

INPAINTING OF VIDEO USING TEXTURE SYNTHESIS AND OPTICAL FLOW TECHNIQUE

P.Ramya, A.Sriram, Dr. N. R Chenthil Kumar, Dr.Elango, Pazhani
Department of Electronics and Communication Engineering
SNS College of Engineering, Coimbatore

Abstract - Texture synthesis is the process of constructing large digital image from a small digital sample image. Texture is modeled by probability distribution function. Inpainting is the process of modifying an video in a form that is not detectable by an ordinary observer. There are numerous and very different approaches to handle the inpainting problem, the most successful algorithms are based upon the following techniques: copy and paste texture synthesis and optical flow technique Motion estimation between frames is performed by employing an optical flow technique. The optical flow fields are used to detect corrupted regions and to restore them. Combining these two building blocks in a variational model and will provide a working algorithm for video inpainting trying to approximate the minimum of the proposed energy functions. In this paper, it is shown that video inpainting can be achieved by combining the two terms of the energy works better than taking each term separately.

Index Terms—Inpainting, texture synthesis, optical flow, variational models.

I. INTRODUCTION

Inpainting is the process of modifying an video in a form that is not detectable by an ordinary observer, and has become a fundamental area of research in image processing. Video inpainting consists in recovering the missing or corrupted parts of an image sequence. Inpainting problem can be expressed in the following way: given an image or video u with a masked region Ω , fill-in each pixel inside Ω with a value taken from Ω^c . Inpainting is the great practical importance of restoring and modifying images and videos, but is also a result of using image inpainting to understand the validity of different image models [1]. Image inpainting algorithms are used to perform the task of filling in missing or destroyed or unwanted regions in images.

In the paper [2], the texture is modeled that the probability distribution of brightness values for one pixel given the brightness values of its spatial neighborhood is independent from the rest of the image. The neighborhood is a square window around the pixel and its size is a global

parameter of the algorithm. One-pass greedy algorithm is used in the texture synthesis. That is, once a pixel is filled-in, its value remains unchanged. The texture synthesis problem is used to finding the correspondence map [3]. Optical flow technique is the pattern of apparent motion of objects, surfaces and edges in a visual scene. It is caused by the relative motion between an observer and the scene. It is used to detect the corrupted regions and to restore them.

The inpainting technique has been generalized to video sequences with occluding objects. The reconstruction of motion fields has been proposed in the field of video completion. Several video inpainting methods are used to minimize the energy [4],[5]. In case of large holes with complicated texture, previously used methods are not suitable to obtain good results. Instead of reconstructing the frame itself by means of inpainting, the reconstruction of the motion field allows for the subsequent restoration of the corrupted region even in difficult cases. This type of motion field reconstruction is called “motion inpainting” [6]. The similar method is used to continue the central motion field to the edges of the image sequence, where the field is lost due to camera shaking. This is done by a basic interpolation scheme between four neighboring vectors and a fast marching method [7]. To obtain a robust motion inpainting approach, which can deal with sudden scene changes by means of Markov Random Field based diffusion and applied it to spatio-temporal error concealment in video coding. To improve motion fields by only computing a few reliable flow vectors and filling in the missing vectors by means of diffusion based motion inpainting approach.

II.METHODLOGY

2.1.Texture Synthesis Method

The texture synthesis process grows a new image outward from an initial seed, one pixel at a time. In this algorithm “grows” texture, pixel by pixel, outwards from an initial seed. If choosing a single pixel as the unit of

synthesis so that the model could capture as much high frequency information as possible [2]. To proceed with synthesis, a probability table for the distribution is needed.

2.1.1 The Algorithm

In this, texture is modeled as a Markov Random Field (MRF). That is, assuming that the probability distribution of brightness values for a pixel given the brightness values of its spatial neighborhood is independent from the rest of the image. The neighborhood of a pixel is modeled as a square window and it is around that pixel. The size of the window is a parameter that specifies how stochastic the user believes this texture to be.

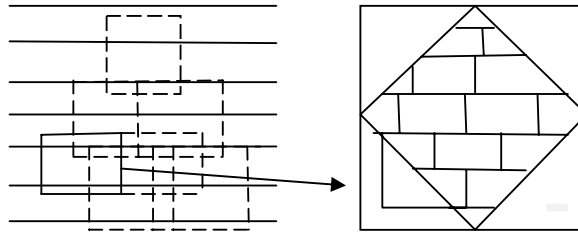


Figure 1. Algorithm overview. A sample texture image (left), a new image is being synthesized one pixel at a time (right).

If the texture is presumed to be mainly regular at high spatial frequencies and mainly stochastic at low spatial frequencies, the size of the window should be on the scale of the biggest regular feature.

2.1.2 Synthesizing one pixel

A method of synthesizing a pixel when its neighborhood pixels are already known. This method can be used for synthesizing the single texture. The correct solution would be to consider the joint probability of all pixels together.

2.1.3 Synthesizing texture

A method of synthesizing a pixel when its neighborhood pixels are already known has been discussed earlier. Unfortunately, this method cannot be used for synthesizing the entire texture or even for hole-filling since for any pixel the values of only some of its neighborhood pixels will be known. The correct solution is to consider the joint probability of all pixels together but this is intractable for images of realistic size.

Instead of using Shannon-inspired heuristic technique the texture is grown in layers outward from a 3-by-3 seed taken randomly from the sample image. Now for any point to be synthesized only some of the pixel values are known. Thus the pixel synthesis algorithm must be modified to tackle unknown neighborhood pixel values. This can be easily done by only matching on the known values and normalizing the error by the total number of known pixels when computing the conditional pdf. This heuristic does not guarantee that the pdf will stay valid as the rest is filled in. One can also treat that this as an initialization step for an iterative approach such as Gibbs sampling. Gibbs sampling produced only very little improvement for most textures. This loss of improvement indicates that the heuristic indeed provides a good approximation to the desired conditional pdf.

2.2 Optical Flow Technique

Optical flow is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer (an eye or a camera) and the scene. Optical flow techniques such as motion detection, object segmentation, time-to-collision and focus of expansion calculations, motion compensated encoding, and stereo disparity measurement utilize this motion of the objects, surfaces and edges. Optical flow fields are used to detect corrupted regions and to restore them [8].

Methods for determining optical flow technique is given as below:

- Phase correlation – inverse of normalized cross-power spectrum
- Block-based method – minimizing sum of squared differences or sum of absolute differences, or maximizing normalized cross-correlation
- Differential methods of estimating optical flow, based on partial derivatives of the image signal and/or the sought flow field and higher-order partial derivatives, such as:
 - Lucas-kanade – regarding image patches and an affine model for the flow field

- Horn-schunck – optimizing a functional based on residuals from the brightness constancy constraint, and a particular regularization term expressing the expected smoothness of the flow field
- Buxton–Buxton – based on a model of the motion of edges in image sequences
- Black–Jepson method – coarse optical flow via correlation
- General variational methods – a range of modifications/extensions of Horn–Schunck, using other data terms and other smoothness terms.
- Discrete optimization methods – the search space is quantized, and then image matching is addressed through label assignment at every pixel, such that the corresponding deformation minimizes the distance between the source and the target image. The optimal solution is often recovered through min-cut max-flow algorithms, linear programming or belief propagation methods

2.2.1 Uses of optical flow

Motion estimation and video compression have developed as a major aspect of optical flow research. Motion estimation is the process of determining motion vectors that describe the transformation from one 2D image to another; usually from adjacent frames in a video sequence. It is an ill-posed problem as the motion is in three dimensions but the images are a projection of the 3D scene onto a 2D plane. The motion vectors may relate to the whole image or specific parts, such as rectangular blocks, arbitrary shaped patches or even per pixel. The motion vectors may be represented by a translational model or many other models that can approximate the motion of a real video camera, such as rotation and translation in all three dimensions and zoom. Applying the motion vectors to an image to synthesize the transformation to the next image is called motion compensation. The combination of motion estimation and motion compensation is a key part of video compression as used by MPEG 1, 2 and 4 as well as many other video codecs. Video compression is a combination of spatial image compression and temporal motion compensation.

While the optical flow field is similar to a dense motion field derived from the techniques of motion estimation, optical flow is not only the determination of the optical flow field itself, but also of its use in estimating the three-dimensional nature and structure of the scene, as well as the 3D motion of objects and the observer relative to the scene.

Optical flow was used by robotics researchers in many areas such as: object detection and tracking, image dominant plane extraction, movement detection, robot navigation and visual odometry. Optical flow information has been recognized as being useful for controlling micro air vehicles

III.COMBINING TWO TECHNIQUES

Combining the texture synthesis and optical flow techniques, video inpainting can be achieved that minimizes the energy functions.

Texture synthesis is the process of constructing a large digital image from a small digital sample image. Texture synthesis has been an active research topic in computer vision both as a way to verify texture analysis methods, as well as in its own right. Potential applications of a successful texture synthesis algorithm are broad, including occlusion fill-in, lossy image and video compression, foreground removal, etc.

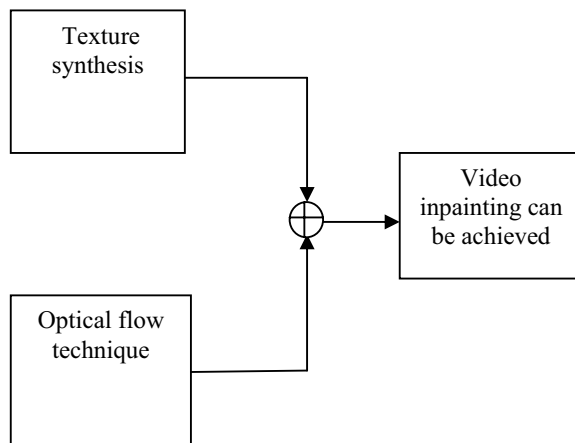


Figure 2: Block diagram for video inpainting

The problem of texture synthesis can be formulated as follows: let us define texture as some visual pattern on an infinite 2-D plane which, at some scale, has a stationary distribution. Given a finite sample from some texture, the goal is to synthesize other samples from the same texture. Without additional assumptions this problem is clearly ill-posed since a given texture sample could have been drawn from an infinite number of different textures. The usual assumption is that the sample is large enough that it somehow captures the stationary of the texture and that the scale of the texture elements (texels) is known. Textures have been traditionally classified as either regular (consisting of repeated texels) or stochastic (without explicit texels). However, almost all real-world textures lie somewhere in between these two extremes and should be captured with a single model. Stochastic texture synthesis methods produce an image by randomly choosing colour values for each pixel, only influenced by basic parameters like minimum brightness, average colour or maximum contrast. These algorithms perform well with stochastic textures only, otherwise they produce completely unsatisfactory results as they ignore any kind of structure within the sample image.

Optical flow is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer and the scene. Optical flow is an approximation of the local image motion based upon local derivatives in a given sequence of images. That is, in 2D it specifies how much each image pixel moves between adjacent images while in 3D it specifies how much each volume voxel moves between adjacent volumes. The 2D image sequences used here are formed under perspective projection via the relative motion of a camera and scene objects. The 3D volume sequences used here were formed under orthographic projection for a stationary sensor and a moving/deforming object. In both cases, the moving patterns cause temporal varieties of the image brightness. It is assumed that all temporal intensity changes are due to motion only.

IV. EXPERIMENTAL RESULTS

Video completion is done frame by frame as follows:

- First, assign priority for each neighboring frames from the damaged frame.
- Motion is computed from neighboring frames using common coverage area.
- Depending on weight priority, motion vectors are transfer into the damaged pixels and undamaged is warped into the damaged area.

This algorithm produces good results for a wide range of textures. The only parameter set by the user is the width of the context window. This parameter corresponds to the human perception of randomness for most textures. Combining the texture synthesis and optical flow technique, video inpainting is obtained. An example of using these techniques is given as below.



(a)



(b)



(c)

Figure 3: Influence of the two terms. (a) input video. (b) inpainted video. (c) output video.

V. CONCLUSION

The two models or building blocks are common to all the most successful inpainting algorithms. It is then combined into one energy functional. A working algorithm for video inpainting trying to approximate the minimum of the energy function is also provided. Experiments show that the combination of two terms of the energy works better than taking each term separately, something which remains consistent when comparing the results with other techniques. Combining texture synthesis and optical flow technique, video inpainting can be achieved.

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