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Two Automatic Training-Based Forced Calibration Algorithms for Left Ventricle Boundary Estimation in Cardiac Images

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Abstract

Pixel classification algorithms [1] based on temporal information, edge detection algorithms based on spatial information [3] when used in combination are not sufficient for boundary estimation of the left ventricle (LV) in Cardiovascular X-ray images. Poor contrast in the LV apex zone [4], the fuzzy region in the inferior wall due to the overlap of the LV with the diaphragm, the inherent noise, and the variability of the modulation transfer function in X-ray imaging systems causes great difficulties in LV segmentation. To over come the above problems, calibration algorithms were developed by Suri et al. [4], [5], [8], [7]. These algorithms are training-based and provides a correction to the pixel-based classification or edge detection raw boundaries. This paper presents two training-based forced calibration algorithms for correcting the raw boundaries produced by classifiers. We force the raw LV contour to pass through the LV apex and then perform the calibration. Over a database of **377** *patient studies having end-diastole and end-systole frames, the mean boundary error for the classifier system is* **5.20** *mm, the two forced calibration algorithms yield an error of* **3.14** *mm and* **3.04** *mm with a standard deviation of* **2.73** *mm and* **2.89** *mm.*

Key Words: Classifier, Left Ventricle, Low Contrast, Boundaries, Force, Bias errors.

I. Introduction

The American Heart Association and the national center for health statistics have shown that cardiovascular diseases rank as America's No. 1 killer. These diseases claim the lives of 41.8 % of the more than 2.3 million Americans who die each year. In 1997 alone, Americans will pay an estimated of 259.1 billion for cardiovascular diseases related medical costs and disability. Especially costly to Americans business are the death of skilled employees between the ages of 35 and 64, where the loss of management and production skills and the cost of training replacement personnel are enormous.

An informative tool of studying cardiac diseases is Ventriculography [5]. The gray scale ventriculograms produced by X-ray imaging systems have very poor contrast with a high level of noise. This makes the LV boundary estimation very difficult. The injected contrast medium non-uniformly mixes with blood in the LV and the apex zone of the LV typically does not receive much dye. As a result, the initial boundaries produced by a pixel-based classifier are underestimated in the apical zone with respect to ground truth (GT) boundaries.

Figure 1 presents a two stage system for boundary estimation developed at the author's laboratories. The first stage (upper half or shown in black) consists of finding the raw boundaries using three kinds of approaches: first, the pixel classification approach [1], second, the edge detection approach [3], and third, the classifier-edge fusion approach. The second stage (lower half or shown in white) is the refinement stage of the left ventricle boundaries obtained from the first stage. This stage is also called the calibration system or correction system behaving like a regularizer to change the unsmoothed left ventricle curves to smooth left ventricle curves. This correction system is also called left ventricle calibration because it calibrates out the errors introduced at stage I. This calibration stage can be thought of as a first layer of neural networks where the global shape parameters are learned by the training system and then applied on the test data to transform them for clinical purposes. Figure 1 also shows the off-line coefficient generation process which takes two inputs: the ideal boundary coordinates (x, y) and the raw boundary coordinates (x, y) generated at stage-I. These coefficients are then applied to the test raw boundary data sets. The off-line coefficients could be generated in three ways; from the edge boundary, from the classifier boundary or from the classifier-edge fusion boundary. The off-line coefficients can then be applied to the test edge boundary, or the test classifier boundary or to the test classifier-edge fused boundary. The final estimated boundary of the entire system undergoes equal arc interpolation and spline fitting followed by its performance evaluation. Suri et al. discussed stage-II in detail in [4], [5] and [8].

The paper focuses on stage-II under special conditions called forcing phenomenon, where the LV contour is made to pass through the apex during calibration procedure as shown in fig. 2. The motivation of doing this is two folds: First, improving the accuracy of the clinical system and second correcting the orientation errors. The basic idea of forced calibration is shown in fig. 3. The difference between the ordinary calibration and forced calibration is an extra information fed to the calibration block to make boundary estimation system more robust and accurate.

Figure 4 shows the basic calibration system, which inputs the GT and raw boundaries. To produce estimates of performance based on this database which are not biased high, we use a cross validation methodology for the calibration algorithms. Our limited database consists of N=**377** patient studies, each having F=2 frames, end-diastole and end-systole, and having a ground truth polygonal boundary of P=100 vertices, and a 100 vertex raw boundary created from pixel-based classifier [1]. The database of N patients studies is partitioned into K subsets each containing $\frac{N}{K}$ studies. We use two calibration algorithms: the *identical coefficient* method and the *independent coefficient* method. Estimates from each calibration transformation are obtained using L of the K subsets. Rotating through all L choose K combinations, we measure the accuracy of the results on the remaining $K-L$ subsets using the polyline distance metric [5]. The mean and standard deviation of the resulting set of $N \times F \times P \times \frac{(K-1)!}{(K-L-1)!\,L!}$ numbers is then used to estimate the overall performance.

Over a database of **377** studies, the mean boundary error under forced apex conditions for the *identical coefficient* and the *independent coefficient* yields an error of **3.14** mm and **3.04** mm with a standard deviation of **2.73** mm and **2.89** mm. On fusing these boundaries [5], the mean error is **2.97** mm.

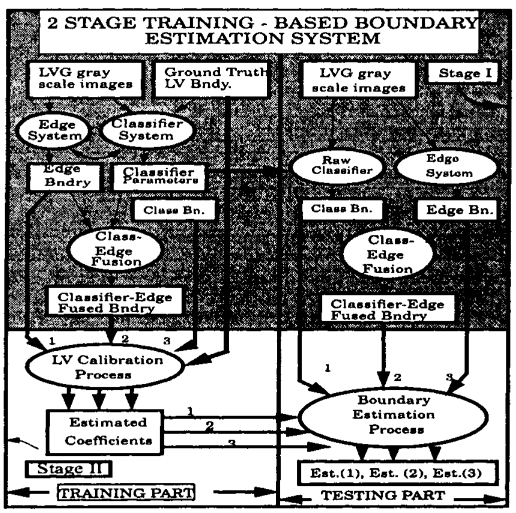

Fig. 1. Two stage system for LV boundary estimation. Stage I: Classifier (1) or Edge (2) or Classifier-Edge Fusion (3), Stage II: Calibration

II. Problem Statement and Algorithm

This section presents the mathematical statements of the two calibration techniques used for estimation of the LV boundaries when the apex position is available. Ground truth boundaries refer to the hand-delineated boundaries drawn by the cardiologist or the trained technician. Raw or classifier boundaries refer to the boundaries produced by the pixel-based classification procedure [1]. In the *identical coefficient* method, each vertex is associated with a set of coefficients. The calibrated x-coordinate for that vertex is computed as the linear combination of raw x- coordinates of the LV boundary using the coefficients associated with that vertex. The calibrated y-coordinate of that vertex is

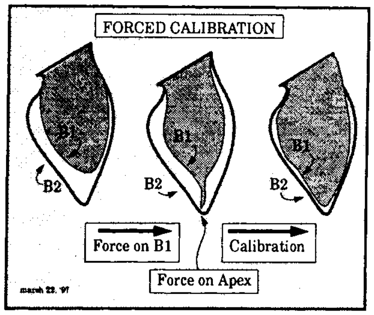

Fig. 2. Forcing on the apex of the left ventricle. Apex point being pulled towards ideal apex and then calibration performed. Forcing the apex means replacing the apex of the raw boundary by ideal apex. Ideal apex is computed automatically by the std. apex computation algorithm.

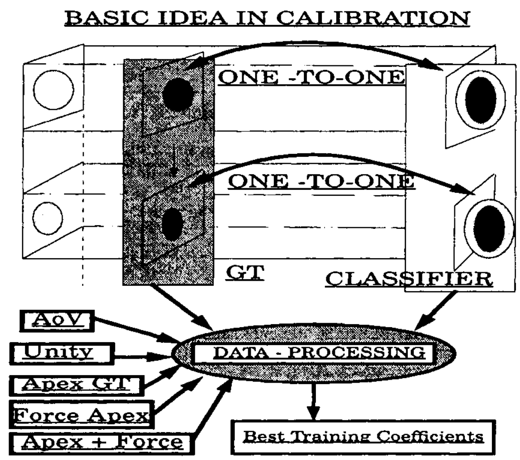

Fig. 3. Padding phenomenon for improving calibration.

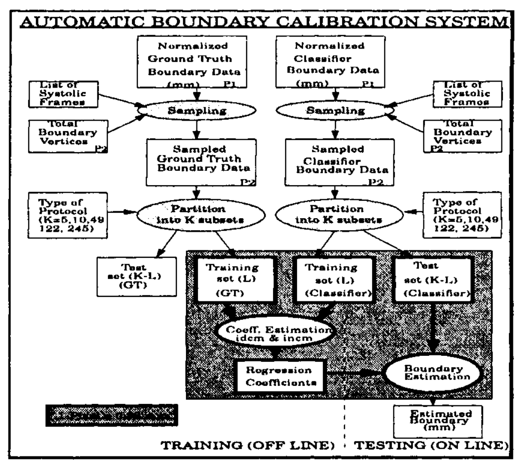

Fig. 4. Calibration system for calibrating the errors of the raw boundaries. It consists of following steps: (i) Input to system is the normalized raw boundaries and ideal boundaries from N studies with F frames and each contour having P_1=100 vertices. (ii) Equal arc sampling, (iii) Partition, (iv) Off-line coefficient estimation. Boundary data is sampled to P_2 vertices, and then partitioned into training (L) and testing (K-L) sets. Regression coefficients are estimated off-line using the training boundaries, and then applied to the on-line testing boundary. All dimensions are in millimeters.

similarly computed as the *same* linear combination of raw y- coordinates of the LV boundary.

In the *independent coefficient* method, the calibrated x-coordinate is computed as the linear combination of raw x- and raw y- coordinates of the LV boundary, using the coefficients associated with that vertex. The calibrated y-coordinate of that vertex is computed with a *different* linear combination of raw x- and y- coordinates. The problem of calibration then reduces to a problem of determining the coefficients of the linear combination. This can be accomplished by solving a regression problem.

A. Identical Coefficient Method (IdCM) for calibration of Left Ventricle Boundaries Utilizing Apex Information

Let $g_n^{'}$=[$x_{1n} \ldots x_{Pn}$] and $h_n^{'}$=[$y_{1n} \ldots y_{Pn}$] be the P-dimensional row vectors of x- coordinates and y- coordinates corresponding to the ground truth boundaries for any patient n, where $n = 1, ..., N$. Let $r_n^{'}$ and $s_n^{'}$ be the P-dimensional row vectors of x- coordinates and y-coordinates for the raw boundary for any patient n, where $n = 1, ..., N$. For the boundary estimation of the LV in ventriculograms using the *identical coefficient* method, we are

- **Given**: Corresponding pairs of ground truth boundary matrix $\mathbf{R}$ $[2N \times P]$ and the raw boundary matrix $\mathbf{Q}$ $[2N \times (P+4)]$, respectively:

$$\mathbf{R} = \begin{pmatrix} g_1^{'} \\ h_1^{'} \\ \cdots \\ g_N^{'} \\ h_N^{'} \end{pmatrix}^{2N \times P} \qquad \mathbf{Q} = \begin{pmatrix} r_1^{'} \ \underbrace{1\, u_{11}\, u_{21}} \ \underbrace{p_1} \\ s_1^{'} \ \underbrace{1\, v_{11}\, v_{21}} \ \underbrace{q_1} \\ \cdots \\ r_N^{'} \ \underbrace{1\, u_{1N}\, u_{2N}} \ \underbrace{p_N} \\ s_N^{'} \ \underbrace{1\, v_{1N}\, v_{2N}} \ \underbrace{q_N} \end{pmatrix}$$

where, (u_{1n}, v_{1n}), (u_{2n}, v_{2n}), $1 \leq n \leq N$ are the coordinates for the anterior aspect (first vertex of the left ventricle contour) and inferior aspect (last vertex of the LV contour) of the AoV plane belonging to the ground truth LV. (p_n, q_n) are the coordinates of the apex position.

- Let $\mathbf{A}$ $[(P+4) \times P]$ represent the unknown regression coefficients matrix.
- The problem is to estimate the coefficient matrix $\mathbf{A}$, to minimize $\| \mathbf{R} - \mathbf{Q}\,\mathbf{A} \|^2$. Then, for any raw boundary matrix $\mathbf{Q}$, the calibrated vertices of the boundary are given by $\mathbf{Q}\hat{\mathbf{A}}$, where $\hat{\mathbf{A}}$ is the estimated coefficients.

Note that from the problem formulation, the coefficients that multiply $g_n^{'}$ also multiply $h_n^{'}$, hence the name *identical coefficient* method. Also note that the new x- coordinates for the n^{th} patient boundary only depend on the old x-coordinates from the n^{th} patient boundary, and the new y-coordinates from the n^{th} patient boundary only depend on the old y- coordinates from the n^{th} patient boundary.

B. Independent Coefficient Method (InCM) for calibration of Left Ventricle Boundaries Utilizing Apex Information

As before, let $g_n^{'}$ and $h_n^{'}$ be the P-dimensional row vectors of x-and y- coordinates for any patient n. Let $r_n^{'}$ and $s_n^{'}$ be the P-dimensional row vectors of x- and y- coordinates of the raw boundary. For the calibrated boundary estimation of the LV in ventriculograms using the *independent coefficient* method, we are:

- **Given**: Corresponding ground truth boundary matrix $\mathbf{R}$ $[N \times 2P]$ and raw boundary matrix $\mathbf{Q}$ $[N \times (2P+7)]$ respectively:

$$\mathbf{R} = \begin{pmatrix} g_1^{'}\ h_1^{'} \\ \cdots \\ g_N^{'}\ h_N^{'} \end{pmatrix} \qquad \mathbf{Q} = \begin{pmatrix} r_N^{'}\ s_N^{'}\ \underbrace{1\, u_{1N}\, v_{1N}\, u_{2N}\, v_{2N}}\ \underbrace{p_N\, q_N} \\ \cdots \\ r_N^{'}\ s_N^{'}\ \underbrace{1\, u_{1N}\, v_{1N}\, u_{2N}\, v_{2N}}\ \underbrace{p_N\, q_N} \end{pmatrix}$$

where, (u_{1n}, v_{1n}), (u_{2n}, v_{2n}), $1 \leq n \leq N$, are the coordinates for the anterior aspect (first vertex of the left ventricle contour) and inferior aspect (last vertex of the left ventricle contour) of the AoV plane of the LV belonging to the ground truth boundary. (p_n, q_n) are the coordinates of the apex position.

- Let $\mathbf{A}$ $[(2P+7) \times 2P]$ be the unknown regression coefficient matrix.
- The problem is to estimate the coefficient matrix $\mathbf{A}$, to minimize $\| \mathbf{R} - \mathbf{Q}\,\mathbf{A} \|^2$. Then for any raw boundary matrix $\mathbf{Q}$, the calibrated vertices of the boundary are given by $\mathbf{Q}\hat{\mathbf{A}}$, where $\hat{\mathbf{A}}$ is the estimated coefficients.

Note that the new (x, y)-coordinates of the vertex of each boundary are a *different* linear combination of the old (x, y)-coordinates for the boundary, hence the name *independent coefficient* method. The above two methods differ in the way the calibration model with apex is set up. The raw boundary matrix $\mathbf{Q}$ in the *identical coefficient* method is of size $2N \times (P+4)$ while in the *independent coefficient* method is of size $N \times (2P+7)$. For the IdCM, the number of coefficients estimated in the $\hat{\mathbf{A}}$ matrix is $(P+4) \times P$. For the *independent coefficient* method, the number of coefficients estimated is $(2\,P+7) \times 2\,P$. Thus, the *independent coefficient* method requires around *four times* the number of coefficients of the *identical coefficient* method to be estimated. This difference represents a significant factor in the ability of the technique to generalize rather than memorize for the data set of **377** patient studies.

Generalizing for any frame t, the minimizing $\hat{\mathbf{A}}$ and estimated boundaries $\hat{\mathbf{R}}_{te}$ on the test set $(\mathbf{Q}_{te})$ is:

$$\underbrace{\hat{\mathbf{A}}_{tr} = (\,\mathbf{Q}_{tr}^T\,\mathbf{Q}_{tr}\,)^{-1}\,\mathbf{Q}_{tr}^T\,\mathbf{R},}\ \underbrace{\hat{\mathbf{R}}_{te} = \mathbf{Q}_{te}\,\hat{\mathbf{A}}_{tr}} \qquad (1)$$

III. Results of Forced Calibration

1) The apex coordinates is forced in the *identical coefficient* method and the *independent coefficient* method. Figure 6 shows the visualization of output estimated boundary from the forced calibration system. The upper figure is for the ED frame and lower figure is for the ES frame.

2) Table I shows three options for the apex condition. First, when no apex information is padded in the calibration process. The second case is when the apex is padded in the calibration process as columns of the matrices. The last case consists of forcing the apex before calibration and padding the apex information. Three rows are: *identical coefficient* , *independent coefficient* , and greedy. The

mean errors ($\frac{ED+ES}{2}$) without apex, with apex and with forced apex are: **3.7** mm, **3.4** mm and **2.97** mm. 3) Figure 5 shows the error per arc length with and without force conditions. The plot compares classifier error vs. ordinary calibration vs. forced calibration. A dip is seen at the apex (around 0.45 of the normalized arc length) for ED and ES frames. Note that the dip moves from 0.5 (for ordinary calibration) to 0.45 (forced calibration) showing the orientation error correction of the LV by 18°.

Comparision of 3 Algorithms w/o, w/, f/ apex			
N=377, K=188, L=187, Test Set=K-L=1, CV case			
Protocol: ${}^{188}C_{187}$			
${}^{K}C_{L}$: Number of Combinations=188			
Training studies = 375, Test studies = 2			
e^{poly}_{NFP}: ($\frac{ED+ES}{2}$) (mm), σ^{poly}_{NFP}: Std. Dev. (mm)			
P	e^{poly}_{NFP}(**w/o**)	e^{poly}_{NFP}(**w/**)	e^{poly}_{NFP}(**f/**)
IdCM	4.09	3.68	3.14*
InCM	3.92	3.59	3.04*
Greedy	3.70	3.4	·2.97*

TABLE I

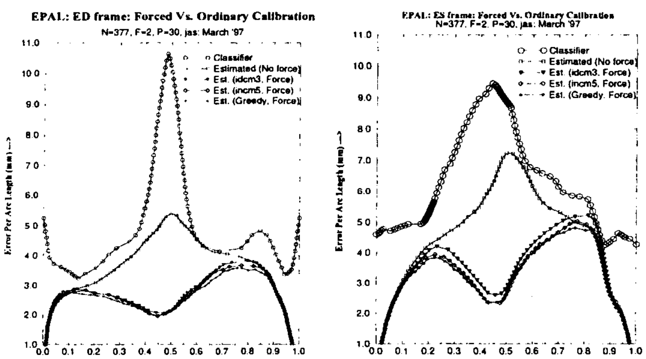

Fig. 5. Error per arc length of ordinary versus forced calibration. **Left**: ED frame, **Right** ES frame. Dip seen in the apex.

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(a1) ED Frame: GT and Calibrated

(a2) ED Frame: GT and Calibrated

Fig. 6. **Upper**: Results of the forced calibration algorithm for ED frame. (a1) Calibrated (thin) vs. ground truth (thick). **Bottom** :(a2) Calibrated (thin) vs. ground truth (thick) for ES frame. Background is gray scale X-ray image. *Calibration Parameters*: N=377, K=187, L=186, F=2, P_1=100, P_2=30, Mean error = 2.97 millimeters.

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