SPEEDED UP GRADIENT VECTOR FLOW B-SPLINE ACTIVE CONTOURS FOR ROBUST AND REAL-TIME TRACKING

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ABSTRACT

Segmentation and tracking methods have been widely explore. However, they are often computationally heavy or require constraining assumptions. We present in this paper a new system for real-time simultaneous segmentation and tracking, without any hypothesis on target appearance, image background or camera properties. The proposed approach (SUGVFB) is an active contour modeled with B-splines and which evolution process is using a speeded up Gradient Vector Flow, characterized by a faster computation of the edge diffusion process. The synergy of these two powerful components enables precise, robust and real-time tracking of complete non-rigid mobile objects. Our method has been validated on synthetic as well as natural video sequences.

Index Terms— Video Real-Time Tracking, Segmentation, Active Contours, B-Splines, Gradient Vector Flow

1. INTRODUCTION

Tracking is one of the fundamental topic in computer vision. A lot of applications such as medical imaging diagnosis, human - computer non invasive interfaces, sport coaching and broadcasting or video-surveillance, are requiring this technique. In this work, we focus on mobile non-rigid objects in color video sequences captured by moving camera. We aim a real-time precise segmentation and tracking of the whole object without any assumption on the target object, image background or camera position. On the one hand, tracking approaches using mean shift [1] or dynamic Bayesian network [2], rely on target appearance models and can only track centroid or rectangle to localize the target object. On the other hand, segmentation methods need usually hypothesis on the background [3] or on camera position [4], to detect the object. Moreover, they are often time consuming [5], disabling a real-time processing of a video sequence.

To achieve simultaneously tracking and segmentation in real-time, we use an active contour [6] approach, modeled by B-splines, computed using [7] algorithm. We couple efficiently this smoothed active contour with a speeded up gradient vector flow external force [8]. In our work, we have used neither prior knowledge of the target nor its trajectory to keep our tracker as flexible as possible in case of object severe deformations and huge appearance changes. In addition, no assumption are made on the camera motion or position. Our system is thus not requiring any further camera calibration. The developed approach provides in real-time the whole target contour using intensity gradient information. Results demonstrate our method robustness and efficiency, even in difficult situations like the presence of disturbing contours in the background.

The paper is structured as follows. In Section 2, we describe our fast active contour method. In Section 3, we validate our approach both on synthetic and natural images. We show our results of contour real-time detection on real video sequences in Section 4. Finally, conclusions are exposed in Section 5.

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2. ACTIVE CONTOURS

Active contour, also called snake and introduced by Kass et al. [6], is an energy minimizing deformable curve whose behavior description uses concepts borrowed from classical mechanics.

We have chosen a parametric active contour method for reaching computational efficiency, as only few sample points are required to describe the target-object boundary. To reconstruct the contour from these sampled points, B-spline formalism is applied to model the active contour $\mathbf{r}(\mathbf{s})$ defined by a weighted sum of N control points $\mathbf{Q}_k$ and basis functions $B_k^n(s)$ [9],

$$\mathbf{r}(s) = \sum_{k=0}^{N-1} B_k^n(s)\mathbf{Q}_k \tag{1}$$

The contour shape is constrained by its own internal energy whilst the external energy drives it towards desired image features, in our case the object edges.

$$\mathbf{r}_t(s,t) = (\alpha\mathbf{r}^{''}(s,t) - \beta\mathbf{r}^{'''}(s,t)) + (\mathbf{v}) \tag{2}$$

The internal force defines the contour physical properties (α: elasticity, β: rigidity) and acts as a smoothness constraint.

The external force $\mathbf{v}$ is application-based, and is used for guiding the active contour toward the image features of interest. For that, we are employing the gradient vector flow (GVF) mechanism [8] with edge map f and regularization parameter μ, because the GVF has an increased capture range and can guide contour to move towards both concave and convex boundaries. Typically, the required number of iterations n [8] [10] to solve the partial eq. 3 for an image of $a \times b$ pixels is $n = \sqrt{a \times b}$.

$$\mathbf{v}_t = \mu \nabla^2 \mathbf{v} - (\mathbf{v} - \nabla f) |\nabla f|^2 \tag{3}$$

The GVF [8] and its variants [5] [10] main disadvantage is the high computational time consumption in order to be generated, compare to the entire contour convergence process as described by the eq. 2. To overcome this problem, we propose a speeded up GVF (SUGVF), characterized by a faster computation of the diffusion process, requiring ten times less iterations than usually recommended to solve eq. 3.

The proposed SUGVFB active contour results from the incorporation of the SUGVF into the B-spline convergence mechanism, creating a positive synergy between internal and external active contour forces and leading to contour precision and robustness towards noise inherent to images. The main advantages of this method are its capability to guarantee the smoothness of the contour dealing well with non-rigid target-objects and its fast computationally speed necessary for real-time applications, with no contour precision sacrifice nor prior models.

3. VALIDATION

In this section, the performance of the GVF, SUGVF and SUGVFB build-on contours are compared on both synthetic and natural images. The traditional GVF contour consists on a parametric active contour without any B-spline formalism, evolving due to the GVF external force, solved for n iterations. The SUGVF contour does not involve B-splines either, and rely on the SUGVF external force, based on the GVF computed with only $n/10$ iterations. The proposed SUGVFB contour is as described in the previous section 2. For each test image, the same initialization and parameters are employed for the GVF, SUGVF and SUGVFB contours.

3.1. Synthetic Images

The performance of GVF, SUGVF and SUGVFB methods have been tested on a black and white image (Fig. 1) and on a noisy one (Fig. 2).

First, we note that the traditional GVF contour presented in Fig. 1(b), needs a ten times longer computational time to achieve the same result as the proposed SUGVFB contour in Fig. 1(d). Second, we observe that our SUGVFB contour delineates exactly the target-object whilst the SUGVF contour is far from the target, as shown in Fig. 1(c).

In the case of noise, the contour precision performances of the SUGVFB method, shown in Fig. 2(d), overtake the GVF and SUGVF ones, as presented in Fig. 2(b) and Fig. 2(c), respectively. Thus, the incorporation of the B-spline mechanism prevents the SUGVFB contour from noise disturbance, all being real-time. Thereby, for less iterations, consequently in a smaller computational time, the SUGVFB method performs with a better contour precision than the traditional GVF contour that is much more disturbed by the clutter.

3.2. Natural Images

The performance of GVF and SUGVFB methods have been also tested on natural images (Fig. 3). For the initialization, both large capture and narrow capture range have been chosen as shown in Fig. 3(a). Moreover, the initial contour could cross the target as the GVF based-on convergence processes, therefore the SUGVFB, own a bi-directional capacity. The traditional GVF is computed using ten times more iterations to calculate the field. Moreover, we can observe that the GVF resulting contour in Fig. 3(b) is disturbed by the background noise or suffer of a lake of precision, whilst the SUGVFB contour could overcome such difficulties as presented in Fig. 3(c). Thus, for natural images as for synthetic images, the proposed SUGVFB outperforms the traditional GVF in both rapidity and precision.

4. APPLICATION: TRACKING

The SUGVFB active contour method, described in section 2, has been successfully applied to real-time tracking of mobile non-rigid objects, as detailed below.

4.1. Implementation

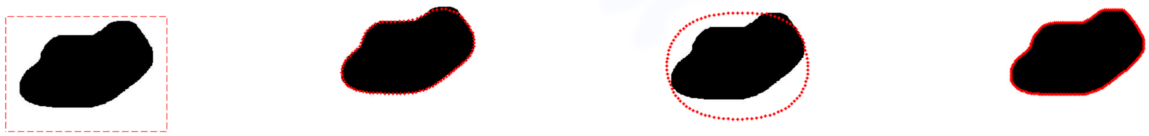
While tracking, the segmentation results of the previous frame are used as initial conditions in the next frame. The B-splines are implemented using the fast B-spline algorithm [7] and the external force is based on the proposed SUGVF.

4.2. Results

SUGVFB active contour method has been validated on real soccer and video-surveillance sequences.

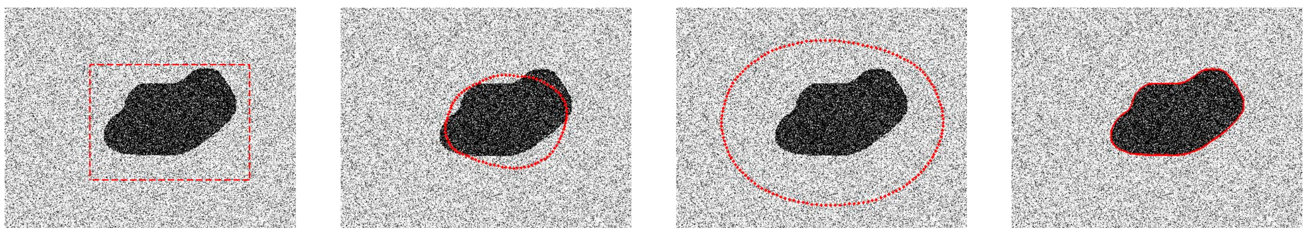
Fig. 4 shows the tracking results of our method on a video-surveillance sequence from a standardized dataset, using a static camera without lense distortion compensation. Because of the coupling of B-splines with SUGVF, the tracker could handle successfully the color similarity between the background and the object. Moreover, as there is no background assumption into our method, the system deals well with target momentary immobility like in Fig. 4(b).

In Fig. 5, our system results are presented for the soccer player tracking in a match recorded by mobile camera. The tracker overcomes the disturbance caused by high gradient



(a) Initialization (b) GVF (c) SUGVF (d) SUGVFB

Fig. 1. Performance of GVF, SUGVF and SUGVFB on a synthetic image, (a) initial contour, (b) GVF, with n iterations, (c) SUGVF (GVF with n/10 iterations), (d) SUGVFB (GVF with n/10 iterations and B-spline formalism).



(a) Initialization (b) GVF (c) SUGVF (d) SUGVFB

Fig. 2. Performance of GVF, SUGVF and SUGVFB on a synthetic image with noise, (a) initial contour, (b) GVF, with n iterations, (c) SUGVF (GVF with n/10 iterations), (d) SUGVFB (GVF with n/10 iterations and B-spline formalism).

area like the white line in Fig. 5(a), thanks to the balance between the B-spline resulting internal forces and the SUGVF based-on external force. For the same reason, our SUGVFB method is also able to support partial occlusions as shown in Fig. 5(b) or background clutter as in Fig. 5(c).

As illustrated, the method is well suited for tracking of non-rigid moving objects and is amenable to real-time implementation. The approach is robust for tracking on background similar to the target appearance (Fig. 4) or with clutter background (Fig. 5). Moreover, the tracker supports well severe deformations of the non-rigid target like in Fig. 5(a) and appearance changes as shown in Fig. 4(a)-(b).

5. CONCLUSIONS

This paper proposed a new system enabling simultaneously tracking and segmentation of mobile objects in video sequence in real-time without any assumption on image background or camera position. The essence of this method consists in a contour modeled by the B-spline formalism, and driven by a speeded up Gradient Vector Flow (SUGVF) external force. As shown in this work, the proposed SUGVFB active contour is converging to the target-object ten times faster than the traditional GVF one, for the same contour precision. In case of noise, the SUGVFB active contour accuracy outperforms the GVF one. Hence, our method is well suited for precise real-time tracking of boundary complex objects.

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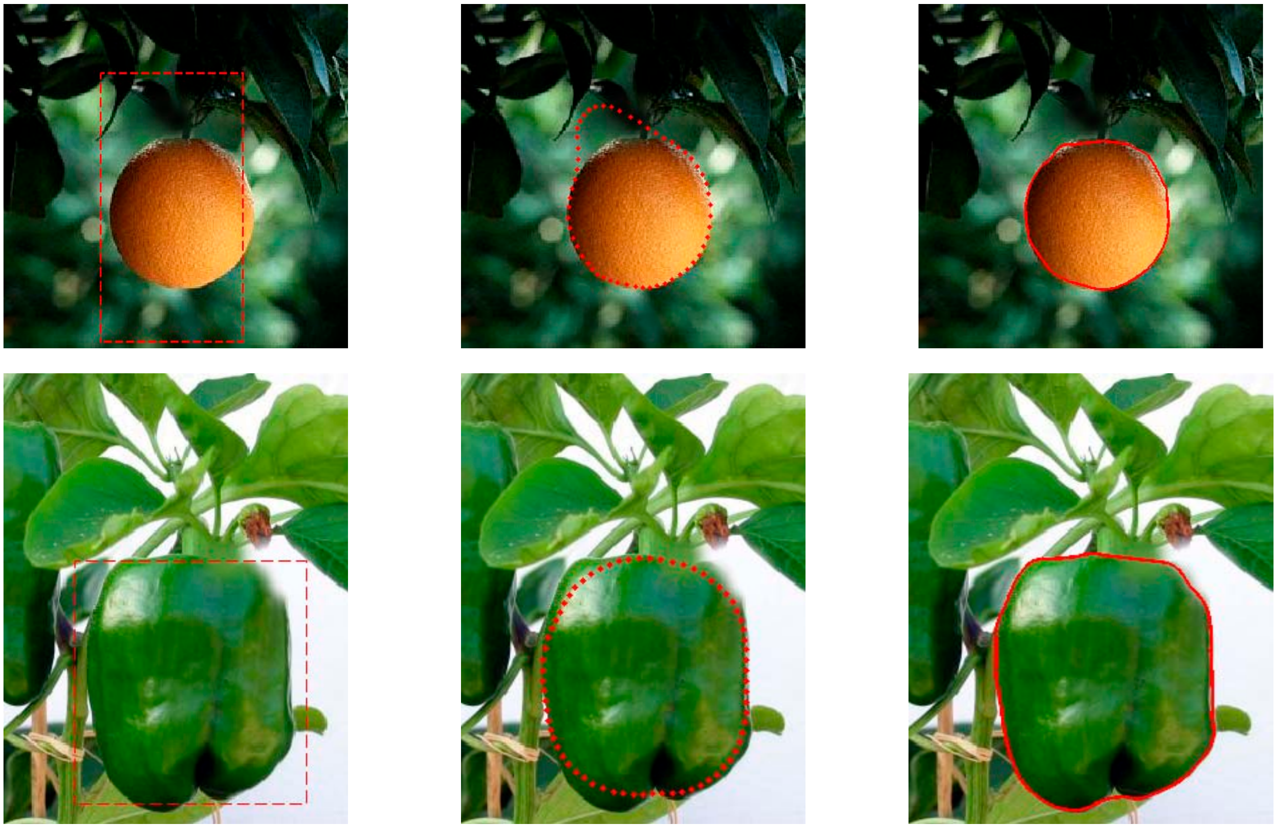
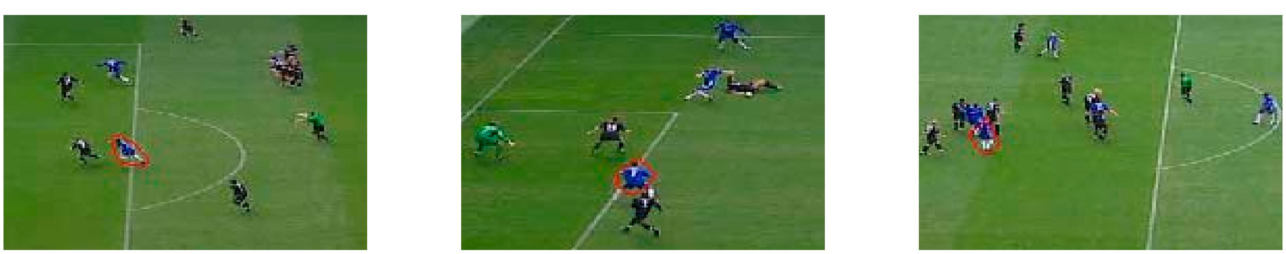


(a) (b) (c)

Fig. 3. Performance of GVF and SUGVFB on natural images, (a) initial contour, (b) GVF, (c) SUGVFB

(a) Frame 616 (b) Frame 909 (b) Frame 943

Fig. 4. SUGVFB Tracking results on video-surveillance sequence of 1000 frames.



(a) Frame 282 (b) Frame 419 (c) Frame 1275

Fig. 5. SUGVFB Tracking results on soccer sequence of 1500 frames.