INTERPRETING EDGE INFORMATION FOR IMPROVED ENDOCARDIUM DELINEATION IN ECHOCARDIOGRAMS

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ABSTRACT

Successful segmentation of the left ventricle in echocardiograms relies on strong edge responses to ensure that segmentation methods converge to the endocardial boundary. However, segmentation methods that do not interpret edge responses using local shape information or global context are often led astray by imaging artifacts. An extension to a boundary fragment model borrowed from computer vision literature is presented as a method for determining which edge responses contribute to the endocardial boundary. To demonstrate its applicability, the proposed method is applied to a data set composed of long-axis echocardiogram slices from five subjects. Results show that the process is effective at locating the endocardium and identifying the edge responses which correspond to the endocardial boundary.

Index Terms— Biomedical image processing, echocardiography

1. INTRODUCTION

Accurate assessment of cardiovascular function is imperative for identifying heart disease at an early stage and assessing the efficacy of treatment. Echocardiography is a widely established technique for assessing cardiac function, but echocardiogram quality is sensitive to the acquisition environment. Imaging artifacts such as speckle, attenuation from adipose tissue, and drop out make developing techniques for automatically evaluating heart function challenging.

The first step towards quantifying cardiac function typically requires accurate segmentation of the left ventricle blood pool. Deformable model and contour based approaches have been used for segmentation, but these models rely heavily on strong endocardial edges for stable convergence. Variants of the geodesic active contour framework have been developed for ultrasound segmentation, using edge responses and local image statistics to drive the zero level set towards the endocardial boundary [1]. However, these methods require very strict initialization otherwise the differences in local image statistics are insufficient to deform the level set. Furthermore, spurious edges as a result of imaging artifacts can lead the level set away from the desired solution.

Both deformable contour and region based methods therefore rely fundamentally on strong edge responses to ensure that they converge to the endocardial boundary. Edge detection methods based on feature asymmetry [2] are effective at producing edge images which correspond to the endocardial boundary. However, when high bandwidth filtering is required to achieve accurate delineation of the endocardium, false and irrelevant edges are also preserved.

This paper describes an approach to identify the edge responses which describe the endocardium boundary. The motivation for this is that only the edges which contribute to the endocardium boundary are relevant for segmentation and these edges should be identifiable by considering local and global shape information. A boundary fragment model used for multiscale object recognition by Shotton et al. has been adapted for this purpose [3].

2. THE BOUNDARY FRAGMENT MODEL

A modified *boundary fragment model* was introduced by Shotton et al. in [3] as a method for object recognition and localization in computer vision. The motivation behind the boundary fragment model is that an object can be recognized and localized based on its edges alone. In Shotton's formulation, an object class is represented by a finite set of learned edge fragments and a boosted classifier is trained to use the fragments to determine the object's scale and centroid position. Extending this work to echocardiogram segmentation, the results of the individual weak learners can be inspected to isolate the edge responses which contribute to the endocardium boundary.

2.1. Echocardiogram edge map generation

To construct and use a boundary fragment model it is necessary to define a procedure for generating an *edge map* from an echocardiogram. An edge map is a binary representation of an image which has 1s at edge pixels (edgels) and 0s at all other pixel positions. Each edgel also has an associated angle which indicates the orientation of the edge.

Locating the endocardial boundary in the echocardiogram amounts to detecting step edge features. Feature detection methods based on the monogenic signal have been shown to

be successful at detecting and measuring these edge features in ultrasound images [2]. In our implementation the echocardiogram is first filtered with a bandpass filter to isolate the edge features at the scale of interest. From the filtered image the monogenic signal is constructed using the Riesz transform [2]. The components of the monogenic signal are then used to construct the *feature asymmetry* image which indicates the location and extent of step edges in the echocardiogram. Non-maximum suppression is used to reduce the feature asymmetry image to a binary image and the monogenic signal components are again used to calculate the orientation of the edge features at each resulting edgel position.

2.2. Boundary fragment model construction

2.2.1. Fragment generation

The first step in constructing the boundary fragment model of the endocardium is to generate a large number of edge fragments from a training set of echocardiograms. For each full edge map derived from the training set, only the edgels contributing to the endocardium are manually identified and the bounding box which encompasses them is determined. The center of the bounding box, $\mathbf{x}_b$, defines the centroid of the left ventricle. Next, random edge fragments are selected by generating random *fragment boxes* within the bounding box according to [3].

Each fragment box within the bounding box defines an *edge fragment*. The edge fragment formally consists of a set E and a vector $\mathbf{x}_f$. E is the set of edgel positions relative to the center of the fragment box. E encodes the local configuration of the edgels which correspond to a section of the endocardium boundary. $\mathbf{x}_f$ is the vector from the centroid of the left ventricle, $\mathbf{x}_b$, to the center of the fragment box. This vector encodes the global placement of the edge fragment. Random rotation and translation transformations are applied to E and $\mathbf{x}_f$ to ensure that the boundary fragment model is also tolerant to these transformations. To improve the tolerance to minor scale changes, the edgel offsets in E and the components of the vector $\mathbf{x_f}$ are scale-normalized by a random scale s which is close to 1.0 [3].

2.2.2. Fragment clustering

To obtain a representative set of edge fragments for the endocardium it is necessary to cluster the generated edge fragments. To cluster the fragments it is necessary to define a distance function which measures the difference between edge fragments. Shotton et al. define *oriented chamfer matching* between edge fragments E and T as [3]:

$$d_{\lambda}^{(T,E)}(\mathbf{x}) = (1-\lambda)\cdot d_{\text{cham}}^{(T,E)}(\mathbf{x}) + \lambda \cdot d_{\text{orient}}^{(T,E)}(\mathbf{x})$$

where λ controls the weight of each distance measure. The chamfer distance $d_{\text{cham}}^{(T,E)}(\mathbf{x})$ is the smallest distance from each edgel in edge fragment T, offset by $\mathbf{x}$, to an edgel in E:

$$d_{\text{cham}}^{(T,E)}(\mathbf{x}) = \frac{1}{\tau|T|}\sum_{\mathbf{x}_t\in T}\min\left(\min_{\mathbf{x}_e\in E}\|(\mathbf{x}_t+\mathbf{x})-\mathbf{x}_e\|_2,\,\tau\right)$$

where τ is the upper limit on the distance and $|T|$ is the number of edgels in fragment T. While the chamfer distance accounts for the translational differences between fragments, the orientation distance $d_{\text{orient}}^{(T,E)}(\mathbf{x})$ quantifies the rotational differences:

$$d_{\text{orient}}^{(T,E)}(\mathbf{x}) = \frac{1}{\pi|T|}\sum_{\mathbf{x}_t\in T}\left|\phi_T(\mathbf{x}_t) - \phi_E\left(\underset{E}{\text{ADT}}(\mathbf{x}_t+\mathbf{x})\right)\right|$$

where $\phi_K(\mathbf{x})$ gives the orientation of the edgel at $\mathbf{x}$ from the fragment set K, and $|\phi_{K_1}(\mathbf{x}_1) - \phi_{K_2}(\mathbf{x}_2)|$ gives the smallest circular difference between $\phi_{K_1}(\mathbf{x}_1)$ and $\phi_{K_2}(\mathbf{x}_2)$. $\text{ADT}_E(\mathbf{x})$ is the argument distance transform and returns the edgel position in E which is closest to the position $\mathbf{x}$. Since edge direction has been completely preserved, $\phi_K(\mathbf{x}) \in [0, 2\pi)$ and division by π therefore ensures that $d_{\text{orient}}^{(T,E)}(\mathbf{x}) \in [0,1]$. Finally, for scale-normalized fragments T_i and T_j – with scales s_i and s_j respectively – the *symmetric distance* is defined as:

$$d_{i,j} = d_{\lambda}^{(s_jT_i, s_jT_j)}(\mathbf{0}) + d_{\lambda}^{(s_iT_j, s_iT_i)}(\mathbf{0})$$

To cluster the fragments the symmetric distance is taken between every pair of edge fragments and k-medoids is used to find the main appearance clusters. The cluster centers are the edge fragments which best represent the local configurations exhibited along sections of the endocardium boundary.

Some fragments may fall within the same appearance cluster but describe different sections of the endocardium. Therefore, the fragments are further clustered based on $\mathbf{x}_f$ using the meanshift algorithm [4]. From each new sub-cluster the mean centroid offset $\overline{\mathbf{x}_f}$ and the radial standard deviation σ is stored. The fragment $\overline{T}$ that has the smallest symmetric fragment distance to all other fragments in the sub-cluster is also saved. These three variables $(\overline{T}, \overline{\mathbf{x}_f}, \sigma)$ constitute an *edge part* F. The set of all edge parts is the *part library* for the endocardium.

2.2.3. Centroid detection and localization

With reference to [3], a classifier for detecting the endocardium centroid and scale is trained using the part library to create the feature vectors. For a hypothesized endocardium scale s and centroid location $\mathbf{x}$, each part F in the part library is fitted onto the echocardiogram edge map within the circular region $\mathcal{R}_F$ centered at $\hat{\mathbf{x}} = \mathbf{x} + s\overline{\mathbf{x}_f}$ with radius $s\sigma$. The optimal position $\mathbf{x}^* \in \mathcal{R}_F$ for the part is where its oriented chamfer distance to the edge map is minimum. The *part response* at the hypothesized centroid location and scale is then defined as:

$$v_{[F,\lambda]}(\mathbf{x}, s) = d_{\lambda}^{(s\overline{T},E)}(\mathbf{x}^*)$$

where E in this case is the set of edgel positions derived from the echocardiogram. The concatenation of all part responses form the feature vector for the chosen centroid $\mathbf{x}$ and scale s.

With a labeled training set of edge maps with positive and negative examples of endocardium centroids, the feature vector at each example position is generated and a boosted classifier (GentleBoost) is trained [3]. The resulting classifier has the form:

$$H(\mathbf{x}, s) = \sum_{m=1}^{M} \begin{cases} a_m & v_{[F_m,\lambda_m]}(\mathbf{x}, s) > \theta_m \\ b_m & v_{[F_m,\lambda_m]}(\mathbf{x}, s) \leq \theta_m \end{cases}$$

where M is the number of weak learners and each summand is a *decision stump* with constants (a_m, b_m). From this definition the classifier returns a positive score when the hypothesized centroid position and scale is supported and negative when it is not.

2.3. Endocardium edge delineation

In Shotton's boundary fragment model the learned centroid classifier is used to test candidate positions across an edge map to determine the centroid and scale of the object of interest. However, for endocardium segmentation more than just object detection and localization is required – the edges which *define* the true boundary must be isolated.

At the detected endocardium centroid position the classifier has its maximum response as a result of the positive responses of a subset of the weak learners. For a given decision stump m, if $v_{[F_m,\lambda_m]} \leq \theta_m$ and $b_m > 0$ then it provides support for the hypothesized endocardium centroid position and scale. It follows that the part F_m must have sufficient image support from the echocardiogram edge map when it is placed at $\mathbf{x}^*$ because its part distance is less than or equal to the learned threshold θ_m. Since F_m was selected during the boosting procedure it is also a discriminative edge part. It is therefore reasonable to assume that edgels in the proximity of the placed fragment contribute to the local boundary of the endocardium. The *relevance* of an edgel at $\mathbf{x}$, given the placement of the part F_m, can therefore be defined as:

$$R_{F_m}(\mathbf{x}) = \left[1 - \frac{1}{\mu} \min\left(\min_{\mathbf{x}_t \in s\overline{T}_m} \|(\mathbf{x} - \mathbf{x}^*) - \mathbf{x}_t\|_2,\, \mu\right)\right] \left[1 - \frac{1}{\omega} \min\left(\left|\phi_E(\mathbf{x}) - \phi_{s\overline{T}_m}\left(\underset{s\overline{T}_m}{\mathrm{ADT}}(\mathbf{x} - \mathbf{x}^*)\right)\right|, \omega\right)\right]$$

where μ and ω are spatial and orientation thresholds respectively. The first factor captures the spatial distance from the edgel at $\mathbf{x}$ to the scaled part fragment $s\overline{T} + \mathbf{x}^*$. The second factor quantifies the difference in orientation between the edgel and the nearest edgel in the scaled part fragment. The total relevance of the edgel at $\mathbf{x}$ is given by:

$$R(\mathbf{x}) = \sum_{m \in \mathcal{M}} b_m \cdot R_{F_m}(\mathbf{x})$$

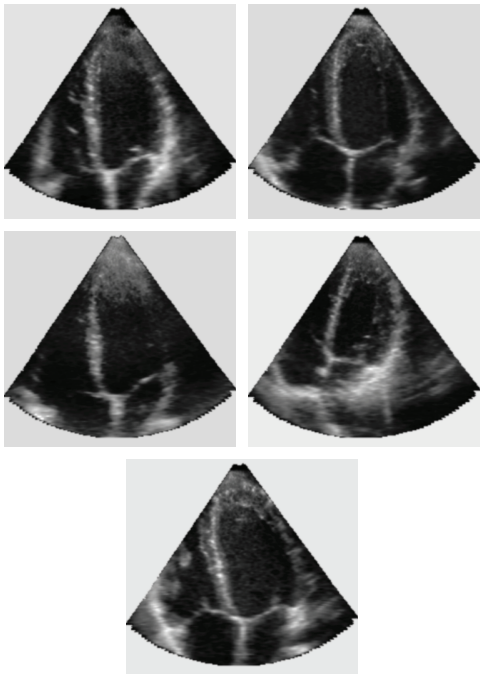


Fig. 1: Example echocardiogram slices from the subjects used for training (top four) and for validation (bottom).

where $\mathcal{M}$ is the set of feature indices where the support condition is true. The *relevance image* is then formed from $R(\mathbf{x})$ at each edgel position $\mathbf{x} \in E$.

3. EXAMPLE EXPERIMENT AND DISCUSSION

To demonstrate the operation and usefulness of the boundary fragment model and relevance images a small experiment is presented. A boundary fragment model has been constructed using 2D four-chamber view slices from 3D echocardiograms. For each subject, five image slices were extracted from the end-diastole frame and corresponding edge maps were subsequently derived. The edgels corresponding to the endocardial boundary were then manually selected. Example slices from each subject are shown in Fig. 1.

The part library was generated from four subjects' echocardiograms and were validated against a fifth echocardiogram from an independent subject. Five hundred fragments were generated from each training edge map. After the two stages of clustering the number of fragments was reduced from 10000 to 231. The centroid classifier was then trained using this part library with the procedure from [3]. Two hundred weak learners were used with only 77 unique edge parts being utilized in the final boosted classifier.

Example results of applying the boundary fragment model are shown in Fig. 2. The first row illustrates the power of the model to identify the centroid and relevant edgels of an image

slice from the validation subject. The second row illustrates the flexibility of the same model when applied to an unseen image slice of different scale and shape from a training subject. Finally, the third row illustrates the success of the model on an unseen image slice from a training subject with a different pose and without the image support of the mitral valve which was present in all end-diastole training slices.

Thresholding the relevance images produces a rough edge map containing the edgels which correspond to the endocardium. Considering only the five validation slices and comparing the relevance edge maps to the manually selected edgels, precision and recall measurements were in the ranges $[0.84, 0.91]$ and $[0.81, 0.96]$ respectively. These results along with Fig. 2 demonstrate the flexibility and power of the boundary fragment model to locate relevant endocardial edge responses.

4. CONCLUSIONS

A boundary fragment model for object detection and localization has been adapted from computer vision literature to quantify the relevance of edge responses in echocardiograms. Specifically, a boundary fragment model for the endocardium has been constructed and the boosted classifier for locating the endocardium has been trained. The classifier is used to locate the endocardium and the individual weak learners of the boosted classifier are examined to determine which edge responses correspond to the boundary of the endocardium.

The presented experiment shows that the boundary fragment model has sufficient flexibility to capture wide variations in shape with a concise fragment set. The positions of the detected centroids match closely to the manually segmented images and the resulting relevance images show accurate delineation of the endocardium. Validation on an extended training set is still required to determine the optimal training procedure for constructing the boundary fragment model and to examine its flexibility to variations in subject anatomy. The method could also be applied to other ultrasound applications and for other imaging modalities.

5. ACKNOWLEDGMENTS

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6. REFERENCES

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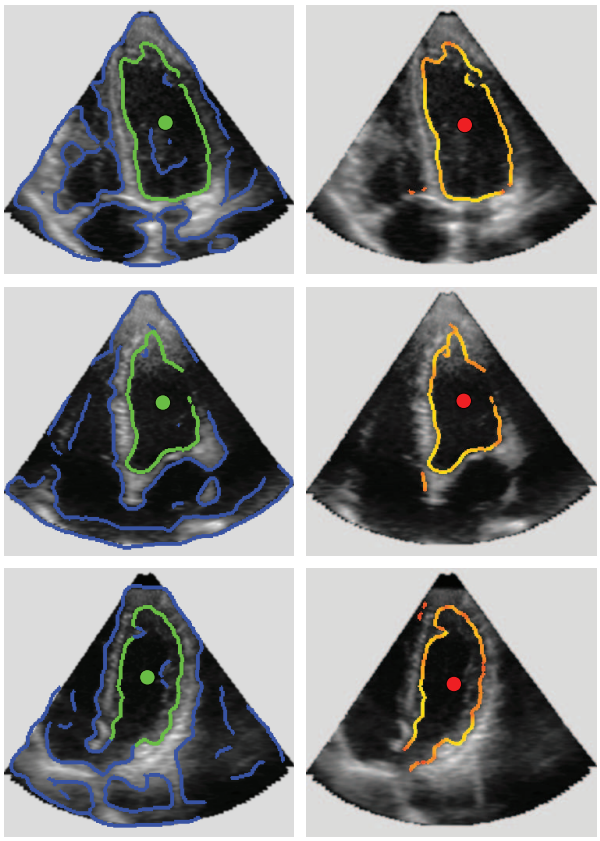


Fig. 2: Example results of applying the boundary fragment model to different test image slices. The left column shows edge maps (blue), manually selected edgels (green), and the derived centroid (green circle). The right column shows the detected centroid (red circle) and relevance images (orange to yellow) superimposed on the same image slice.

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