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Stitching contaminated images

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ABSTRACT

Image stitching has long been studied in computer vision and has been applied to many fields. However, when the input images contain moving objects and meanwhile are noisy or partially contaminated, it remains a challenge to get a satisfactory clean panorama. In this paper, we propose to tackle both the challenges, i.e., denoising and stitching, by proposing a new energy function in a unified way. Such an energy model is however non-submodule, making the widely used optimization algorithms, such as graph cuts, hard to be used directly. We then generalize the recently proposed Graduated Non-Convexity and Concavity Procedure (GNCCP) to approximately minimize the energy. Comparative experiments validate the efficacy of the proposed energy function on both image denoising and stitching. Besides, the results also show the validity of the generalized-GNCCP on minimizing non-submodule function.

1. Introduction

Image stitching is the technique to combine two or more images into a high resolution and wide viewing composite. It has been successfully applied in many fields, such as in ocean exploration [1] and street map [2]. Many conventional stitching algorithms [3,4] are capable of taking overlapping images of the same scene and stitching them to form a panorama. These algorithms generally have quite a few prerequisites to produce satisfactory results: limited camera translation and limited moving objects in the scene. When the input images suffer a large structural deformation and contain moving objects, unfortunately, most algorithms tend to get a panorama which contains heavy blurring or ghosting area. Especially, when the input images are noisy or partially contaminated, current stitching algorithms are not capable of denoising and recovering the contaminated area to get a clean panorama. Though we can first denoise the images and then stich them, it suffers at least the following two shortcomings. First, it is time-costing since we have to sequentially implement the two tasks one by one, and second, it neglects the inherent interaction and local smoothness between them since such a two-step method tackles the two tasks separately. Compared with the two step method for image denoising and stitching, our method makes full use of the redundant information in the image set to denoise and recover the contaminated area by choosing the original uncontaminated pixels, based on the local smoothness principle, to form a clean and seamless panorama. On the other hand, traditional denoising method is not capable of recovering contaminated area. Actually, a intuitively more reasonable way is to consistently and simultaneously handle both tasks in a same framework, which is the main motivation of our work.

Generally speaking, image stitching includes two sub-procedures, i.e., image registration and image blending. Image registration involves transforming images from different views into the same coordinate system, while image blending takes the registered images as input to create a wide viewing panorama. Each registered image only contains part of the whole scene, so in the blending process a proper strategy should be taken to choose the right part of each registered image to form a seamless panorama. Traditional blending technique, such as weighted average [3], can get a satisfactory result only when there are no moving objects and noise or contaminated area. Some other researchers used the optimal seam method [4] to deal with the moving objects. By introducing Dijkstra's algorithm [5], the method can find a path avoiding cutting through the moving objects, which, therefore, makes the moving objects all in or all out of the panorama. However, it cannot denoise the image or recover the contaminated area.

In this paper, we propose a new energy function which can simultaneously handle image denoising and seamless stitching in a consistent way. We assume that the registered images contain all

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the information necessary to create a whole scene, though each image is partially contaminated and only contains part of the scene. So theoretically it is possible to create a seamless panorama using the input images. Image stitching can be typically formulated as a pixel-labeling problem in computer vision, which selects one particular image (by assigning each image one label) at each pixel to form a seamless panorama. In this paper we propose a new energy function for such a pixel labelling problem, which considers both moving objects and partially contaminated images. Such an energy function is however non-submodule, making the frequently used graph-cuts [6,7] algorithm cannot be used directly, or can only be used by discarding the non-submodule terms in the energy function.

In view of this, in our paper we generalized the recently proposed Graduated Non-Convexity and Concavity Procedure (GNCCP) [8] to minimize the energy function, which was firstly proposed to approximate the optimization over partial permutation matrices. The proposed GNCCP based algorithm has no constraint on the types of energies. Extensive experiment results witness that the proposed method can stitch images containing moving objects and contaminated area. Therefore, the main contribution of this paper is two-fold. First, a new energy function is proposed to tackle image denoising and stitching in a unified way, and second, we generalize GNCCP to approximately minimize it.

Section 2 gives a brief review of related works in the literature, and Section 3 is devoted to the proposed techniques. After giving comparative experiments in Section 4, Section 5 concludes the article.

2. Related works

Stitching two or more images together to create a seamless panorama typically involves image registration and blending techniques. For image registration, we need to estimate a transformation matrix relating different images. For image blending, to get a seamless panorama, proper strategies should be adopted to deal with the moving objects in the overlapping area, as well as the image noise and contaminated area. Below we give a brief description of the algorithms proposed in the literature.

2.1. Image registration

In general, the image registration techniques can be classified into area-based methods and feature-based methods [9]. In the last two decades, together with the emergence of a bunch of splendid local feature descriptors [10,11], the feature-based methods become more popular in image registration. The success of feature-based methods can be attributed to the rotation and scale invariance of the features, thus they can be used to register images with significant deformations, while the area-based methods are only applicable on images with only translational and rotational transformations.

2.2. Image blending

Early in the image mosaic research, researchers [12] tried to eliminate the blurring and visible seams by a weighted average method, which is called feathering. However, when the mis-registration is significant and moving objects exist, the feathering usually results in visual artefacts and ghosting in the composite. Some other researchers used the optimal seam method [4] to deal with the moving objects. By introducing Dijkstra's algorithm [5], the method can find a path avoiding cutting through the moving objects, which, therefore, makes the moving objects all in or all out of the composite. Unfortunately, this method may fail when the light exposure difference is significant, because it may treat the areas with different light exposures as areas with moving objects. Uyttendaele et al. [13] proposed to use the region of difference (ROD) to find the regions where the moving objects lie and then choose the right region to keep, which to some extent improved the optimal seam method. However, none of the above algorithms have taken the contaminated area into consideration.

The most relevant works in the literature were [14–16], which use the energy minimization method to solve the blending problem. By building an energy function, it encourages to put a seam where images have strong edges to form a panorama. This method works well on images with moving objects and mis-registration. However, the energy function built in [14,15] prefers short seams, which cannot recover the contaminated area. By contrast, our proposed energy function encourages to select pixels to minimize the inconsistency between neighbors, which can thus remove moving objects and recover the contaminated area at the same time. Such an energy function becomes however non-submodular, making the frequently used graph-cuts hard to be directly used. To tackle the problem, we generalize the recently proposed Graduated Non-Convexity and Concavity Procedure (GNCCP) to approximately solve the problem, which has no constraint on the format of energy function and was also shown to have a tight error bound on the pixel labelling problem [17]. It should be noted that this paper is in some sense a journal version of our conference paper in [16]. GNCCP is used as the energy minimization method in both paper. The main difference is that in the conference paper, we mainly focus on getting a satisfactory panorama on the lunar surface images. While in this paper we proposed a new energy function to stitching contaminated images, which can make good use of the redundancy in the overlapping area to recover the contaminated area and stitching them together at the same time.

3. Proposed algorithm

An overview of our algorithmic framework is shown in Fig. 1, where a typical example is given to illustrate the proposed method. First the input images are projected to the same coordination by a Speeded Up Robust Features (SURF) [10] feature based image registration method, followed by a pixel-labeling computation procedure and finally a gradient domain blending of the images to produce a final result. In the pixel-labeling procedure, the label of each pixel is computed by an energy minimization method.

3.1. Image registration

Image registration is to geometrically align the images to the same coordination system, and typically consists of two steps, feature correspondence and image transformation. For each successive pair images I_n and I_{n-1} in the image set, we adopt the SURF [10] feature based algorithm to estimate the geometric transformation matrix $T(n)$ of the two images, as described below:

Feature extraction and correspondence. Salient and distinctive points of the input images I_1, I_2 are automatically detected by SURF, which is proven to be quite robust again noise, scale and rotation [18]. For each feature point, it has a 64-dimensional descriptor gathering the information of the surrounding area. In this paper, we denote the descriptors of image I_1 and I_2 as D_1 and D_2, where $D_1 \in \Re^{M\times 64}$, $D_2 \in \Re^{N\times 64}$, and M, N are the number of feature points of I_1, I_2 respectively.

Generally, feature correspondence can be solved by nearest neighbor algorithm [19] and graph matching [20,21]. In this paper, taking the efficiency into consideration, we match the features by descriptor between images using a fast approximate nearest