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Non-Rigid Object Contour Tracking via a Novel Supervised Level Set Model

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Abstract— *We present a novel approach to non-rigid objects contour tracking in this paper based on a supervised level set model (SLSM). In contrast to most existing trackers that use bounding box to specify the tracked target, the proposed method extracts the accurate contours of the target as tracking output, which achieves better description of the non-rigid objects while reduces background pollution to the target model. Moreover, conventional level set models only emphasize the regional intensity consistency and consider no priors. Differently, the curve evolution of the proposed SLSM is object-oriented and supervised by the specific knowledge of the targets we want to track. Therefore, the SLSM can ensure a more accurate convergence to the exact targets in tracking applications. In particular, we firstly construct the appearance model for the target in an online boosting manner due to its strong discriminative power between the object and the background. Then, the learnt target model is incorporated to model the probabilities of the level set contour by a Bayesian manner, leading the curve converge to the candidate region with maximum likelihood of being the target. Finally, the accurate target region qualifies the samples fed to the boosting procedure as well as the target model prepared for the next time step. We firstly describe the proposed mechanism of two-phase SLSM for single target tracking, then give its generalized multi-phase version for dealing with multi-target tracking cases. Positive decrease rate is used to adjust the learning pace over time, enabling tracking to continue under partial and total occlusion. Experimental results on a number of challenging sequences validate the*

effectiveness of the proposed method. Index Terms— Object tracking, level sets, curve evolution, boosting, appearance modeling.

I. INTRODUCTION

Object tracking, which refers to the task of generating the trajectories of the moving objects in a sequence of images, is a challenging research topic in the field of computer vision. The problem and its difficulty depend on several factors, such as the amount of prior knowledge about the target object and the number and type of parameters being tracked, e.g., location, scale, detailed contour. Although there has been some success with building trackers for specific object classes, Manuscript received November 19, 2014; revised May 1, 2015 and May 26, 2015; accepted June 7, 2015. Date of publication June 18, 2015; date of current version July 7, 2015. This work was supported in part by the National Natural Science Foundation of China under Grant 61472103 and Grant 61300111 and in part by the Key Program under Grant 61133003. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Kiyoharu Aizawa. (Corresponding author: Hongxun Yao.) The authors are with the Department of Computer Science and Technology, Harbin Institute of Technology, China (e-mail: sunxintyc@ 163.com; h.yao@hit.edu.cn; s.zhang@hit.edu.cn; lidonghit@hit.edu.cn). Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org. Digital Object Identifier 10.1109/TIP.2015.2447213 tracking generic real-world objects has remained challenging due to unstable lighting condition, pose variations, scale changes, view-point changes, and camera noise etc. Early tracking methods use fixed appearance model to describe the target, which are unable to successfully track the target over long time. To overcome this drawback, some tracking algorithms try to update the target appearance over time in an online manner. The appearance models adopted by these methods include histogram subspace models [4] as well as sparse representation models . Besides, some researchers resort to adopting discriminative learning methods to make the trackers easy to distinguish the target from its background. The methods based on boosting and SVMs show impressive performance and attract much attention. In contrast with constructing two separate models for the target and background respectively, classifier learning based approaches are more inclined to seize properties of most discrimination between them. Despite having the promising performance, these traditional trackers face a practical problem that they use rectangular bounding box or oval to approximate the tracked target. However, objects in practice may have complex shapes that cannot be well described by simple geometric shapes, see Fig. 1(a) for some examples. Since the rectangle box used for presenting the tracked target directly determines the samples to be extracted in the subsequent target appearance modeling/unpdate step, it is a critical factor to tracking performance. Inaccurate target presentation easily results in performance loss due to the pollution of non-object regions residing inside the rectangle box. In order to better fit the object shape, some methods adopt the scale selection mechanism that aims to search for the best scale that covers the target accurately. An intuitive idea is to run the algorithm in different scales, then select the one maximizing the object function of the tracking algorithm. Further, this selection mechanism is also extended to orientation. By simultaneously controlling both the scale and orientation, the statistic bias for the target distribution can be controlled, see Fig.1(a), and this, to some extent, makes better target description and tracking estimation. Nevertheless, all these scale/orientation adjustments are still based on simple geometric shapes (such as rectangle and oval), which will inevitably introduce a large number of background pixels when used for presenting real-world object with complex shapes. Ideally, a better manner to describe the target is to use the accurate contour along the target's surface.

Fig. 1. Motivation: (a) shows the typical bounding box presentation on complex object with scale/orientation adaption. (b)-(g) gives some contour tracking examples of the proposed method in various challenging cases, whose frame numbers are 511, 14,

108, 151, 418, 205 respectively in their sequences. the literature have been made to use silhouette or contour, segmenting technique for dynamic tracking In contrast with explicit representation of contours in parametric active contour models, such as snake model level set technique is an implicit representation of contours and able to deal with changes in topology. The basic idea of the level set approach is to embed the contour as the zero level set of the graph of a higher dimensional function. Then evolve the graph so that this level set moves according to the prescribed flow until it minimizes an image-based energy function. Binary level set model, proposed in uses a two-valued level set function to replace the signed distance function used in traditional Chan-Vese manner. Since it avoids the re-initialized process of the level set function in each iteration as well as the cumbersome numerical realization, it greatly improves the computational efficiency and hence is more suitable for tracking tasks. Nevertheless, from a performance perspective, the binary level set model is more inclined to segment out the region with consistent intensity, which is similar to the threshold segmentation method. Though, recently, some works have been proposed to apply level set models to visual tracking, introducing the prior target knowledge in a level set formalism has been still challenging, since the level set framework aims at optimally grouping regions whose pixels have similar feature signatures. This makes it difficult for level set approaches to reliably segment and track real-world, multi-mode objects in front of complex, cluttered backgrounds. In this paper, we present a novel supervised level set model (named SLSM) for real-world objects contour tracking. Instead of acting towards intensity consistent direction, the curve evolution of the SLSM is target-oriented and supervised by the knowledge of the specific targets in tracking application. Boosting approach is used for online construction of the target appearance model due to its strong ability in distinguishing the target from its background. Then the learned target model is incorporated to model the level set contour probabilities by a Bayesian manner, leading the curve converge to the candidate region with maximum likelihood of being the tracked target. Finally, samples extracted from accurate target region are fed back to the boosting procedure for target appearance update. We use the positive decrease rate to adjust the target learning pace over time, which enables tracking to continue under partial and total occlusion. In this paper, we firstly describe the proposed mechanise of 2-phase SLSM for single target tracking, whose preliminary results were also presented in the early conference paper Then we novelly propose the generalized multi-phase SLSM for dealing with multi-target tracking cases. Fig.1(b-g) shows some tracking examples of our method in various challenging cases..

II. RELATED WORK

A. Tracking Methods With Online Appearance

Learning Han and Davis deal with the variations of lighting condition, pose, scale, and view-point over time by approximately estimating the pixel-wise color density in a sequential manner. The work of Grabner and Bischoflearn a binary classifier as implicit appearance model and apply it in each new frame to locate the position of the target. Babenko et al. introduce multiple instance learning into online tracking where samples are grouped into positive and negative bags or sets. Recently, a semi-supervised learning approach is developed in which positive and negative samples are selected via an online classifier with structural constraints. In the authors focus on the problem of longterm object tracking and propose a detection-based approach which learns appearance models from a large negative training set. In the authors propose an online learning method using an incremental linear discriminant analysis for discriminating the appearances between multiple tracked objects. All these tracking methods, however, use bounding box to describe the tracked target. Scale and orientation selection mechanism have been adopted in this kind of trackers to better fit the object shapes. B. Scale/Orientation Selection for Better Fit to Object Shape After the intuitive ±10% mechanism in R. Collins propose a method using difference of Gaussian mean shift kernel for efficient blobs tracking through scale space. Khan et al. in derive a multi-mode anisotropic mean shift, where the center, size and orientation of the box are simultaneously estimated during the tracking. In the authors present a probabilistic formulation of kernel-based tracking method where the EM estimation in conjunction with KL-divergence are used to develop a target-center and kernel bandwidth update scheme. the authors extend the original mean shift approach to handle orientation space and scale space.

The method estimates the motion, including the location, orientation and scale, of the interested object window simultaneously. Although these adjustments, to some extent, can help with better target presentation, these methods still use simple geometric shapes to specify the target region. Hence it is difficult for them to ideally therewith the tracked object shape. In contrast, the proposed method is capable of tracking the accurate contours of the targets. C. Dynamic Tracking Methods for Non-Rigid Objects Zhao et al. in focus on the human shape modeling and track humans in crowded environments where occlusion persistently occurs. Ramanan et al. in firstly construct an appearance model for the target, which is then used as detecting model for tracking. They report good results on articulated person tracking. In the authors model human body as a combination of singleton parts and symmetric pairs of parts, and treat the human pose tracking as a multi-target tracking problem where the "targets" are associated by an underlying articulated structure. In the authors propose a strategy that learns online key poses of the tracked person as multiple reference models to drive a shape tracking method of human. These methods, however, basically assume that specific classes of the targets are given. Kwon and Lee use a patch-based dynamic appearance model in conjunction with an adaptive Basin Hopping Monte Carlo sampling method to track a non-rigid object, where no specific class information of the target is requested, neither does the off-line training phase. Similarly, our method is applicable to general realworld objects and utilizes the accurate contours to describe the target as well as qualified samples for learning the target appearance. D. Close Work on Segmentation Based Tracking Methods Bibby and Reid derive a probabilistic framework for robust tracking of multiple previously unseen objects. The observed image data is used to compute a posterior over the object poses, shapes and relative depths where the shapes are implicit contours represented using level sets. In Godec et al. present a novel tracking-by-detection approach to non-rigid object tracking based on the generalized Hough-transform. They couple the voting based detection and back-projection with a rough segmentation based on GrabCut. Afterwards, Stefan et al. in improve the above HoughTrack to a faster version by using pixel-based descriptors. In the authors introduce the Mumford-Shah model into the particle filter framework. Once the particle filter gives the candidate positions in prediction step, the active curve evolution is included to give the candidate contours. Shape information has also been considered in the form of static or dynamic priors. Those try to constrain the active curve using the statistics of a set of training shapes, either by performing the optimization in a subspace or by bringing in the shape constraints on the variational level However, they need to encompass the entire shape variability, which is impractical for real-world applications. In contrast, our method encodes the tracked target knowledge by the manner of boosting classifier learning and supervises the curve acting direction by the current learned target model.

III. THE 2-PHASE SUPERVISED LEVEL SET MODEL

In this section, we analyze the general curve acting principle of the level set model which gives the antecedent of our improvements. Then we describe the proposed 2-phase supervised level set model in detail, which is competent in dealing with real-world object tracking problems. A. Curve Acting Principle In binary level set model a piecewise constant-valued function u is used to approximate the intensity distribution of image I. The contour C, embedded as the zero level set of the level set function φ, divides the image into two regions 1 and 2. In region 1, φ = 1 and u = c1 while in region 2, φ = −1 and u = c2. So the piecewise constant-valued function can be defined as u = c1 2 (φ + 1) − c2 2 (φ − 1) (1) where c1 and c2 are positive constants. Then the energy function of the active contour model can be defined as Eimage = EB(c1, c2,φ) = 1 2 |u(c1, c2,φ) − I| 2 dxdy + μ |∇φ| dxdy + 1 τ W(φ) dxdy (2) where μ and τ are the proportional coefficients. The first item is used to measure the similarity of the two-valued function u with the image I, and makes the function u more close to the intensity distribution of image I. The second item is used to measure the length of the curve C, playing the role of smoothing region boundaries. The last item is for the binary constraint. In conventional level set methods, there is no any prior knowledge taken into account and the positive constants c1, c2 can be obtained directly by minimizing the energy function c1 = I(1 + φ) dx dy (1 + φ) dx dy , c2 = I(1 − φ) dx dy (1 − φ) dx dy (3) where, we can see, c1 and c2 are the average intensities of image I in region 1 and 2. So when we minimize the

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energy function Eimage, we want the function u more close to the image I, that is, the region with average intensity is close to the original image. As a result, this definition of u makes the level set model more inclined to segment out the region with consistent 3389

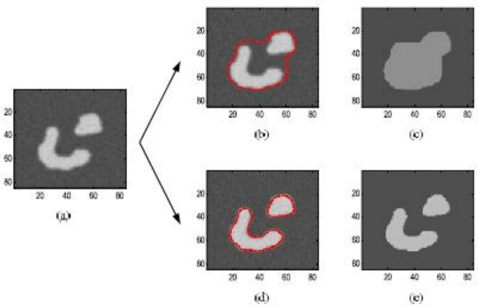

Fig. 2. Illustration of the role of function u used in level set energy function. (a) is the original image in size of 84×84; (b) represents the inaccurate contour while (c) represents its corresponding piecewise constant-valued function u, which we can see has a great difference compared to the original image; (d) represents the accurate contour and (e) represents its function u respectively, which is more close to the original image. intensity (see Fig. 2), which is similar to the threshold segmentation method. However, objects may consist of inconsistent intensities which occurs most often in practice. Additionally, in the context of tracking, we usually have a specific target of interest, which can be exploited to supervise the evolution of the curve and refine its acting direction.

B. Online Appearance Modeling

We construct the online appearance model in an implicit manner of boosting classification as in In contrast with distinguishing between the object and background by modeling two separate models respectively, treating the separation as a binary classification problem is more inclined to seize properties of most discrimination between them, as well as decrease pollution from the similar background pixels. The boosting-based appearance modeling procedure can be summed up with several keys (Algorithm 1). We apply this implicit target model as a detector in the arriving frame. For each sample evaluated, within the search region, we can obtain a confidence score indicating the likelihood it derives from the target object. In mean shift algorithm is implemented for searching the peak and a rectangle is used for presenting the result. However, although the tracker locks onto most competitive samples, it may ignore the contribution of the other. Additionally, the inevitable background pixels mixed inside

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the rectangle may pollute the subsequent target update process. Differently, we introduce these scores into the proposed SLSM (see Fig. 3) as prior target knowledge to supervise the curve evolution and give a global optimal result of target contour, which can also supply the boosting procedure with qualified samples as well as deal with the re-scale problem in mean shift algorithm.

C. Level Set Formulation

Our goal is to estimate the target contour from a sequence of images. Let Ik : x → Rm denote the image at time k that maps a pixel x = [x y] T ∈ R2 to a value, where the value is a scalar in the case of a grayscale image (m = 1) or a three-element vector for an RGB image (m = 3). Algorithm 1 On-line AdaBoost Appearance Construction Let C(s) = [x(s) y(s)] T ,s ∈ [0, 1], denote a closed curve in R2. An implicit function φ(x, y) is defined such that the zeroth level set of φ is C, that is, φ(x, y) = 0 if and only if C(s) = [x y] T for some s ∈ [0, 1]. In response to the low efficiency of the traditional level set models, the proposed SLSM maintains the advantage of using two-valued level set function φ to replace the traditional signed distance function φ(x, y, k) = ————————————————

1, if [x y] T inside Ck −1, if [x y] T outside Ck (4) Using this simple form can avoid the re-initialized process of the level set function in each iteration as well as the cumbersome numerical realization. Given all the observations I0:k up to time k, boosting score map Sk , we model the probability of contour Ck at time k by considering both the region and edge cues in a Bayesian manner as p(Ck |I0:k , Sk) ∝ ptb(Sk |Ck) region pe(Ik |Ck) edge p(Ck) prior (5) where ptb(Sk |Ck) presents the likelihood that the regions inside and outside Ck are the target object and background, respectively; and pe(Ik |Ck) gives the likelihood that the contour is on image edge; p(Ck) is the prior probability of the contour, where we encode the length prior for smoothing region boundary.

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Algorithm 1 On-line AdaBoost Appearance Constructi

Input: new examples $\{\mathbf{x}_i, y_i\}_{i=1}^{M}$, $y_i \in \{-1, +1\}$
Output: strong classifier $H(x)$
Initialization: the importance weight $\{w_i\}_{i=1}^{M} = \frac{1}{M}$

For each iteration j do:

- Make $\{w_i\}_{i=1}^{M}$ a distribution.
- Choose weak classifier $h_j(\mathbf{x})$ with the lowest error pool (for first K iterations) or train new weak cla $h_j(\mathbf{x})$ (for last $J-K$ iterations, J is the total ite number).
- Calculate the error err and voting weight α_j fo classifier $h_j(\mathbf{x})$.
- Update importance weight by the classification res classifier $h_j(\mathbf{x})$.

The updated strong classifier is given by $sign(H(x))$, $H(x) = \sum_{j=1}^{J} \alpha_j \cdot h_j(\mathbf{x})$.

Here, the assumption we depend on is that the measurements are independent of each other. When we maximize the probability of (5), obviously, we expect to obtain the contour that surrounds the target region and exactly converges to its edge. Let R+ be the region of the image inside the curve and R− the region outside the curve. The region-based probability ptb(Sk |Ck) in (5) can be decomposed as ptb(Sk |Ck) ∝ pt(Sk |R+) target pb(Sk |R−) background (6) where pt(Sk |R+) captures the target probabilities inside Ck , and pb(Sk |R−) captures the background probabilities

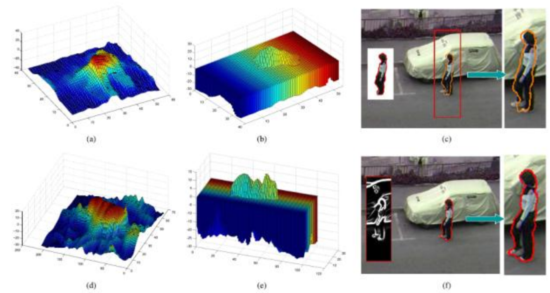

Fig. 3. Tracking principle of the proposed 2-phase SLSM method. We firstly in (a) show the score map of an unicolored sequence (ship sequence, see Fig.1(b)) constructed in boosting manner, and (b) is the corresponding histogram. Then we take a multi-colored sequence as an example to illustrate the proposed algorithm (c)-(f).

IV. THE MULTI-PHASE SUPERVISED LEVEL SET MODEL

In above 2-phase supervised level set model, with only one level set function, we can represent and track only one target. In this section, we generalize the 2-phase SLSM to the multi-phase version with which we can deal with multitarget tracking cases. We use several active contours to enclose and represent the multiple tracked targets. Similarly, we firstly construct the appearance models for these tracked targets, then use them as prior knowledge to supervise and refine the evolution of the active contours. One can employ any existing appearance modeling method to construct these target models. In this work, for convenience, we use the same way as in part B of Sec. III to learn the appearance model for each tracked target. Specifically, let us consider N tracked targets. For each target i, we construct its implicit appearance model T (i) by the manner of boosting classifier learning using Algorithm 1. In the new arriving frame, a larger ring of neighboring pixels surrounding the initial target region is included as an extension to form the search region of the ith target. Then the learnt target model T (i) is applied as a detector within the search region so that each sample evaluated gets a confidence score S(i) (x), indicating the likelihood of the pixel x belonging to the target i. We denote the appearance models of all N targets as T = {T (i) }N i=1, and the score maps of all targets as S = {S(i) (x)}N i=1. We include them as the prior targets knowledge into the level set formulation to supervise the active contours evolution and obtain the multi-target contour tracking results. This is explained next.

V. CONCLUSION

We have presented a novel supervised level set model (named SLSM) in this paper for non-rigid objects contour tracking. By considering the context of tracking, we refined the curve evolution of the SLSM by the specific knowledge of the targets we want to track, which is learned in an online boosting manner. Hence, in contrast with conventional intensity consistency based level set methods, our approach is object-oriented and can lead a more accurate convergence to the exact targets in tracking applications. We firstly proposed the mechanise of 2-phase SLSM for single target tracking, then proposed the generalized multi-phase SLSM for dealing with multi-target cases. Experimental results on a number of challenging video sequences have verified that the proposed method is effective in many complicate scenes.

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