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Unsteady camera zoom stabilization using slope estimation over interest warping vectors[☆]

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ABSTRACT

Projections being based on global image representative are considered as simplified and efficient stabilization solutions under poor textural or imaging conditions. The existing projection algorithms are investigated only for translation or rotation stabilization, but the image captured with unsteady camera also suffers from undesired zoom-in/out effect. This paper presents a new zoom estimation algorithm for extended projection applicability. Camera focusing generally being effective around its optical axis, produces zooming around the image center. This image-centered zoom results in an opposite relative motion (stretching/compression) in two halves of the image projections. A novel concept of utilizing this relative longitudinal projection motion is proposed for camera zoom estimation. Derivative dynamic time warping is used for image projection alignment and the effect of mismatched-warping singularities leading to motion estimation error is removed by selecting some key warping vectors labeled as *Interest Warping Vectors*. Slope values of these interest warping vectors in the two projection-halves are utilized for zoom factor estimation and the approach is also generalized for arbitrary zoom-center under forward translation. Robustness of the proposed algorithm tested with artificial textural artifacts is verified with motion accuracy analysis on various sequentially zoomed test and real-world images within 0.8 to 1.2 scale factor range.

1. Introduction

Image stabilization of an unsteady camera-shoot aims to compensate the undesired vibration induced motions. These vibrations could be the result of a shaky platform with mounted camera or a human body tremor in case of hand-held imaging devices. Motions to be estimated are mostly categorized as translation, rotation, zoom or a combination of these. In any stabilization system, motion estimation is considered as a crucial part as its accuracy directly affects the system efficiency. Existing motion estimation techniques can be broadly classified as intensity and feature based techniques. Feature based techniques efficiently handle affine motion stabilization with the added advantage of reduced time complexity [6,10,11]. However, their efficiency heavily depends on the accurate and robust feature extraction. It has been observed that their performance deteriorates under poor textural conditions like significant blur and low illumination level due to insufficient amount of extracted features. Intensity based techniques are suggested as better option for poor textural cases but most of them are limited to the translation and rotation estimation only [5,8,9,15]. Under intensity based techniques, the gradient optical flow method [3] is a good alternative for estimating affine motion. However it is computationally involved. Multigrid [4] and coarse-to-overfine [1] based approaches provide real-time stabilization, but at the core, optical flow based techniques do not faithfully respond to sharp intensity changes and give wrong intensity-flow estimation under localized intensity variation. Another class of intensity based techniques uses integral projections as the global image representation and provides a simple efficient motion estimation alternative to block based local area image analysis. Projection based techniques result in better motion estimation under poor texture and local intensity variations, but their applicability is limited to translation and rotation motion estimation [2,9,12,13]. Recently, a least square approach over projection warping vectors has been introduced for combined translation and zoom estimation adding a new dimension to the existing projection based stabilization techniques [14]. The method provides similarity motion stabilization but the presence of miswarping vectors limits zoom accuracy within small zoom/scale factor range of 0.98 – 1.02.

In this paper, a new zoom estimation technique based on image-projection warping is proposed, where the mismatching singularity is eliminated by working on some selected warping vectors labeled

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as *interest warping vectors*. Slope values of these interest vectors, with respect to the central projection-warping vector (or the mid-point vector) is utilized to get the image scaling factor. For an unsteady platform with forward motion can induce zooming around a point other than the frame center, hence a generalized formulation for arbitrary zoom center is also presented. The proposed technique extends the use of projection based algorithms for zoom motion estimation with better accuracy and extended scale factor range within [0.8 1.2]. A motion accuracy analysis for 1.3×zoom, imposed at an increment of 0.01 scale factor along with various artifacts like noise, blur and low intensity is presented over different test images. The proposed method gives better zoom accuracy in comparison to the existing least square based zoom estimation approach [14].

Rest of the paper is organized as follows: Section 2 presents a brief background on projection extraction and a projection-perspective of camera zooming. The concept of interest vector selection and the proposed zoom estimation technique are discussed in Section 3. Section 4 presents the result analysis of the proposed method over various test and real-world images. Concluding remarks are presented in Section 5.

2. Camera zoom: a projection perspective

Steady camera zooming is performed using lens movements to get a close or far view of a scene with respect to its original position. The camera zooming is computed around the image center which actually corresponds to camera focal axis. Fig. 1(a) shows camera zooming action by changing the focal distance from F to F' with the two corresponding shots displayed with points K (and K'). Change in the focal length causes displaced position of point K to K'. Assuming the zooming center to be at image center, the new position of each pixel under zoom-in action tries to move away from the center causing opposite displacement in two halves of the frame. Fig. 1(b) shows a pictorial view of scaled-images and the corresponding vertical projections under the zoom-in/out actions. The arrows in the projection represent the conceptual matching of individual elements of the two halves. The image I_{UP} and I_{DOWN} are obtained by zoom-in and zoom-out actions respectively. The horizontal and vertical integral projections, i.e. P_H and P_V of the image I of size R×C are obtained using column and row-wise intensity accumulation given by (1.a, 1.b) respectively.

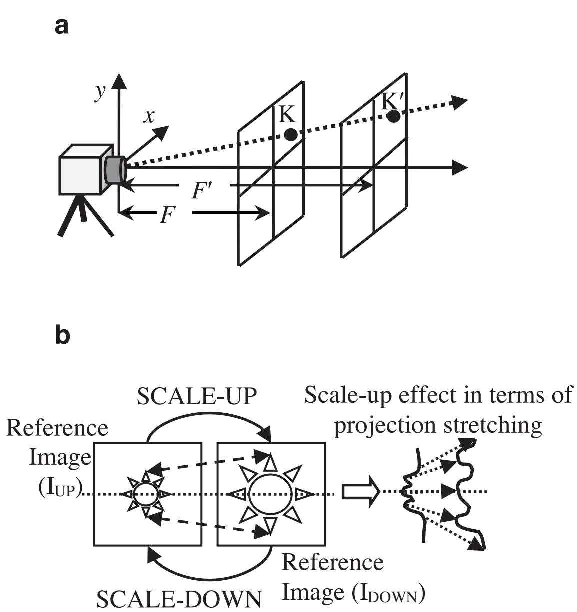

Fig. 1. Camera zooming concept (a) visualization with camera lens set-up and (b) corresponding image-projection perspective.

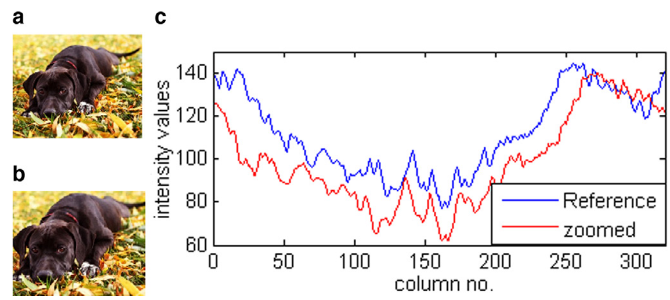

Fig. 2. Image-scaling in projection (a) test image *dog*, (b) zoomed-in target image and (c) corresponding horizontal projections.

$$P_H(j) = \frac{1}{R}\sum_{i=1}^{R} I(i, j); \quad \forall j \in [1 : C] \tag{1.a}$$

$$P_V(i) = \frac{1}{C}\sum_{j=1}^{C} I(i, j); \quad \forall i \in [1 : R] \tag{1.b}$$

Relative image translation and scaling can be conveniently observed in their corresponding projections. In Fig. 2, a test image '*dog*' is zoomed around center by a factor of 1.2 representing the camera lens zooming. The original and the zoomed test image *dog* is shown in Fig. 2(a) and Fig. 2(b) respectively. A zoom induced motion in the corresponding horizontal projections shown in Fig. 2(c) is observed as an opposite stretching in the two halves of the frame projection relative to its center.

3. Proposed zoom estimation technique

In this section, a new zoom estimation algorithm based on slope analysis over extracted interest warping vectors is proposed. The algorithm utilizes the derivative curve warping for image projection alignment and the proposed interest vectors are selected for inherent mismatch singularity vector elimination. In order to present the algorithm and self-containability of the paper, the concept of derivative image projection warping is briefly introduced here.

3.1. Derivative projection warping

The derivative projections DP in the two directions are obtained using left-point difference estimation over integral projections. Horizontal derivate projection of the test and target images is given by (2), where C represents the width of image I.

$$DP_H(j) = P_H(i) - P_H(i-1); \text{ where } 1 < i \leq C \text{ and } j = i - 1 \tag{2}$$

The horizontal derivative projections DP_H of the original test and the zoomed-target image are warped using Derivative Dynamic Time Warping (DDTW) [7]. Warping distance matrix 'D', using absolute difference between each combination of test and target DP elements, is given by (3).

$$D(i, j) = \left|DP_H^{test}(i) - DP_H^{target}(j)\right|; \quad \forall i \in [1 : C-1] \tag{3}$$

Using the dynamic programming implementation of the DDTW, accumulated distance matrix 'AD' is computed as (4). The optimal warping path P_{opt} is extracted over AD using (5), where each element