

Some of an image inpainting techniques can complete holes based on both spatial and frequency features [6]. Structural properties, such as edges of an objects, are extracted from the spatial domain and used to complete an object with its structural property extended [9, 13]. In addition, another image completion approach [14] uses automatic semantic scene matching to search for potential scenes in a very large image database.

The fact that video inpainting dealing with moving objects in time and must consider not only spatial continuity of such objects, but also their temporal continuity. In this regard, a simple application of inpainting approaches designed for images sequentially to each frame leads to unsatisfactory results. One of problems is the appearance of so-called "ghosts". A small change of lighting or the movement of surrounding pixels can lead to a significant change in the result of recovery.

The problem of video inpainting can be divided into the following categories [15]: stationary video with moving objects; nonstationary video with still objects; nonstationary video with moving objects (could be occluded), including all camera motions.

Existing methods of video inpainting can be divided into several classes:

1) There are approaches similar to methods of static images inpainting. The main varieties: the methods based on partial differential equations (PDE), methods based on a synthesis of textures.
2) Methods using the space-time recovery provide good quality of restoration, but usually quite costly in terms of computation.
3) Methods, separating the original video sequence to a set of layers (in simple case background and foreground). Each layer is restored individually and performed compound-treated layers.

In [16] described method of inpainting is individually restored each frame. This method relates to methods based on solving partial differential equations to restore an unknown area, analogies between the image and an incompressible fluid. The dynamics of an incompressible fluid is described by Navier-Stokes equation. For the transition from liquid to an image using the following analogy is used as a function of the flow appears bright. As the flow rate acts as a vector perpendicular to the gradient vector at a given point in the image, the twist is equal to smoothness, the estimated gradient. The method leads to a complete loss of information about the texture. This method is applicable only to small objects, its application to large areas leads to unsatisfactory results.

In the method of [17] missing region sequences were also recovered with the help of a suitable replacement in the accessible part of the video. This provides a global space-time continuity. This is achieved by considering the problem as a global optimization problem.

Patwardhan et al. [18] suggest a rather simpler method for inpainting stationary background and moving foreground in videos. To inpaint the stationary background a relatively simple spatio-temporal priority scheme is employed where undamaged pixels are copied from frames temporally close to the damaged frame, followed by a spatial filling in step which replaces the damaged region with the best matching patch so as to maintain a consistent background throughout the sequence. This algorithm provides high-quality visual recovery, but it demands computing resources to search for similar patches.

This approach was extended processing of the video sequences in the work [19] where the authors have attempted to provide both spatial and temporal continuity. Searching similar patch is performed not only on the current frame, but throughout the video sequence, or in some bounded area of it. In [20, 21] there have been made some attempts to use various optimizations: object tracking, mosaic images, separation of video sequence to set of moving.

The main drawbacks of the known methods are based on the fact that the most of them are unable to recover the curved edges and can be applicable only for scratches and small defects removal. It should be also noted that these methods often blur image in the recovery of large areas with missing pixels. Most of these methods are computationally very demanding and inappropriate for implementation on modern mobile platforms.

In this paper we propose a framework for video reconstruction, aimed at achieving high-quality results in the context of film post-production. Our proposed method uses existing exemplar-based techniques and extends them to process videos. A novel algorithm for automatic image inpainting is based on 2D autoregressive texture model, exemplar-based and structure curve construction. It is shown that this approach allows to restore the curved edges and provide more flexibility for curve design in damaged image by interpolating the boundaries of objects by cubic splines.

The rest of the paper is organized as follows. Section 2 describes the proposed method. This is followed by a description of the basic idea of the proposed video inpainting approach based on texture model and structure curve construction. Experimental results are given in Section 3, followed by the Conclusion section.

2 The Proposed Video Inpainting Method

2.1 Mathematical model

In this work we use geometric image model as a frame model of a video sequence [22]. Any image can be divided into several areas such as texture regions, non-texture and edges on the local geometric features. There are texture areas in an image, separated by boundaries. These boundaries may have a thickness of several pixels and have a different spatial configuration. In this case, we assume that the boundaries are smooth in the sense that they can be approximated by polynomials of low orders. Thus, the region with missing pixel values may be surrounded by one or more regions, separated by edges.

A discrete image defined on a $I \times J$ rectangular grid is denoted $\left\{Y_{i,j}^t\right\}\left(i=\overline{1,I}, j=\overline{1,J}, t=\overline{t,T}\right)$ and can be represented as follows: $Y_{i,j}^t = (1-M_{i,j}^t)\cdot S_{i,j}^t + M_{i,j}^t \cdot R_{i,j}^t$, where $S_{i,j}^t$ are the true image pixels; $M=\left[M_{i,j}^t\right]$ is a binary mask of distorted values of pixels (1 − corresponds to missing pixels, 0 – corresponds to the true pixels); $R_{i,j}^t$ are missing pixels; I is the number of rows, J is the number of columns and T is the number of the frames.

Fig. 1 shows the image model, where the region Y is schematically presented in the form of three sub-regions, representing several types of texture regions, γ_1, γ_2 are the boundaries of the image with the first texture, γ_3, γ_4 are the boundaries of the image with the second texture, R are missing pixels intersecting with the boundaries γ_1, γ_2, γ_3 and γ_4.

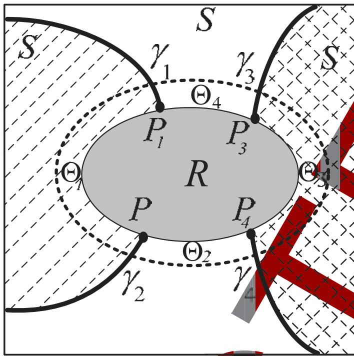


Fig. 1 – *The image model.*

2.1 The proposed method

In this article we will discuss the video inpainting proposal put forward by Patwardhan et al. [23] which describes a simple, fundamental approach to the problem making it ideal for the purposes of introducing and illustrating the core concepts in the field. The special feature of this method is the ability to restore the video, shot by a moving camera. In fact, this method is a generalization of the exemplar based method in case of video sequences that adds to the spatial time continuity. Recovery area may be different: moving object, static object and other. It also can be background or foreground objects. It can be blocked by other objects or can block them. The algorithm includes preprocessing stage and two work phases. At the preprocessing stage a rough segmentation of each frame in the foreground and the background is performed. After this step some regions can still be empty. For its restoration a search for similar blocks of the current frame is used. The diagram of this method is shown in Fig. 2. This algorithm has some disadvantages. Searching patches in the texture restoration requires significant computational complexity to restore large texture areas. The exemplar-based methods use a non-parametric sampling model and texture synthesis. Often an image does not have enough patches to copy from because the patch size is large or the mask is placed on a singular location on the image where similar patches cannot be found. The problem of choosing similar exemplar using only part of patch is common for all exemplar-based inpainting methods. We will tackle this problem by first stage restoration using AR model for prediction lost pixels in the patch.

The purpose of this work is to modify the algorithm proposed by Patwardhan in order to overcome all above mentioned drawbacks.

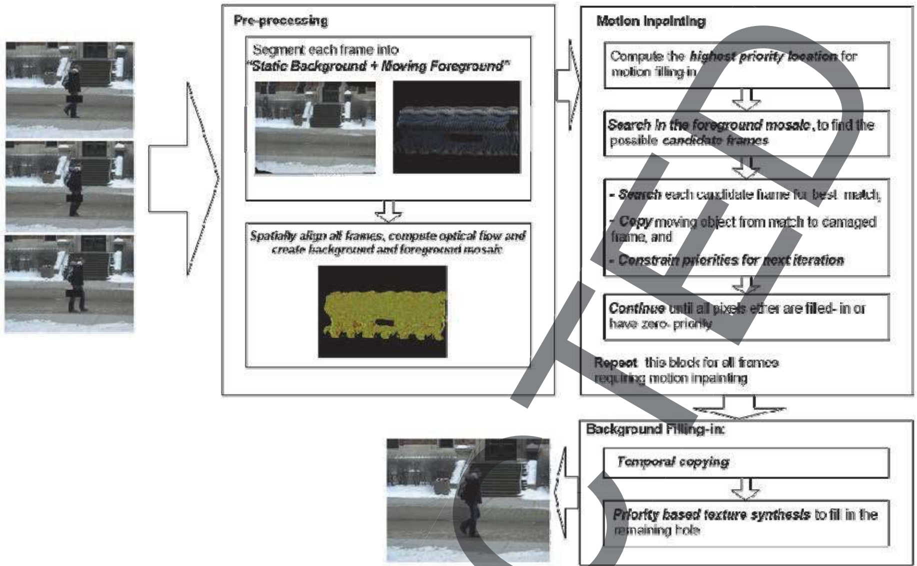


Fig. 2 – *Algorithm of video inpainting method.*

Proposed approach allows to remove objects or restore missing or tainted regions presented in a video sequence by utilizing spatial and temporal information from neighboring scenes. The algorithm iteratively performs following operations: achieving frame; updating the scene model; updating positions of moving objects; replacing parts of the frame occupied by the objects marked for remove with use of a background model. In this paper, we extend an image inpainting algorithm based texture and structure reconstruction by incorporating an improved strategy for video [22]. We introduce a novel algorithm for automatic image inpainting based on 2D autoregressive texture model and structure curve construction. An image inpainting approach based on the construction of a composite curve for the restoration of the edges of objects in a frame using the concepts of parametric and geometric continuity is presented. After edge restoration stage, a texture restoration using 2D autoregressive texture model and exemplar-based method are carried out. The image intensity is locally modeled by a first spatial autoregressive model with support in a strongly causal prediction region on the plane.

At the preprocessing stage a rough segmentation of each frame in the foreground and the background is performed. Segmentation is used to construct a mosaic image, which helps reduce the time of searching for similar patches [23]. The foreground objects to be inpainted are pepresented in a repetitive motion pattern and are not changed in size and pose significantly. The occluded moving foreground objects are inpainted by a two-stage process using the stored object templates. The partial objects are first completed with the appropriate object templates selected by minimizing a window-based dissimilarity measure. Between a window of partially-occluded objects and a window of object templates from the database, we define the dissimilarity measure as the Sum of the Squared Differences (SSD) in their overlapping region plus a penalty based on the area of the non-overlapping region. The first step in treatment is the restoration of moving foreground objects, which "overlap" the restored area. After that there is a recovery of the remaining area by copying blocks from adjacent frames. After this step some regions can still be empty – for its restoration is used to search for similar blocks of the current frame.

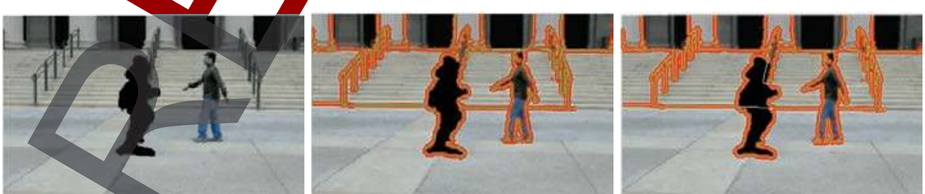
We propose modification of this method in background restoration step. One of the most important and ubiquitous tasks in image analysis is segmentation. This is a critical intermediate step in all high level object-recognition tasks. In this paper we used a method for segmenting images that was developed by Chan and Vese in [24]. This is a powerful, flexible method that can successfully segment many types of images, including some that would be difficult or impossible to segment with classical thresholding or gradient-based methods. The Chan-Vese algorithm is an example of a geometric active contour model.

The Chan–Vese (CV) model is an alternative solution to the Mumford–Shah problem solved the optimization of by minimizing the following energy functional:

$$E^{CV}(c_1,c_2,C) = \mu \cdot Length(C) + \\ +\lambda_1 \int\limits_{inside\ (C)} |u_0(x,y)-c_1|^2 \,\mathrm{d}x\,\mathrm{d}y + \lambda_2 \int\limits_{outside\ (C)} |u_0(x,y)-c_2|^2 \,\mathrm{d}x\,\mathrm{d}y, \tag{1}$$

here μ, λ_1 and λ_2 are positive constant, usually fixing $\lambda_1 = \lambda_2 = 1$, c_1 and c_2 are the intensity averages of u_0 inside C and outside C, respectively.

The first step is to find a correspondence between the boundaries that are crossing regions with missing pixels $R_{i,j}$.



a) b) c)

Fig. 3 – *Segmentation of the test frame.*

In the next step of the algorithm we analyze the edges $\gamma_1,\gamma_2..\gamma_k..\gamma_L$, $k=\overline{1,L}$ (Fig. 1) crossing the area with a missing pixels R and their correlation to the same boundary. For example, in Fig 1, γ_1, γ_2 are parts of the first boundary γ_{1-2} and γ_3, γ_4 are parts of the second boundary γ_{3-4}.

For the cubic spline interpolation of each of the curves parts pairs the concepts of parametric and geometric continuity are used. For the resulting pairs of the points P_k and P_l on the edges in the true image and non-zero tangent vectors $\boldsymbol{Q}_k$ and $\boldsymbol{Q}_l$, the cubic Hermite curve is determined with the vector equation in following form [22]:

$$\boldsymbol{B}(t)=(1-3t^2+2t^2)P_k+t^2(3-2t)P_l+t(1-2t+t^2)\boldsymbol{Q}_k-t^2(1-t)\boldsymbol{Q}_l,\ 0\le t\le 1.$$

For a recovery procedure of edges on the basis of spline interpolation, we can see more details in [22]. In Fig. 3c the example of structure curve construction is given.

The texture restoration algorithm is a modification of the example-based image inpainting algorithm proposed by Criminisi et al. [9]. The main drawbacks of EBM include: visible boundaries on the reconstructed image between similar patches; an incorrect restoration in absencke of similar blocks; a dependence of reconstruction error on a block size. One of the major problems in original inpainting method is a process of searching the patch with the maximum similarity to a selected patch using mean squared error metric. As a result, the algorithm will produce visually poor result. Thus, the searching criterion is the best match using only part of patch may lead to some images to uncorrected reconstruction since a searching method uses small part of the patches.

The pixels belonging to the boundary of the recovery region will be denoted by $\delta S_{i,j}$, where: $i=\overline{1,N}, j=\overline{1,M}$. At the first step of the algorithm, for each pixel boundary δS we choose a square block Ψ_p in order to find the most similar patch. In most cases in such block many pixels are absent that leads to significant error in searching a similar patch. We will tackle this problem by first stage restoration using AR model for prediction lost pixels in the patch.

Most of the images of interest, for example, the images of cultivated fields and concentration of population are naturally rich in texture, level of gray, etc. During the past decades, image representation and image texture recovery have been important and challenging topic. The spatial autoregressive model (2D-AR model) has been extensively used to represent images [25].

The 2D-AR model does not require a large number of parameters to represent different real scenarios [26]. In particular, the first-order 2D-AR model is able to represent a wide range of texture images.

We represent a patch as 2D Random field [27]:

$$\hat{\Psi}_p = \sum_{m \in s(o,p]} \varphi_m \cdot X_{s-m} + \sum_{n \in s(o,q]} \vartheta_n \cdot \eta_{s-n} + \eta_s, \quad (2)$$

where $(\varphi_m)_{m \in s(o,p]}$ and $(\vartheta_n)_{n \in s(o,q]}$ denotes, respectively the autoregressive and moving average parameters with $\varphi_0 = \vartheta_0 = 1$, and η_s denotes a sequence of distributed centered random variables with variance σ^2.

For finite order AR model the parameters can be estimated by using a 2D extension of the Yule-Walker equations [28].

After a texture restoration using 2D autoregressive texture model the exemplar-based method is carried out for each $\hat{\Psi}_p$. On the true image S we find patch ψ_q, for which the Euclidean distance is minimal:

$$D_E(\hat{\Psi}_p, \psi_q) = \sqrt{\sum (\hat{\Psi}_p - \psi_q)^2} \longrightarrow \min. \quad (3)$$

The pixels in a missing area R are restored by copying the corresponding pixels of the block ψ_q found within the restored boundaries.

3 Experimental Results

The effectiveness of the presented scheme is verified on the test frames of a video sequence with missing pixels. After applying the missing mask, all frames have been inpainted by the proposed method and the method proposed by Patwardhan in [23]. In Fig. 4 and Fig. 5 examples of frames restoration (a - the image with a missing pixels, b – the foreground restoration by the Patwardhan method, c – the foreground restoration by the proposed method, d - the background restoration by the Patwardhan method, e – the background restoration by the proposed method) are shown.

A main feature of the test frames is the fact that the regions with missing pixels are located at the intersection of the curve boundaries that need to be extrapolated. The test images have several texture and structure regions with different geometrical characteristics. The method proposed by Patwardhan failed in restoration in the absence of similar blocks. The results show that the proposed method can correctly restore the structure and texture regions. It's worth noting that the method does not smear during the restoration of large areas of missing pixels.

The effectiveness of the presented scheme is verified on the test frames of a video sequence with missing pixels presented. After applying the missing mask, all frames have been inpainted by the proposed method and state-of-the-art methods [8, 14].

Fig. 4 – *Examples of image restoration.*

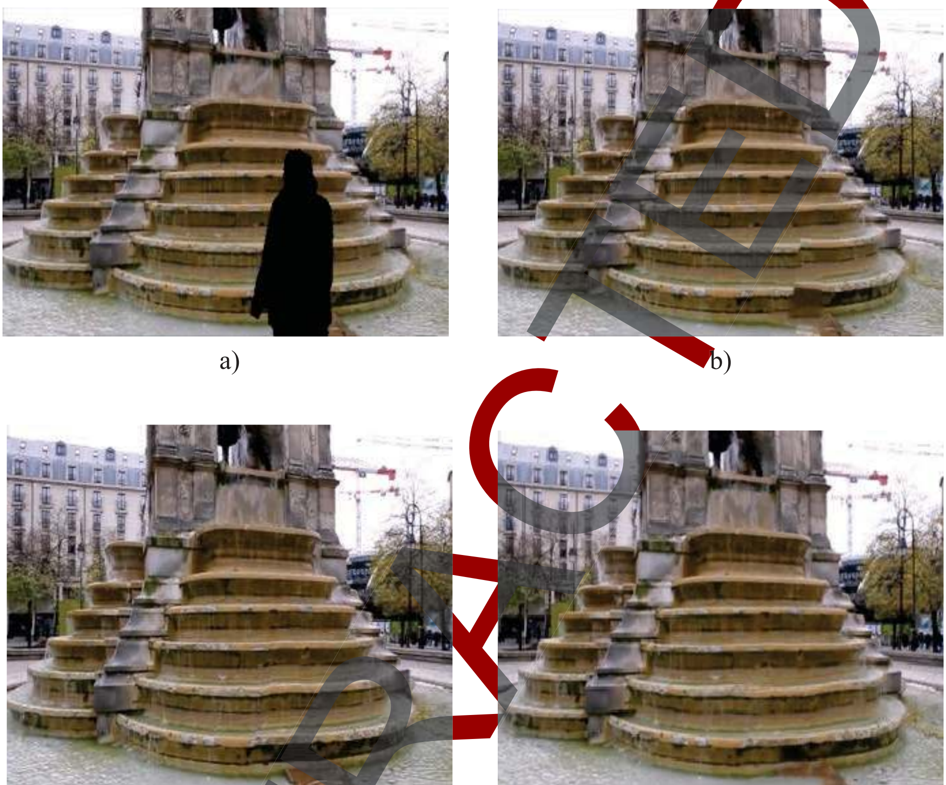
In this example we will consider the problem of inpainting dynamic textures, e.g. sequences whose frames are relatively unstructured, but possessing some overall stationary properties. In Fig. 6 examples of video completion (a - the image with a missing pixels, b - the restoration by the Wexler method, c - the restoration by the Newson method, d - the restoration by the proposed method) are shown. We can see that our technique is batter then others even in moderate dynamic background.

The error concealment examples are given in Fig. 7. In this example, practically the entire missing region can be completed by proposed method (Fig. 7d) better then result of the image reconstructed by the Adobe Photoshop CS5 (Fig. 7c). The boundary pixel values of the house and wood of the images are correctly restored using the proposed method. It's also worth noting that the proposed method has some incorrect restoration of image and smear the texture and structure during the restoration of large areas of the missing pixels. Note what the Photoshop result has a blurring problem.

Fig. 5 – *Examples of image restoration.*

The effectiveness of the presented scheme is verified on the test frames of a video sequence with missing pixels. In Fig. 8 example of video completion (a, c – the frames with a missing pixels; b, d – the restoration by the proposed method) is shown. In the two figures, the original input images contain a significant amount of missing image areas.

The boundary pixel values of the objects of the images are correctly restored using the proposed method. It's also worth noting that the method does not blur the texture and structure during the restoration of large areas of missing pixels.



a) b)

c) d)

Fig. 6 – *Examples of video inpainting.*

Fig. 9, 10 present the results of example of video completion and comparison with method [29] (a – the frames with a missing pixels; b – the restoration by the method [29]; c – the restoration by the proposed method).

These experimental results have demonstrated that the results Figs. 9 and 10b look jaggy on the moving object, while our result Figs. 9 and 10c looks more natural and better. To fill the missing areas from other frames the proposed completion approach separate the moving objects from the static background and deal with them respectively in completion.

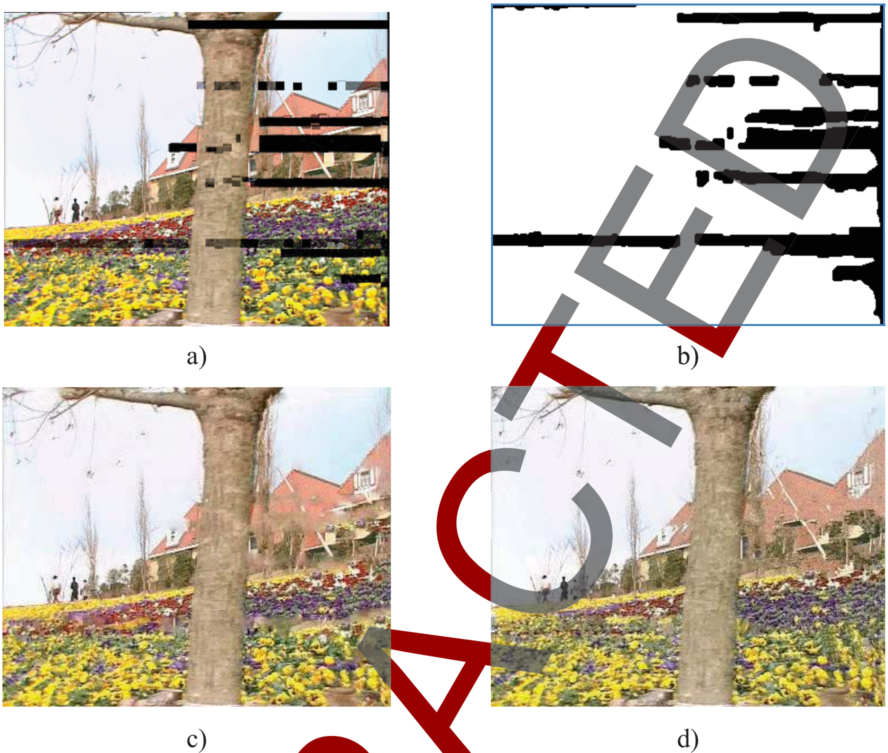


Fig. 7 – *Examples of image restoration.*

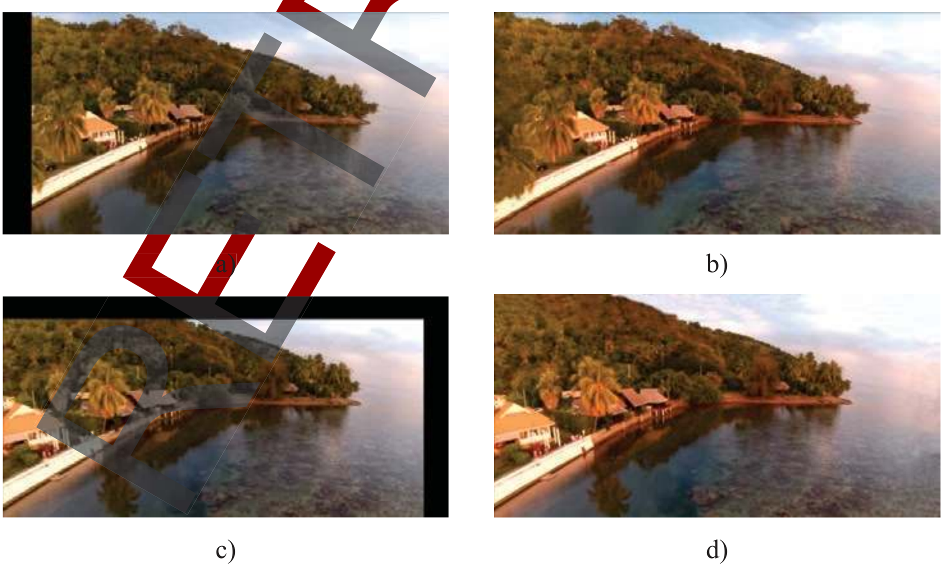


Fig. 8 – *Examples of video completion.*

a) b) c)

Fig. 9 – *Example of video completion.*

a) b) c)

Fig. 10 – *Example of video completion.*

4 Conclusion

The paper presents a video inpainting algorithm based on the texture and structure reconstruction of video sequence. The technique is based on combining motion based inpainting with spatial inpainting, using image mosaics. If there are moving objects to be restored, they are filled in first, independently in changing background from one frame to another. The background is filled-in by extending spatial texture synthesis techniques based on a separate reconstruction of a composite curve for the restoration of the edges of objects and texture synthesis using 2D autoregressive texture model. Several examples presented in this paper demonstrate the effectiveness of the algorithm in restoration of static background and moving foreground of the video sequences having different geometrical characteristics.

In further work we are planning to test other methods of texture segmentation having been developed before [30, 31] and method of the fast exemplar retrieval based on binary hashes [32].

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