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Effects of texture addition on optical flow performance in images with poor texture☆

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ABSTRACT

This paper investigates the effects of adding texture to images with poorly-textured regions on optical flow performance, namely the accuracy of foreground boundary detection and computation time. Despite significant improvements in optical flow computations, poor texture still remains a challenge to even the most accurate methods. Accordingly, we explored the effects of simple modification of images, rather than the algorithms. To localize and add texture to poorly-textured regions in the background, which induce the propagation of foreground optical flow, we first perform a texture segmentation using Laws' masks and generate a texture map. Next, using a binary frame difference, we constrain the poorly-textured regions to those with negligible motion. Finally, we calculate the optical flow for the modified images with added texture using the best optical flow methods available. It is shown that if the threshold used for binarizing the frame difference is in a specific range determined empirically, variations in the final foreground detection will be insignificant. Employing the texture addition in conjunction with leading optical flow methods on multiple real and animation sequences with different texture distributions revealed considerable advantages, including improvement in the accuracy of foreground boundary preservation, prevention of object merging, and reduction in the computation time. The F-measure and the Boundary Displacement Error metrics were used to evaluate the similarity between detected and ground-truth foreground masks. Furthermore, preventing foreground optical flow propagation and reduction in the computation time are discussed using analysis of optical flow convergence.

1. Introduction

Accurate optical flow computation is crucial in many computer vision tasks, including motion estimation, object detection, and tracking. Three decades after the seminal contribution by Horn and Schunck [1], accuracy of optical flow computation methods have been improved significantly. However, images with poor texture, especially in the background, which occur in many sequences, still remain a major challenge in this field [2]. Since solving for optical flow components using the optical flow constraint is an ill-posed problem with two unknowns and one equation, there is a need for extra constraint(s). Spatial smoothness of optical flow components introduced by Horn and Schunck (HS) is one of the most common constraints used in different publications with various modifications, such as in [3–6]. The smoothness constraint causes the blurring of computed motion at the object boundaries, together with spread of foreground non-zero flow to the neighboring background pixels.

As we will see in Section 2.1, while making optical flow computation possible, in images with poorly-textured regions, the smoothness constraint leads to some disadvantages, such as considerable deformations in the size and the shape of the detected foreground objects, and accordingly in the position of the center area, which results in errors for foreground diagnosis and tracking. This is shown in the first row of Fig. 1 for a sequence, where a wooden model (only the upper body) and its cast shadows are moving against a background with poor texture. The first and second frames are shown in parts (a) and (b), respectively; the magnitude of optical flow calculated by the method in [4] is shown in part (c), where propagation of the object flow to the neighboring background pixels with poor texture has deformed the object shape and lead to difficulty in foreground detection. In images with multiple moving objects within a small region, smoothness of optical flow can lead to objects merging. This is illustrated in the second row of Fig. 1, where multiple cars with cast shadows are moving close to each other on a highway with insufficient texture. The first and second frames are shown in parts (d) and (e), respectively; the magnitude of optical flow calculated by the method in [6] is shown in part (f), where object merging is observable. The other negative effect of computing optical flow for poorly-textured regions is the considerable computation time due to solving the time-consuming Laplace equation with boundary conditions.

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0262-8856/

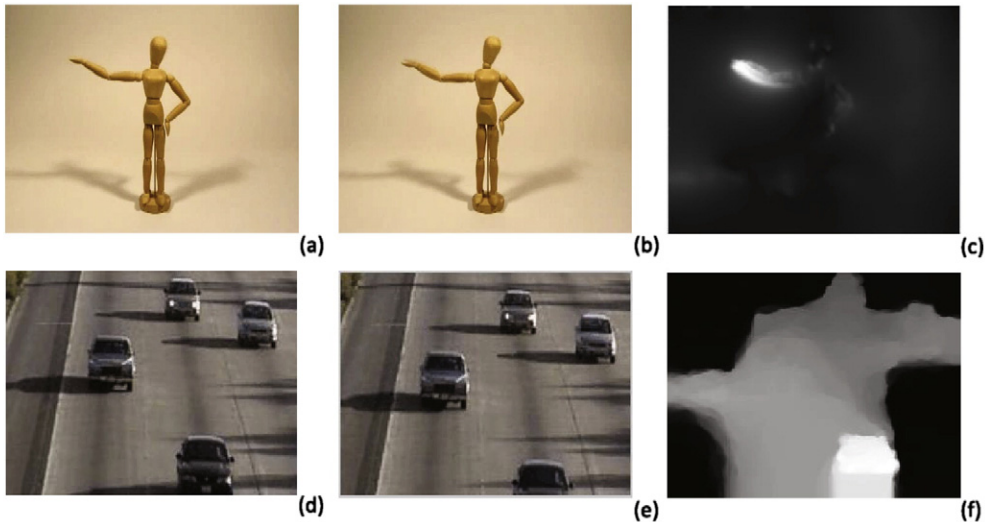

Fig. 1. Negative effects of the smoothness constraint on images with poorly-textured regions: First frame of the wooden model sequence (a); second frame of the wooden model sequence (b); optical flow magnitude computed according to [4] where the object shape is distorted (c); first frame of the highway sequence (d); second frame of the highway Sequence (e); optical flow magnitude computed according to [6] where object merging has occurred (f).

Researchers have attempted to overcome the negative effects of the smoothness term following the HS contribution. Nagel and Enkelmann [7] employed oriented derivatives for the smoothness term, observing that the motion boundaries coincide with the abrupt light intensity transitions. Using heuristically determined smoothness across and along the object boundaries, Alvarez et al. [8] proposed a modification for improving the method by Nagel and Enkelmann. A manually-designed probabilistic model using Markov Random Field (MRF) and a statistical model using patch-based motion discontinuity were used to relate the light intensity edges and motion boundaries by Black [9] and Fleet et al. [10], respectively. Lei et al. [11] adopted a variable weight for the effectiveness of the smoothness term in the HS formulation. The variable weight coefficient is adaptive through a threshold function based on the detection of the gray boundaries and on the real-time detection of the movement boundaries in the iterative process. The method by Nir et al. [12] solves for six affine parameters at each pixel position instead of two flow components. Sun as well as Werlberger et al. [13,2] modified the total energy function by adding non-local smoothness terms that employ adaptive weights for each pixel, which is basically equivalent to using median filtering after every warping step.

The approach of anisotropic weighting of the smoothness term is a breakthrough employed recently, including substitution of the standard quadratic penalizing function by the anisotropic Huber-L^1 Norm, first introduced in [14] and used in [15] and [16], applying smaller weights along the intensity boundaries compared to the orthogonal direction in [2]. A similar approach was proposed by Zimmer et al. [17] in which the brightness constancy is used to determine the weights rather than the intensity gradient. Harmonic constraint has been imposed on the isotropic gradient vector field to create the anisotropic diffusion in [18] and [19], where the authors utilized divergence and curl of the vector field. Aubert et al. [20] added an extra term, which penalizes computing motion in homogeneous blocks and only allows for large values of optical flow components in textured regions. Divergence controls the amount of diffusion, and the curl term controls the diffusion direction.

Despite significant improvements in the suppression of motion blurring at the object boundaries, even accurate and sophisticated leading

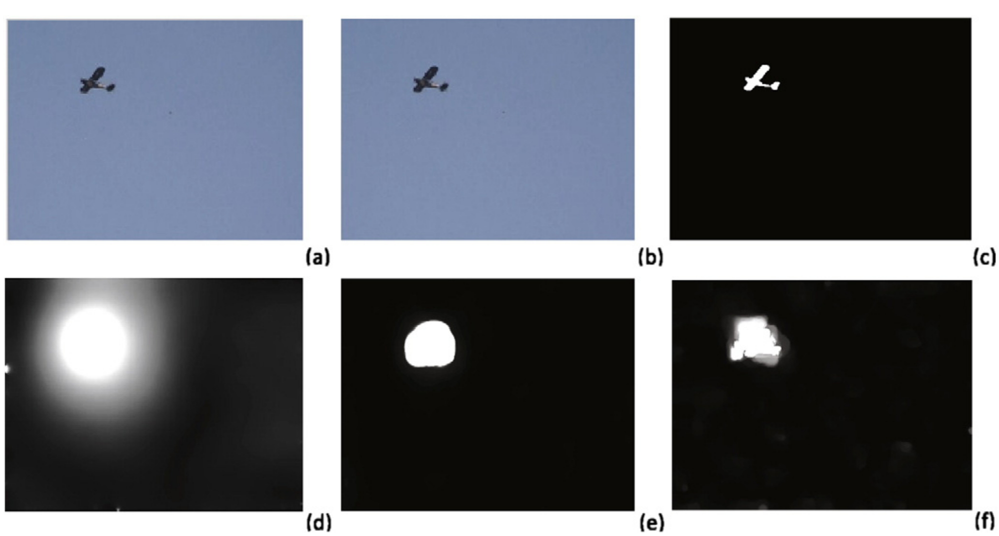

Fig. 2. First frame of the airplane sequence (a); second frame of the airplane sequence (b); ground-truth of the foreground (c); magnitude of optical flow computed according to [4] (d); magnitude of optical flow computed according to [6] (e); magnitude of optical flow computed according to [13] (f).