Projecting Active Contours with Diminutive Sequence Optimality

D. Baswaraj[1], Dr. A. Govardhan[2] and Dr. P. Premchand[3]

[1] CMR Institute of Technology, Hyderabad (AP, India)

Received: 13 December 2012 Accepted: 3 January 2013 Published: 15 January 2013

Abstract

Active contours are widely used in image segmentation. To cope with missing or misleading features in image frames taken in contexts such as spatial and surveillance, researchers have commence various ways to model the preceding of shapes and use the prior to constrict active contours. However, the shape prior is frequently learnt from a large set of annotated data, which is not constantly accessible in practice. In addition, it is often doubted that the existing shapes in the training set will be sufficient to model the new instance in the testing image. In this paper we propose to use the diminutive sequence of image frames to learn the missing contour of the input images. The central median minimization is a simple and effective way to impose the proposed constraint on existing active contour models. Moreover, we extend a fast algorithm to solve the projected model by using the hastened proximal method. The Experiments done using image frames acquired from surveillance, which demonstrated that the proposed method can consistently improve the performance of active contour models and increase the robustness against image defects such as missing boundaries.

Index terms—

1 Introduction

mage segmentation is a fundamental task in many applications. Among various techniques, the active contour model is widely used. A contour is evolved by minimizing certain energies to match the object boundary while preserving the smoothness of the contour [2]. The active contour is usually represented by landmarks [18] or level sets [20,8]. A variety of image features have been used to guide the active contour, typically including image gradient [7,31], region statistics [34,8], color and texture [14].

In real purposes, the presentation of the active contour model is prone to be dishonored by missing or misleading features. For example, segmentation of the left ventricle in ultrasound images is still an unresolved problem due to the characteristic artifacts in ultrasound such as attenuation, speckle and signal dropout [23]. To improve the robustness of active contours, the shape prior is often used. The prior knowledge of the shape to be segmented is modeled based on a set of manuallyannotated shapes to guide the segmentation. Previous deformable template models [32,27,17,21] can be regarded as the early efforts towards knowledge-based segmentation. In more recent works, the shape prior was applied by regularizing the distance from the active contour to the template in a level-set framework [10,24,9]. Another category of methods popularly used for shape prior modeling is the active shape model or point distribution model [11]. Briefly speaking, each shape is denoted by a vector and regarded as a point in the shape space. Then, the principal component analysis is carried out to obtain the mean and several most significant modes of shape variations, which establish a low-dimensional space to describe the favorable shapes. During the segmentation of a new image, the candidate shape is constrained in the shape space [19,29]. Also, dynamic models can be integrated to model the temporal continuity when tracking an object in a sequence [12,35]. Other extensions of the active shape model include manifold learning [15] and sparse representation **??**3:5], to name a few.

While the shape prior has proven to be a powerful tool in segmentation, it has two limitations: 1. Previous methods for shape prior modeling require a large set of annotated data, which is not always accessible in practice.

4. We applied the proposed method to sequence of surveillance face images and demonstrated that the Diminutive sequence optimality regularization could significantly improve the robustness of the active contour model. The rest of this paper is organized as follows: Section 2 introduces the basic theory and the formulation of our method. Section 3 describes the algorithm to solve our model. Section 4 demonstrates the merits of our method by experiments. Finally, Section 5 concludes the paper with some discussions.

2 II.

3 Formulation a) Diminutive Sequence Optimality Measure

To apply a Diminutive sequence optimality constraint to active contours, a proper measure to estimate that any of images are akin to source is desired. Characteristically, the akin among two contours is measured by scheming the distances between the equivalent points on the contours, and the minuscule sequence optimality can be calculated by the sum of pair-wise distances among contours. The main drawback of this technique is that the contour distance is not invariant below akin transformation.

Here, we propose to use the matrix rank to measure the Diminutive sequence optimality of shapes. Suppose each shape is represented by a vector. Multiple shapes form a matrix. Intuitively, the rank of the matrix measures the correlation among the shapes. For example, the rank equals to 1 if the shapes are identical, and the rank may increase if some shapes change. Moreover, we can show that the shape matrix is still lowrank if the shape change is due to the akin transformation such as translation, scaling and rotation. For example, let vector p n n C C C × ? ? has the following property 1 ([,...,]) 6 n rank C C ? (1)

Intrinsically, the rank of the shape matrix describes the degree of freedom of the shape change. The low-rank constraint will allow the global change of contours such as translation, scaling, rotation and principal deformation to fit the image data while truncating the local variation caused by image defects. segment the object in these images. To keep the contours similar to each other, we propose to segment the images by min 1 ( )n X i i i f C = ? Subject to ( ) , rank X K ? (2) Where 1 [,...,] n X C C = and K is a predefined constant. ( ) i i

f C Is the energy of an active contour model to evolve the contour in each frame, such as snake [18], geodesic active contour [7], and regionbased models [34,8]. For example, the region-based energy in [8] reads1 2 2 2 1 2 ( ) (( )) (( )) ( ) i i i i i f C I X u dx I X u dx length C ? ? ? = ? + ? + * ? ?**(3)**

Where 1

? and

4 2

? represent the regions inside and outside the contour, and 1 u and 2 u denote the mean intensity of 1? and 2 ? , respectively.

Since rank is a discrete operator which is both difficult to optimize and too rigid as a regularization method, we propose to use the following relaxed form as the objective function:min 1 ( ) n X i i i f C X ? * = + ? (4)

Here, rank(X) in (**??**) is replaced by the central median X * , i.e. the sum of singular values of X.

Recently, the central median minimization has been widely used in low-rank modeling such as matrix completion [6] and robust principal component analysis [5]. As a tight convex surrogate to the rank operator [16], the central median has several good properties: Firstly, the convexity of the central median makes it possible to develop fast and convergent algorithms in optimization. Secondly, the central median is a continuous function, which is important for a good process of regularize in many applications. For instance, in our problem, the small perturbation in the shapes may result in a large increase of rank(X), while X * may rarely change.

5 Algorithm

In this section, we will discuss how to solve the optimization problem observed in (Eq4). If regularizing process not opted X * , (Eq4) can be locally minimized by changeover descent, which gives the curve evolution steps in typical active contour models. In our model, it is difficult to apply changeover descent directly due to the central median, which is coarse and its partial changeover is hard to compute. ( ) ( ) X F X R X ? + (5)

Where ( ) F X a differentiable is function and ( ) R X corresponds to a convex penalty which can be coarse. Our problem is in this category with1 ( ) ( ) n i i i F X f C = = ? and ( ) R X X * =

.The basic step in Proximal Gradient is to make the following quadratic approximation to F(X) based on the previous estimate' X per iteration. Add Eq 6 2 2 (, ') (') ('), ' ' ( ), 2 1 [' (')] ( ) 2 F F Q X X F X F X X X X X R X X X F X R X const µ µ ? µ ? µ = + ?? ? ? + ? + = ? ? ? + + ? ?**(6)**

Where .,. ? ? means the inner product, . F denotes the Frobenius norm, and ? is a constant. It is shown in [22] that, if F(X) is differentiable with Lipschitz continuous gradient, the sequence generated by the following iteration will converge to a stationary point of the function in (**??**) with a convergence rate of1 ( ) k ? . 1 2 min arg (,) 2 min 1 1 arg [( )] ( ) 2 2 k k k k F X Q X X X X X F X R X µ ? µ µ + = = ? ? ? +**(7)**

The next question is how to solve the update step in (Eq7). For our problem, the lemma proven in [4] has been taken to define the proposed hastened propinquity changeover algorithm.

6 Lemma 1 Given

m n X × ? ?

, the solution to the problem2 * min 1 2 F X Z X X ? ? +**(8)**

is given by* ( ) X D Z ? =

, wheremin(,)**1**( ) ( ) m n T i i i i D Z u v ? ? ? = = ? + ?**(9)**

The intuition of our algorithm is that, per iteration, we first evolve the active contours according to the image-based forces and then impose the Diminutive sequence optimality regularization via singular value threshold. The overall algorithm is summarized here. Hastened propinquity changeover algorithm 2. 0 fork = ? Maximum number of iterations do 3.

1 1

7 ( )

k k k k k k t Y X X X t ? ? ? = + ? 4. For 1 i n = ? do 5. 1 ( ) k k k i i i i y y f y µ ? ? ? 6. end for 7. 1 ( ) k k X D Y ? µ + = 8. 2 1 1 1 4( ) 2 k k t t + + + = 9. If 1 k k X X

8 Performance Analysis and Results Exploration

In this section, we evaluate the proposed method on both synthesized data and surveillance face image sequence. To demonstrate the advantages of the Diminutive sequence optimality constraint, we compare the results of the same active contour model before and after applying the proposed constraint. We select the region-based active contour in (3) as the basic model, which is less sensitive to initialization and has fewer parameters to tune compared with edge-based methods.

In our execution, we initialize the energetic contours as0 0,..., 0 [ ] X C C =

, where 0 C is a coarse outline of the object placed manually in an image. Three parameters need to be selected in our algorithm. ? in (Eq3) controls the smoothness of each contour, ? in Recently, the Proximal Gradient (PG) method [1,22] is used to solve the following category of problems 1. The bottom row of figure 2 indicates the results obtained from different strategies. There are two comments worth mentioning. Firstly, the contour shapes are globally consistent with each other throughout the sequence, which is attributed to the Diminutive sequence optimality constraint. Hence, the contours are more resistant to local misleading features. Secondly, the constrained shape model is still flexible enough to adapt the deformation of the object shape. The problem of our method is that it cannot address the universal bias of the model. Therefore, the region-based active contours cannot attach closely to the true boundary. In practice, more appealing results can be obtained by including more energy terms such as edge-based energies, which is out of the scope of this paper. The results are summarized in Table 1. Regarding the mean of the metrics, a smaller MAD/HD or a larger Dice coefficient indicates a more accurate segmentation. Generally, the performance with the proposed constraint is better than that without the constraint. The improvement in the diminutive sequence trained distance is the most notable, which measures the largest error for each contour. This is due to the fact that part of the segmentation result is corrupted by the missing boundary while this error can be corrected by adding the shape constraint. Regarding the standard deviation of the metrics, a smaller standard deviation indicates the more stable performance. The standard deviation with the proposed constraint is distinctly lower than that without the constraint, which shows the significance of the proposed constraint to improve the robustness of the active contour model. In our experiments, we selected ? empirically and applied the same ? to all sequences. The curve in Figure **??** shows that the accuracy changes smoothly over ? and the performance is stable in a wide range. Another alternative way is to choose a constant K specifying the degree of freedom allowed for shape variation and then solve the model with a decreasing sequence of ? until ( ) rank X reaches K.

9 d) Convergence and Computational Time

Our algorithm is executed in java and tested on a desktop through a Intel i7 3.4GHz CPU and 3GB RAM. The experiments showed that the algorithm with the shape constraint converged faster than that without shape constraint. This can be explained by the fact that the added constraint will make the active contour model better regularized, which results in faster convergence and fewer iterations. The results indicating that the algorithm with the proposed constraint is even faster in computation compared to that without the constraint.

V.

10 Conclusion

In this paper, we proposed a simple and effective way to regularize the Diminutive sequence optimality of shapes in the active contour model based on low-rank modeling and rank minimization. We use the position similarities to represent the contour instead of level sets. The reason is that the low-rank property in (Eq1) will not hold if the level-set representation is used. For instance, if there are n contours represented by the zero-level sets of n signed distance functions (SDFs) and the contours are identical in shape but different in location, the matrix consisting of the vector SDFs has a rank of n, which is full-rank. Other divergent methods for image segmentation also have this issue. A limitation of using the shape akin constraint is the possibility of removing frame-specific details of the shapes. The trade-off between noise removal and signal preserving is a fundamental challenge in many problems. A possible solution in our problem is to refine the segmentation by running an active contour model that is more sensitive to local features with our results being both initialization and templates to constrain the curve evolution. In future the formation and projection of the missing contour structure can be done by determining through support vector machines, which trained by the optimal contour features of the diminutive sequence. [1] [2]

Figure 1: ©

Figure 2:

Figure 3: (

[1] Fmodel better regularized and require minimal iteration to converge.

Figure 4:

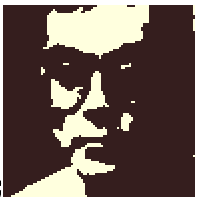
2 

Figure 5: Figure 2 :

Figure 6: F

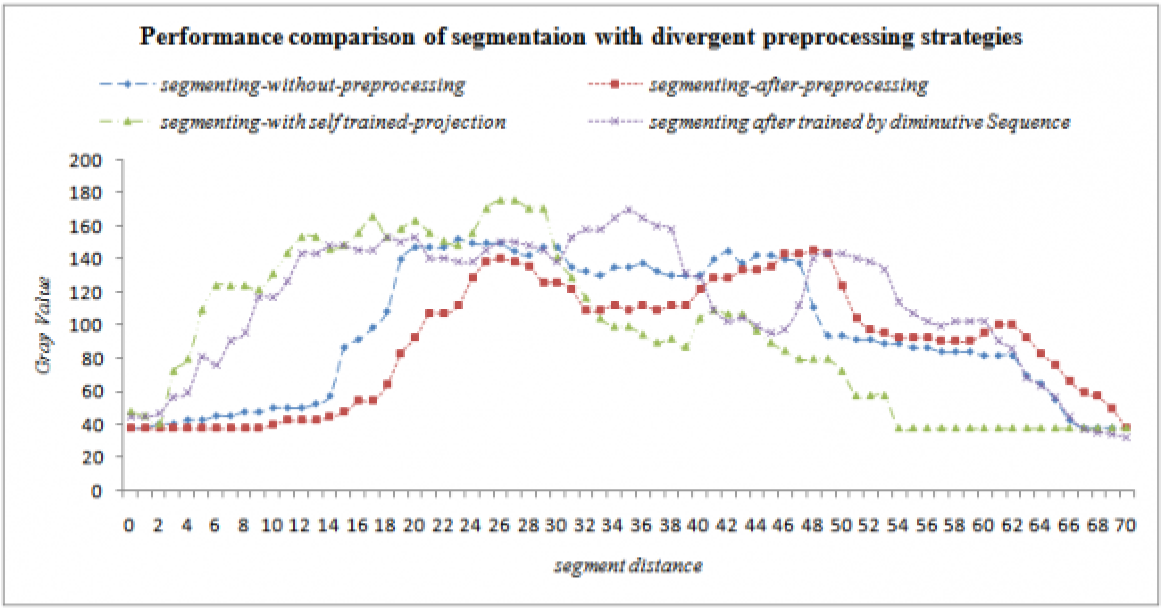
1 

Figure 7: Figure 1 :

Figure 8: F

1

	Projecting Active Contours with Diminutive Sequence Optimality				
Distance	Segmenting-Without-Preprocessing	Segmenting-After-Preprocessing	Segmenting-with Self Trained-Projection	Segmenting after Trained by Diminutive Sequence	
0	37.6667	37.6667	47.4921	44.8643	
1	37.6667	37.6667	45.0357	44.8643	
2	40.0941	37.6667	40.123	47.2636	
3	40.0941	37.6667	72.0556	56.8605	
4	42.5216	37.6667	79.4246	59.2597	
5	42.5216	37.6667	108.9008	80.8527	
6 7	44.949 44.949	37.6667 37.6667	123.6389 123.6389	76.0543 90.4496	013
8 9	47.3765 47.3765	37.6667 37.6667	123.6389	116.8411 116.8411	Year
10	49.8039	40.0659	121.1825 131.0079	95.2481	2
11	49.8039	42.4651	143.2897	126.438	
12	49.8039	42.4651	153.1151	143.2326	
13	52.2314	42.4651	153.1151	143.2326	
14	57.0863	44.8643	145.746	148.031	
15	86.2157	47.2636	148.2024	148.031	
16	91.0706	54.4612	155.5714	145.6318	
17	98.3529	54.4612	165.3968	145.6318	
18	108.0627	64.0581	153.1151	152.8295	
19	139.6196	83.2519	158.0278	150.4302	
20	146.902	92.8488	162.9405	152.8295	
21	146.902	107.2442	155.5714	140.8333	
22	146.902	107.2442	150.6587	140.8333	
23	151.7569	112.0426	148.2024	138.4341	
24	149.3294	128.8372	155.5714	138.4341	
25	149.3294	138.4341	170.3095	145.6318	
26	149.3294 144.4745	140.8333	175.2222	150.4302 150.4302	(
27		138.4341	175.2222		DDDDDDDD)F
28	142.0471	136.0349	170.3095	148.031	
29	146.902	126.438	170.3095	145.6318	
30	146.902	126.438	140.8333	138.4341	
31	134.7647	121.6395	128.5516	152.8295	
32	132.3372	109.6434	116.2698	157.6279	
33	129.9098	109.6434	103.9881	157.6279	
34	134.7647	112.0426	99.0754	164.8256	
35	134.7647	109.6434	99.0754	169.624	
36	137.1922	112.0426	94.1627	164.8256	
37	132.3372	109.6434	89.25	160.0271	
38	129.9098	112.0426	91.7064	157.6279	
39	129.9098	112.0426	86.7937	131.2364	
40	129.9098	121.6395	103.9881	128.8372	
41	[illegible]	[illegible]	[illegible]	[illegible]	

[Beck and Teboulle ()] 'A fast iterative shrinkagethresholding algorithm for linear inverse problems'. M Beck , Teboulle . *SIAM Journal on Imaging Sciences* 2009. 2 p. .

[Paragios ()] 'A level set approach for shape-driven segmentation and tracking of the left ventricle'. N Paragios . *IEEE Transactions on Medical Imaging* 2003. 22 (6) p. .

[Cremers et al. ()] 'A review of statistical approaches to level set segmentation: integrating color, texture, motion and shape'. D M Cremers , R Rousson , Deriche . *International Journal of Computer Vision* 2007. 72 (2) p. .

[Cai et al. ()] 'A singular value thresholding algorithm for matrix completion'. J E Cai , Z Candes , Shen . *SIAM Journal on Optimization* 1956. 2010. 20.

[Blake and Isard ()] *Active contours*, M Blake , Isard . 2000. Springer.

[Chan and Vese ()] 'Active contours without edges'. T Chan , L Vese . *IEEE Transactions on Image Processing* 2001. 10 (2) p. .

[Cootes et al. ()] *Active shape models -their training and application. Computer Vision and Image Understanding*, T C Cootes , D Taylor , J Cooper , Graham . 1995. 61 p. .

[Staib and Duncan ()] 'Boundary finding with parametrically deformable models'. L Staib , J Duncan . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 1992. 14 (11) p. .

[Cremers et al. ()] 'Convex relaxation techniques for segmentation, stereo and multiview reconstruction'. T Cremers , K Pock , A Kolev , Chambolle . *Markov Random Fields for Vision and Image Processing*, 2011. MIT Press.

[Cremers ()] 'Dynamical statistical shape priors for level set-based tracking'. Cremers . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2006. 28 (8) p. .

[Yuille et al. ()] 'Feature extraction from faces using deformable templates'. P Yuille , D Hallinan , Cohen . *International Journal of Computer Vision* 1992. 8 (2) p. 99.

[Caselles et al. ()] 'Geodesic active contours'. V Caselles , R Kimmel , G Sapiro . *International Journal of Computer Vision* 1997. 22 (1) p. .

[Nesterov ()] *Gradient methods for minimizing composite objective function. CORE Discussion Papers*, Y Nesterov . 2007.

[Chan and Zhu ()] 'Level set based shape prior segmentation'. T Chan , W Zhu . *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, (the IEEE Conference on Computer Vision and Pattern Recognition) 2005.

[Fazel ()] *Matrix rank minimization with applications*, M Fazel . 2002. Stanford University (PhD thesis)

[Tsai et al. ()] 'Modelbased curve evolution technique for image segmentation'. A Tsai
III. C. Tempany. D. Tucker. A. Fan. W. Grimson. and A. Willsky , W YezziJr
III. C. Tempany. D. Tucker. A. Fan. W. Grimson. and A. Willsky , Wells
III. C. Tempany. D. Tucker. A. Fan. W. Grimson. and A. Willsky . *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, (the IEEE Conference on Computer Vision and Pattern Recognition) 2001.

[Vidal and Hartley ()] 'Motion segmentation with missing data using powerfactorization and gpca'. R Vidal , R Hartley . *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, (the IEEE Conference on Computer Vision and Pattern Recognition) 2004.

[Jain et al. ()] 'Object matching using deformable templates'. . Y Jain , S Zhong , Lakshmanan . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 1996. 18 (3) p. .

[Metaxas ()] *Physics-based deformable models: applications to computer vision, graphics, and medical imaging*, Metaxas . 1996. Kluwer Academic Publishers.

[Bregler et al. ()] 'Recovering non-rigid 3d shape from image streams'. A Bregler , H Hertzmann , Biermann . *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, (IEEE Conference on Computer Vision and Pattern Recognition) 2000.

[Zhu and Yuille ()] 'Region competition: Unifying snakes, region growing, and bayes/mdl for multiband image segmentation'. S Zhu , A Yuille . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 1996. 18 (9) p. .

[Candes et al. ()] 'Robust principal component analysis'. E X Candes , Y Li , J Ma , Wright . *Journal of the ACM* 2011. 58 (3) p. 11.

[Zhu et al. ()] 'Segmentation of the left ventricle from cardiac mi' images using a subject-specific dynamical model'. Y X Zhu , A Papademetris , J Sinusas , Duncan . *IEEE Transactions on Medical Imaging* 2010. 29 (3) p. .

[Malladi et al. ()] 'Shape modeling with front propagation: A level set approach'. R Malladi , J Sethian , B Vemuri . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 1995. 17 (2) p. .

[Etyngier et al. ()] 'Shape priors using manifold learning techniques'. P Etyngier , F Segonne , R Keriven . *Proceedings of IEEE International Conference on Computer Vision*, (IEEE International Conference on Computer Vision) 2007.

[Xu and Prince ()] 'Snakes, shapes, and gradient vector flow'. J Xu , Prince . *IEEE Transactions on Image Processing* 1998. 7 (3) p. .

[Witkin and Terzopoulos ()] 'Snakes: Active contour models'. M Kass A Witkin , D Terzopoulos . *International Journal of Computer Vision* 1988. 1 (4) p. .

[Torresani and Bregler ()] 'Space-time tracking'. L Torresani , C Bregler . *Proceedings of the European Conference on Computer Vision*, (the European Conference on Computer Vision) 2002.

[Srivastava et al. ()] 'Statistical shape analysis: Clustering, learning, and testing'. S H Srivastava , W Joshi , X Mio , Liu . *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2005. 27 (4) p. .

[Leventon et al. ()] 'Statistical shape influence in geodesic active contours'. M Leventon , W Grimson , O Faugeras . *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, (the IEEE Conference on Computer Vision and Pattern Recognition) 2000.

[Zhang et al. ()] *Towards robust and effective shape modeling: Sparse shape composition. Medical image analysis*, S Y Zhang , M Zhan , J Dewan , D N Huang , X S Metaxas , Zhou . 2012. 16 p. .

[Noble and Boukerroui ()] 'Ultrasound image segmentation: A survey'. J Noble , D Boukerroui . *IEEE Transactions on Medical Imaging* 2006. 25 (8) p. .

[Sidi et al. ()] 'Unsupervised co-segmentation of a set of shapes via descriptor-space spectral clustering'. O O Sidi , Y Van Kaick , H Kleiman , D Zhang , Cohen-Or . *ACM Transactions on Graphics* 2011. 30 (6) p. 126.

[Chen et al. ()] 'Using prior shapes in geometric active contours in a variational framework'. Y H Chen , S Tagare , F Thiruvenkadam , D Huang , K Wilson , R Gopinath , E Briggs , Geiser . *International Journal of Computer Vision* 2002. 50 (3) p. .