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Two Automatic Calibration Algorithms for Left Ventricle Boundary Estimation in X-ray Images

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Abstract

Non-homogeneous mixing of the dye with the blood in the left ventricle and low contrast in the apex zone causes pixel-based classifiers [1] to yield boundaries which are not close physician traced boundaries. They have a systematic positional and orientational bias, with under-estimation in the apex zone. This paper develops two calibration algorithms, the identical coefficient and the independent coefficient. These algorithms transform the two sets of given training boundaries: physician traced and the classifier, to yield the off-line parameters, depending upon the number of partitions of the database. Vertices of the left ventricle boundary are then estimated on-line by applying these transformed parameters. The performance of the calibration system based on the polyline distance metric yields a mean error of 3.7 and 3.6 millimeters for above algorithms over 6x10^4 vertices in the data base of 291 patient studies. Both calibration algorithms remove the bias and reduce the boundary error in the apex zone. For end-diastole frame, the system reduces the error by 8.5 millimeters in the apex zone over the pixel-based classifier boundaries produced by image processing algorithms.

Keywords— **X-rays, Left Ventricle, Automatic, Heart Motion, Boundaries, Calibration, Training, Low Contrast**

I. Introduction

In the X-ray ventriculograms, the boundary at the left ventricle (LV) *apex* moves at a different rate than the *inferior* and *anterior* walls during the heart cycle [2]. Besides this, the gray scale ventriculograms have poor contrast with a high level of noise. This noise is due to the scattering of radiation by tissue volume which is not related to the ventricle [3], artifacts generated by breathing of the patient during catheterization procedure, and interference of ribs and diaphragms with the LV. This makes the LV boundary estimation very difficult. The injected contrast medium (a Barium compound dye) 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 *fall short* (*under estimated*) in the *apex* zone with respect to the ground truth boundaries [1].

In the inferior wall region, the papillary muscles have a non-uniform structure unlike the anterior wall region. This non-uniformity causes further variation in the apparent boundary during the heart cycle. As a result the *initial or raw boundary* position of the *inferior walls* are sometimes *over estimated.* The calibration algorithms developed in this paper remove all systematic position, orientation, and shape errors from the initial classifier boundaries produced by image processing algorithms.

Our limited database consists of N=291 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]. To produce estimates of performance based on this database which are not biased high, we use a *cross validation* methodology for both the calibration algorithms. The database of N patients studies is partitioned into K subsets each containing $\frac{N}{K}$ studies. 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. Because of the small number of patient studies N, and large number of parameters (about 200 times N) in the transformation, there is a danger of *memorization* rather than *generalization* in the estimation of the *transformation parameters.* Therefore, the number of vertices, P on the left ventricle polygon must be carefully choosen. As P decreases, the generalization will be better but the representation of the true LV shape will get worse, thereby causing higher error with respect to the ground truth. As P increases, generalization will be lost but the representation of the true LV shape will get better. With the other parameters N, K, and L fixed, there will be an *optimal* number of boundary vertices balancing the *representation error* with the *memorization error.* Our protocol finds this *optimal number* for both calibration algorithms.

II. Problem Statement: Calibration Methods

Ground truth boundaries refer to the hand delineated boundaries drawn by the cardiologist or the trained technician. Raw or perturbed or classifier boundaries refer to the boundaries produced by image processing algorithms based on pixel classification [1].

In the *identical coefficient method*, each LV boundary 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 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.

The initial (x, y) coordinates of the LV boundaries both from ground truth and classifier are converted from pixels to millimeter using *magnification correction factor*, (1 pixel = 2.5 mm). These input raw and ground truth boundaries are now in a 100 vertices polygon format with unit dimensions in milli-meters, we therefore *resample and interpolate* each of these polygons into *equally spaced* vertices before it undergoes the calibration procedure discussed below.

A. Identical Coefficient Method (IdCM) for any frame

Let g_n' and h_n' be the row vectors of x-coordinates and y-coordinates respectively for the ground truth LV boundary for patient n, where $n = 1, ..., N$. Let r_n' and s_n' be the row vectors of x-coordinates and y-coordinates respectively for the classifier boundary for any patient n, where $n = 1, ..., N$. For any frame of heart cycle t, the calibrated boundary of the LV in ventriculograms using the *IdCM*, we are:

- **Given**: Corresponding pairs of ground truth boundaries $\mathbf{R}$ $[2N \times P]$, and the classifier boundaries $\mathbf{Q}$ $[2N \times (P+3)]$, respectively:

$$\mathbf{R} = \begin{pmatrix} g_1' \\ h_1' \\ \cdots \\ g_N' \\ h_N' \end{pmatrix} \qquad \mathbf{Q} = \begin{pmatrix} r_1' \; \underbrace{1\, u_{11}\, u_{21}} \\ s_1' \; \underbrace{1\, v_{11}\, v_{21}} \\ \cdots \\ r_N' \; \underbrace{1\, u_{1N}\, u_{2N}} \\ s_N' \; \underbrace{1\, u_{1N}\, u_{2N}} \end{pmatrix} \tag{1}$$

where, (u_{1n}, v_{1n}), (u_{1n}, v_{1n}) and (u_{2n}, v_{2n}), (u_{2n}, v_{2n}) are the coordinates for the anterior aspect (first vertex of left ventricle contour (LVC)) and inferior aspect (last vertex of LVC) of the aortic valve (AoV) plane of the LV from ground truth boundary for patient n. One column with unity is introduced due take care of any translation effect or bias offset.

- Let $\mathbf{A}$ $[(P+3) \times P]$ be the unknown regression coefficient matrix.

B. Independent Coefficient Method (InCM) for any frame

Using the same notation: g_n', h_n', r_n' and s_n', the calibrated boundary of the LV in ventriculograms using the *InCM*, we are:

- **Given**: Corresponding ground truth boundaries $\mathbf{R}$ $[N \times 2P]$, and the classifier boundaries $\mathbf{Q}$ $[N \times (2P+5)]$ respectively:

$$\mathbf{R} = \begin{pmatrix} g_1' \; h_1' \\ \cdots \\ \cdots \\ g_N' \; h_N' \end{pmatrix} \qquad \mathbf{Q} = \begin{pmatrix} r_1' \; s_1' \; \underbrace{1\, u_{11}\, v_{11}\, u_{21}\, v_{21}} \\ \cdots \\ \cdots \\ r_N' \; s_N' \; \underbrace{1\, u_{1N}\, v_{1N}\, u_{2N}\, v_{2N}} \end{pmatrix} \tag{2}$$

where, symbols have same meaning.

- Let $\mathbf{A}$ $[(2P+5) \times 2P]$ be unknown regression coefficient matrix.

In both the above boundary calibration problems, we estimate the coefficient matrix $\mathbf{A}$, to minimize $\| \mathbf{R} - \mathbf{Q}\,\mathbf{A} \|^2$. Then for any classifier boundary matrix $\mathbf{Q}$ produced by the image processing algorithm, the calibrated coordinates of the boundary are given by $\mathbf{Q}\hat{\mathbf{A}}$, where $\hat{\mathbf{A}}$ is the estimated coefficients. The above two methods are different in the way the calibration model is set up. In IdCM formulation, the coefficients that multiply g_n' also multiply h_n', hence the name *identical coefficient method.* In InCM, the new (x, y)-coordinates of the vertices of each boundary is a *different* linear combination of the old (x, y)-coordinates for the polygon, hence the name *independent coefficient method.* For IdCM, the number of coefficients estimated in the $\hat{\mathbf{A}}$ matrix is $(P+3) \times P$. For InCM, the number of coefficients estimated is $(2P+5) \times 2P$. Thus the InCM requires around *4 times* the number of coefficients of IdCM, and this difference represents a significant factor in the ability of the technique to *generalize* rather than *memorize* for our data size (N).

III. Algorithm, Results and Discussions

The object process diagram for the boundary calibration system is shown in Fig. (1). It has 2 parts, off-line coefficients estimation (training part) and on-line boundary estimation (testing part). Generalizing for any frame t, the minimizing $\hat{\mathbf{A}}$ and estimated boundaries $\hat{\mathbf{R}}_{te}$ on the test set $(\mathbf{Q}_{te})$ as:

$$\underbrace{\hat{\mathbf{A}}_{tr} = (\, \mathbf{Q}_{tr}^T\, \mathbf{Q}_{tr}\,)^{-1}\, \mathbf{Q}_{tr}^T\, \mathbf{R}}, \; \underbrace{\hat{\mathbf{R}}_{te} = \mathbf{Q}_{te}\, \hat{\mathbf{A}}_{tr}} \tag{3}$$

The performance of the boundary calibrator on $\hat{\mathbf{R}}_{te}$ is done using the polyline distance metric. The polyline distance between two polygons representing boundary B_1 (ground truth) and B_2 (calibrated) is symmetrically defined as the average distance between a vertex of one polygon to the boundary of the other polygon (for derivation, see [5]). Fig. (2) shows the mean error vs. the number of boundary (P_2) vertices taken on LVC for optimization. We see that IdCM performs better than InCM for all 6 protocols (different K values or partitions) and for all the frames of the systolic cycle. The reason being that we do not have enough patient studies to do good generalization for InCM. IdCM yields 3.7 mm at 30 optimized vertices while InCM yields 3.6 mm at 15 optimized vertices. Fig. (3) shows the visualization of input and output of the boundary calibration system. Fig. (3a1) shows the ground truth and classifier boundary with gray scale in back ground for the end-diastole frame and fig. (3a2) shows the ground truth and the calibrated boundary.

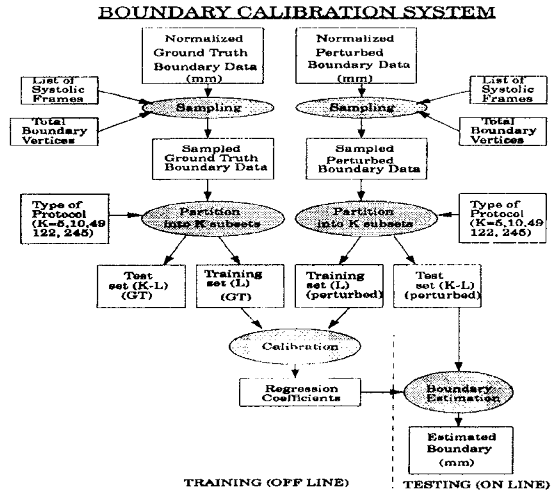
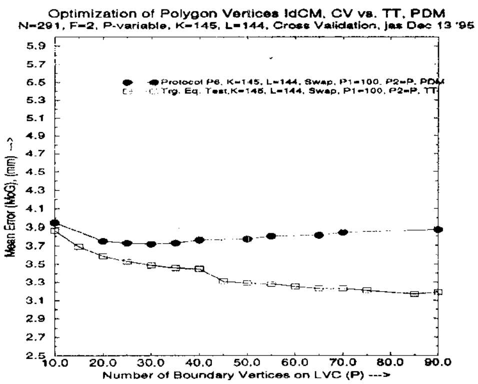
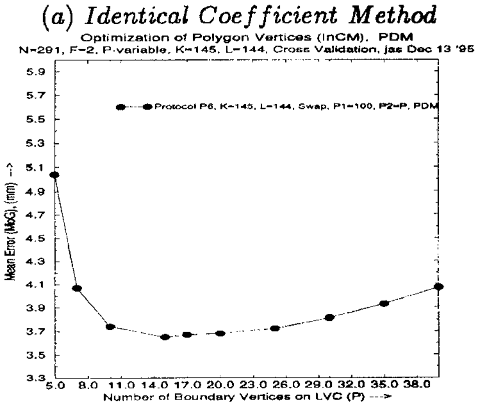


Fig. 1. Object process diagram for the *boundary calibration system*. Boundary data is sampled to P_2 vertices, and then partitioned into training (L) and testing (K-L) sets. Regression coefficients are estimated off-line using the training boundaries, and then applied to the on-line testing boundary. All dimensions are in milli-meters.



(*a*) *Identical Coefficient Method*



(*b*) *Independent Coefficient Method*

Fig. 2. Optimization Curves: Mean error Vs. Number of boundary vertices on left ventricle contour (LVC). The error first decreases and then starts increasing for cross-validation (CV) case. The number of vertices which correspond to the least error is the ***optimal number of vertices*** on LVC. Error decreases all the way if the test boundary also lies in training set (TT case). (a) IdCM, (b) InCM. *Calibration Parameters*: N=291, K=145, L=144, F=2, P_1=100, $5 \leq P_2 \leq 40$ varying along abscissa. Error is computed using the polyline distance metric (See ref. 5). We observe that InCM reaches operating point faster than IdCM but with less number of vertices on LVC.

(a1) ED Frame: GT and Classifier or Raw

(a2) ED Frame: GT and Calibrated (Estimated)

Fig. 3. **Upper**: Results of the IdCM algorithm for ED frame. (a1) Classifier (thin) vs. ground truth (thick). **Bottom** :(a2) Calibrated (thin) vs. ground truth (thick). Background is gray scale X-ray image. *Calibration Parameters*: N=291, K=145, L=144, F=2, P_1=100, P_2=30, Mean end frame error $(\frac{ED+ES}{2})$ = 1.30 mm, Mean error = 3.7 millimeters. The system can visualize the calibrated LV boundaries for the entire data base of 291 studies.

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