DIRECTION SELECTIVE VECTOR FIELD CONVOLUTION FOR CONTOUR DETECTION

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ABSTRACT

Active contour methods are widely used for efficient contour detection. This paper proposes a novel contribution for the Harris based Vector Field Convolution (HVFC) method, using the orientation information of feature points in the image by analyzing the gradient information in the small neighborhood. Based on the orientation information, relevant edges are emphasized and an improved edge map is used in the iterative process. The main advantage of the introduced Directional HVFC (DHVFC) method is the ability of exploiting orientation information for increased contour detection accuracy even in case of high curvature boundaries and strong background clutter. The quantitative and qualitative evaluation and comparison with other state-of-the-art methods show that the additional directional information increases the detection performance.

Index Terms— Active Contour, Harris based Vector Field Convolution, Direction Selectivity

1. INTRODUCTION

The principles of the active contour (snake) theory were introduced in [1] for robust object contour detection, where internal and external forces were controlling the evolution of the curve, exploiting information simultaneously from the shape of the curve and from image characteristics. Since then, several modifications were proposed, compensating some of the drawbacks of the original method, which can be grouped into parametric [2], [3], [4], [5] or region based [6], [7] approaches.

The advantages of region based active contours are that they are not sensible to the initial location, they can detect multiple objects, even with complex boundaries. However, they have problems with open edges and they cannot handle intensity changes inside objects. Moreover the speed of their convergence is low.

Parametric snakes are usually sensitive to noise, parameter and initialization and the detection of high curvature contours is problematic. Addressing these difficulties, a group of these method [2], [4], [5] tries to redefine and improve the external energy, representing the image characteristics.

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To increase the detection accuracy of high curvature boundary parts, in our previous work [8], we introduced the Harris based Vector Field Convolution (HVFC method), where we applied a modification of the characteristic function of Harris corner detector [9] in the external energy part. Feature points, generated as local maxima of the function, were used for contour initialization. We also extended the method for the Gradient Vector Flow (GVF) [2] in [5]. Experiments showed that the method was able to find high curvature boundaries more accurately, but it could not handle background clutter efficiently. As complex background also generated local maxima in the modified characteristic function, the final feature map had high emphasis also on the background.

This paper introduces a novel idea for compensating this drawback of the HVFC method, by exploiting orientation information in the close proximity of the feature points. Previously, there has been some attempts to use directional information for active contour detection, like [7] and [10] concentrating on region based approaches and [3] for the GVF. [7] showed that directionality can be added to the conformal active contour framework, resulting in a well-defined minimization problem. [10] defined a new metric by adding a term that penalizes the misalignment of the curve with the image gradient multiplying the resulting metric by a conformal factor that depends on the edge intensity. Dynamic Directional GVF (DDGVF) [3] handled directions in a different way, and concentrated on positive and negative step edges. To do so, it used the gradient in both x and y directions and dealt with the external force field for the two directions separately. The main advantage of this method was the handling of the edges of different directions.

In our case, edges with different crossing directions (corners) are handled with the previously introduced Harris based edge map [8], orientation information of the feature points helps to reduce the false detection due to background clutter by integrating directionality into an improved edge map for the external energy function in the Directional Harris based Vector Field Convolution (DHVFC) algorithm. The performance of the algorithm is tested on the Weizmann dataset [11] and the proposed method is also compared to other state-of-the-art methods [4], [8], [3].

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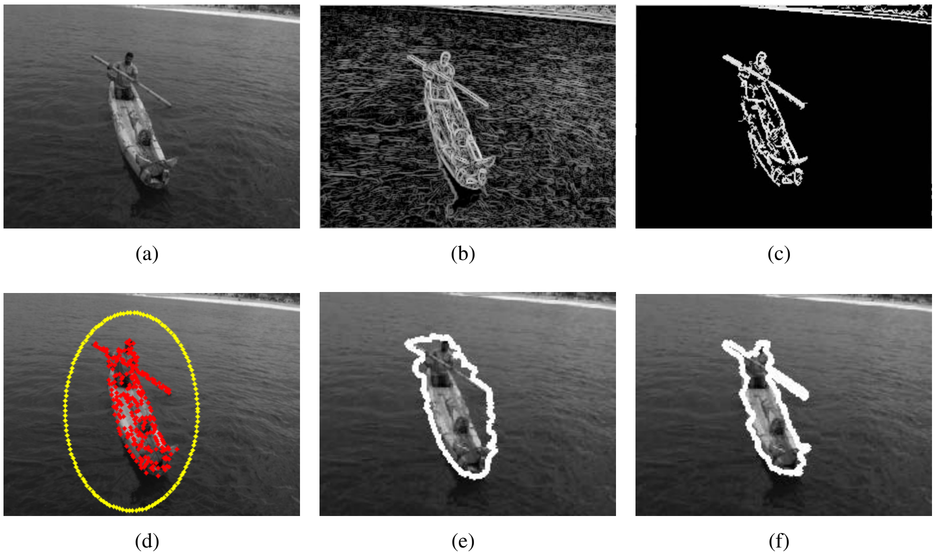


Fig. 1. Main steps of the direction selective contour detection: (a) is the original 'boat' image from Weizmann dataset; (d) shows the marked ROI in yellow and the generated feature point set in red; (b)-(c): the HVFC and improved DHVFC edge maps, (e)-(f): the result of the contour detection for HVFC and DHVFC.

2. ACTIVE CONTOUR THEORY

The aim of the parametric active contour theory [1] is to find the curve, denoted by $\mathbf{x}(s) = [x(s), y(s)]$, $s \in [0, 1]$, that minimizes the following energy function:

$$E = \int_0^1 \frac{1}{2}(\alpha\,|\mathbf{x'}(s)|^2 + \beta\,|\mathbf{x''}(s)|^2) + E_{\text{ext}}(v(s))\text{d}s, \quad (1)$$

where α is the elasticity parameter and β is the rigidity parameter of the internal energy; $\mathbf{x'}(s)$ and $\mathbf{x''}(s)$ are the first and second order derivatives with respect to arclength s. E_{ext} is the external energy which is derived from the image, representing the constraints of the image itself:

$$E_{ext} = \int\int \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2\,|\mathbf{v} - \nabla f|^2\,dxdy, \quad (2)$$

where μ is a regularization parameter and ∇ is the gradient operator. f is the edge map generated from the I image, one of its generally used forms (G_σ is Gaussian function with σ standard deviation):

$$f(x, y) = |\nabla(G_\sigma(x, y) * I(x, y))|\,. \quad (3)$$

2.1. Vector Field Convolution

Vector Field Convolution (VFC) [4] compensated some drawbacks of GVF [2], like high computational cost, noise and parameter sensitivity. The novelty of the algorithm was an external force field, calculated as the convolution of a vector field kernel and the f edge map:

$$\mathbf{f}_{\text{VFC}}(x, y) = f(x, y) * \mathbf{k}(x, y), \quad (4)$$

$\mathbf{k}(x, y)$ kernel is defined as a multiplication of a unit vector pointing to the kernel origin and a magnitude function.

2.2. Harris based Vector Field Convolution

As the f edge map (Eq. 3) is not able to emphasize high curvature boundary parts, in our previous work [8] we introduced a modification for the edge map inspired by the Harris corner detector's characteristic function. (An extended work, adapted also for the GVF method, was published in [5].) The principle behind this idea is that high curvature boundary parts cohere with corners, therefore a corner detector's characteristic function can be applied for such detections efficiently. The aim of the original characteristic function is to emphasize only corners, thus it has to be modified when used for contour detection purposes. The following alteration was proposed for the f edge map in [8]:

$$\mathbf{f}_{\text{HVFC}} = |\nabla(G_\sigma(x, y) * R_{\text{logmax}}(x, y))| * \mathbf{k}(x, y), \quad (5)$$

$$R_{\text{logmax}} = \max(0, \log[\max(\lambda_1, \lambda_2)]), \quad (6)$$

λ_1 and λ_2 denote the eigenvalues of the Harris matrix and log is the natural logarithm. For further explanation see [8].

The point set, generated as local maxima of the R_{logmax} function, is used for contour initialization. The convex hull of the point set is calculated and the iterative method is started from this polygon. This is also used in the iterative part of the proposed approach.

One drawback of using the R_{logmax} function is that it also emphasizes the feature information in the background. Thus, in case of large background clutter, large feature values appear in the $\mathbf{f}_{\mathrm{HVFC}}$ map for the background, causing the contour to converge incorrectly (see Figure 1(b) and 1(e)). To eliminate the disadvantage, the idea is to integrate orientation information into the $\mathbf{f}_{\mathrm{HVFC}}$ map, for emphasizing relevant contours and preserving the benefits of the R_{logmax} function at the same time.

3. DIRECTIONAL HARRIS BASED VECTOR FIELD CONVOLUTION

By exploiting additional knowledge of directionality, a higher level feature can be constructed for more accurate detection. To do this, the local gradient orientation density was analyzed in the small neighborhood of each feature point (Figure 1(d) in red) to find the main direction. Let us denote the gradient vector by ∇g_i with $\|\nabla g_i\|$ magnitude and φ_i^{∇} orientation for the i^{th} point. By defining the $n \times n$ neighborhood of the point with $W_n(i)$ (where n depends on the resolution), the weighted density of φ_i^{∇} is as follows:

$$\lambda_i(\varphi) = \frac{1}{N_i} \sum_{r \in W_n(i)} \frac{1}{h} \cdot \|\nabla g_r\| \cdot k\left(\frac{\varphi - \varphi_r^{\nabla}}{h}\right), \quad (7)$$

with $N_i = \sum_{r \in W_n(i)} \|\nabla g_r\|$ and $k(.)$ kernel function with h bandwidth parameter. The main orientation for i^{th} feature point is defined as:

$$\varphi_i = \underset{\varphi \in [-90,+90]}{\operatorname{argmax}} \{\lambda_i\}. \quad (8)$$

After calculating the direction for all feature points, relevant edges are extracted with Morphological Feature Contrast (MFC) operator [12] which is able to extract isolated structures while suppressing texture details of textured background. It is based on the following equations for dark and bright features:

$$\psi_{MFC}^{+}(a) = |a - \rho_{r_2}\tau_{r_1}(a)|^{+}, \quad (9)$$

$$\psi_{MFC}^{-}(I) = |\tau_{r_2}\rho_{r_1}(a) - a|^{+}, \quad (10)$$

where τ is a morphological closing, ρ is a morphological opening, r_1 and r_2 are the size of the structuring elements and a is the signal or image. An extension of MFC is designed for extracting linear features handling orientation: after removing texture with ψ_{MFC}^{+} and ψ_{MFC}^{-} operators, a subsequent ρ_{lin} filter is applied with linear SE at the calculated orientation. See [12] for further explanation.

After applying the MFC operator, the resulting feature enhanced (background suppressed) image I_{MFC} is fused with the R_{logmax}, to keep only those features of R_{logmax} which are connected to relevant features in I_{MFC}. The improved edge map, R_{MFC} (Figure 1(c)) combines the advantage of HVFC's high curvature boundary detection together with the handling of large background clutter. The improved feature map of the DHVFC method becomes:

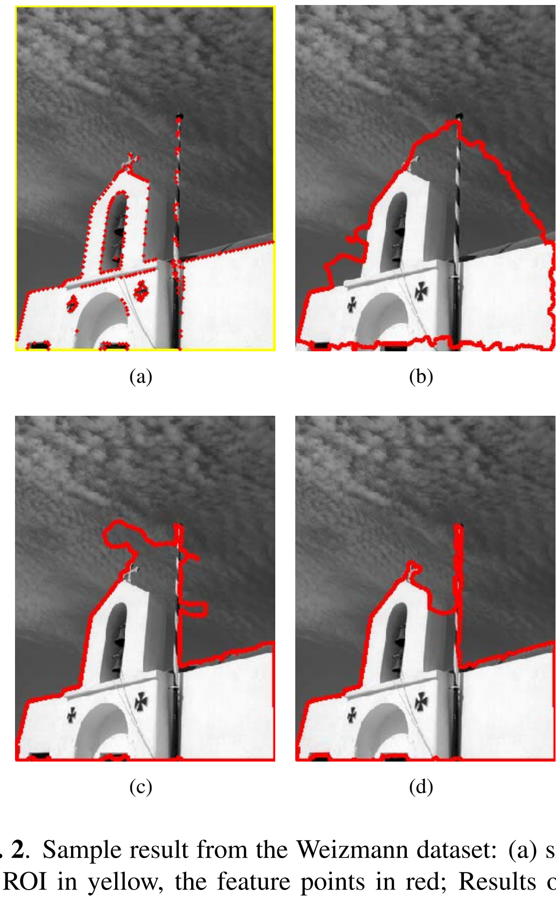
$$\mathbf{f}_{\mathrm{DHVFC}} = |\nabla(G_\sigma(x,y) * R_{\mathrm{MFC}}(x,y))| * \mathbf{k}(x,y). \quad (11)$$

The iterative part is the same as for VFC and HVFC [5].

4. EXPERIMENTS

We have tested the proposed method quantitatively on the Weizmann dataset [11], which consists of 100 images, showing single objects. In this experiment we have compared the DHVFC method to HVFC [8] and VFC [4] approaches. In the second part, we have performed qualitative evaluation on two selected images from [3] and compared the DHVFC method to DDGVF [3] and HVFC [8]. In both quantitatve and qualitative cases the initial ROI was marked as an ellipse and the starting contour was calculated as the convex hull of the extracted feature point set within the ROI for VFC, HVFC and DHVFC methods.

To eliminate differences caused by different parameters, the same parameter settings was used for DHVFC, HVFC and VFC methods in the iterative phase, following [4].



(a) (b) (c) (d)

Fig. 2. Sample result from the Weizmann dataset: (a) shows the ROI in yellow, the feature points in red; Results of the detection: (b) VFC; (c) HVFC; (d) DHVFC.

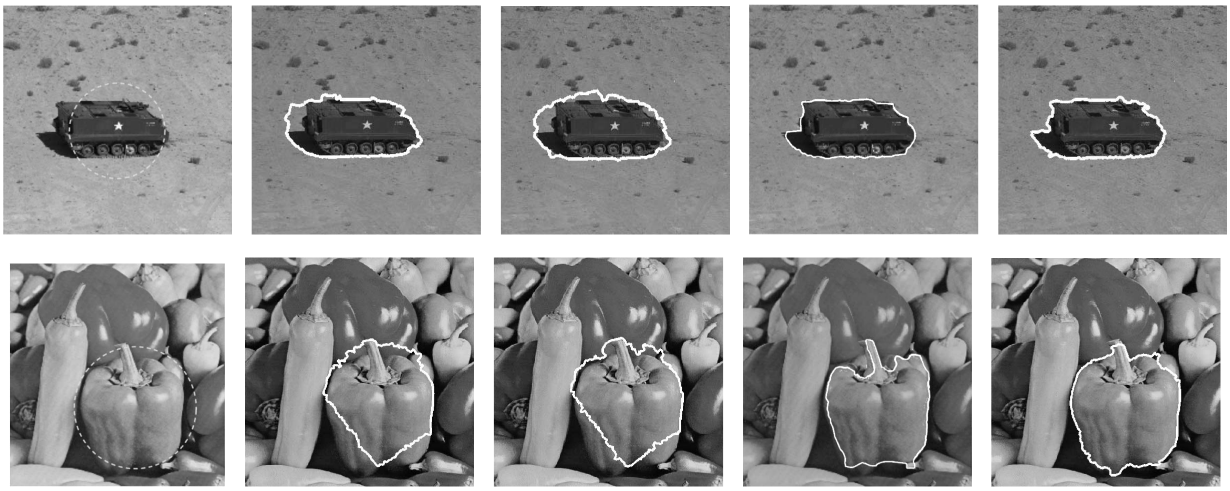


Fig. 3. Qualitative comparison for specific images from [3]: The first column shows the marked ROI; then the detection results: second for VFC [4], third for HVFC [8], fourth for DDGVF [3], fifth for DHVFC (proposed) method.

Table 1 shows the average F-measure, Recall and Precision values calculated for the compared VFC, HVFC and DHVFC methods. While the average Precision value of DHVFC is similar to the result of the other two methods, the average Recall and F-measure values are exceeding the performance of VFC and HVFC approaches.

Figure 2 shows an image selected from the Weizmann dataset and the detection results for the compared VFC, HVFC and DHVFC methods. In this case, no ROI was selected manually, the algorithm was started on the whole image, indicated in yellow in Figure 2(a). Results show that DHVFC combines the advantages of HVFC and directionality and outperforms the other two approaches.

Figure 3 shows the qualitative comparison of VFC, HVFC, DDGVF and DHVFC methods for images 'APC' and 'peppers'. Note that, the marked ROI and the result of DDGVF method (first and fourth columns) are directly from [3], causing a small visual difference. The qualitative results show that for image 'APC', the variance of the background cause problems for VFC and HVFC methods, but DDGVF and DHVFC are able to find the contour more accurately. However, the fine details of the vehicle (like in the top right corner) and the peak of its shadow is missed by DDGVF. DHVFC is the only method which is able to find these high curvature contour parts efficiently. In the second row of Figure 3, DDGVF and DHVFC perform better than VFC and HVFC again. While DDGVF misses the back part of the vegetable, DHVFC is able to find the upper part of the pepper more accurately. Similarly, in the bottom of the object, the DDGVF contour does not follow the boundary of the pepper, but the stem of the other vegetable on the right; meanwhile, DHVFC detects the contour correctly.

Algorithm	F-measure	Recall	Precision
VFC	0.79 ± 0.14	0.72 ± 0.20	0.92 ± 0.08
HVFC	0.82 ± 0.14	0.74 ± 0.19	$\mathbf{0.96 \pm 0.07}$
DHVFC	$\mathbf{0.85 \pm 0.13}$	$\mathbf{0.82 \pm 0.18}$	0.92 ± 0.08

Table 1. Average F-measure, Recall and Precision (mean $\pm$ standard deviation) for VFC [4], HVFC [8] and the proposed DHVFC algorithms for the Weizmann dataset.

5. CONCLUSION

In this paper, a novel direction selective edge map has been introduced for parametric active contour detection. The novelty of the method is the exploitation of orientation information in the small neighborhood of the feature points to design an improved feature map for existing HVFC method to provide more accurate detection in case of large background clutter. The proposed DHVFC method outperforms existing vector field based methods and introduces a novel interpretation of orientation for parametric active contours. Future work will investigate further possibilities of the integration of orientation information with active contour approaches.

6. REFERENCES

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