LEFT VENTRICLE IMAGE LANDMARKS EXTRACTION USING SUPPORT VECTOR MACHINES

Miguel A. Vera
Laboratorio de Física
Departamento de Ciencias, Universidad de Los Andes–Táchira, San Cristóbal 5001, Venezuela

Antonio J. Bravo
Grupo de Bioingeniería
Decanato de Investigación, Universidad Nacional Experimental del Táchira, San Cristóbal 5001, Venezuela

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Abstract: This paper introduces an approach for efficient myocardial landmarks detection in angiograms. Several anatomical landmarks located on the left ventricle are obtained by mean of a support vector machine. Training set corresponds a dataset of landmark and non-landmark 31×31 pixel patterns. Our support vector machine uses the structural risk minimization principle as inference rule and radial basis function kernel. In the training phase false positives were not registered and in the detection phase 100% of recognition was obtained.

1 INTRODUCTION

Landmarks detection from medical images represents a stage useful stage to extracting sufficient information which describes an examined anatomical structure. The extracted image landmarks are used in various applications of medical image analysis, such as segmentation (Bosch et al., 2002), shape–model construction (Frangi et al., 2002) and motion analysis (Chandrashekara et al., 2004).

In clinical routine cardiologist uses heart cavities images for the assessment of morphology and function of the heart (Marcus and Dellsperger, 1991). Contrast cineangiography based on X–rays provide a projected image of the cardiac structures (Macovski, 1983). These images have enough information of dimension and shape of heart cavities during the entire cardiac cycle. The left ventricle is considered the main cavity of the heart.

Left ventricle images are obtained from cineangiography, after the injection of a contrast medium in the cavities of the heart aiming to enhance the contrast with respect to other tissues. Ventriculographic image analysis requires a precise description of ventricular shape in order to quantify the parameters associated with the cardiovascular function (Kennedy et al., 1970) (Ratib, 2000) or alternatively for performing the visualization of this anatomical structure (Medina et al., 2004). The accurate description of ventricular shape and their quantitative analysis is important, since cardiovascular disease (CVD) accounts for one third of the deaths in the world (WHO, 2002).

Recently, several robust methods for ventriculographic image segmentation have been proposed. Suzuki *et al.* (Suzuki et al., 2004) have developed a ventricular contour detector based on neural networks (NN). The detector was implemented using a multilayer neural network which was trained through a back–propagation algorithm. The training set includes left ventricle images and ventricular contours traced by a cardiologist. Validation was performed by comparison of the area enclosed by the estimated contour with respect to the reference contour traced by the cardiologist. The average contour error obtained at end–diastole was 6.2%. Oost *et al.* (Oost et al., 2005) have proposed a ventricular cavity automatic segmentation method based on Active Appearance Models (AAMs) and dynamic programming (DP). The active appearance model is used to exploit the existing correlations in shape and texture between end-diastole and end-systole images. A dynamic programming algorithm was used to incorporate cardiac motion features to the method. The method was evaluated by using 140 images. The average border positioning error was smaller than 1.45 mm. These methods provided an accurate representation of ventricular borders, however, they are not yet fully validated and accepted by clinicians as a gold standard.

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Segmentation techniques some times require a previous stage in which an initial set of points is located near the shape to detect (Fu and Mui, 1981). In cardiac imaging left ventricle anatomical landmarks as apex, basal regions and aortic valve points are useful to define the left ventricle shape.

The objective of this work is to develop an approach based on machines learning to detecting several anatomical landmarks located on the left ventricle (LV) contour. This is a classification problem because the machine learning task is to classify example among a discrete set of possible categories or classes. Our approach utilizes densitometric information and a support vector machine (SVM) for the reliable localization of landmarks in ventriculographic images.

2 SUPPORT VECTOR MACHINES

Support Vector Machine (SVM) is a learning technique based in the framework of statistical learning theory (Vapnik, 1995). These machines learning can be seen as a method for training polynomial, neural network or radial basis function classifiers. The SVM training process is based on the idea of minimizing an upper bound on the generalization error by mean structural risk minimization induction principle (Vapnik, 1982).

SVMs have been applied successfully in practical problems such as pattern classification (Osuna et al., 1997b) and nonlinear function estimation problems (Smola, 1998). A classifier based on SVM is a machine learning that uses a hyperplane to separate patterns classes (Burges, 1998). If the classification task is a two–class pattern recognition problem, where we assume that we have a set of examples:

$$\mathbf{z}_i = \left\{ \{\mathbf{x}_i, y_i\} \mid \mathbf{x}_i \in \mathbf{R}^N \,\wedge\, y_i \in \{-1,+1\} \,\wedge i = 1..l \right\}$$

the hyperplane corresponds to a decision function:

$$f_\alpha(\mathbf{x}) : \mathbf{R}^N \longrightarrow \{-1,+1\} \ . \tag{1}$$

which provides the smallest possible value for the risk (Schölkopf et al., 1995). The SVM classifier is defined by the family function $f_\alpha(\mathbf{x})$ which mappings $\mathbf{x}_i \mapsto y_i$. A deterministic process is implanted to reach the machine's task: to learn the mapping $\mathbf{x}_i \mapsto y_i$. In this process given a set of examples $\mathbf{x}$, a particular value of the α parameter is chosen for the same output $f_\alpha(\mathbf{x})$. The process to choice a α that mapping $\mathbf{x}_i \mapsto f_\alpha(\mathbf{x})$ is an optimization process called *Training a Support Vector Machine* (Osuna et al., 1997b).

For linearly separable data, the classification problem is solved finding the best hyperplane that separates the data. Osuna and collaborators (Osuna et al., 1997a) show that the decision surface in the linear case using Lagrange Multipliers like optimization technique can be written as:

$$f_\alpha(\mathbf{x}) = sign\left(\sum_{i=1}^{l} y_i \lambda_i (\mathbf{x} \cdot \mathbf{x}_i) + b \right) \ , \tag{2}$$

where λ_i are non–negative Lagrange multipliers.

The main problem in real classification task is that linear decision surfaces (hyperplane) are not appropriate. In this case is necessary to map the dataset to higher dimensional *feature space* (some other Euclidean space $\Re$) using the following mapping:

$$\Phi : \mathbf{R}^N \mapsto \Re \ . \tag{3}$$

In the feature space we work with linear classification. For that reason, the so–called *kernel function* (K) is introduced to compute scalar products of the form $\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)$:

$$K(\mathbf{x}_i, \mathbf{x}_j) \equiv \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j) \ . \tag{4}$$

Using (2) and (4) the SVM solution is expressed as:

$$f_\alpha(\mathbf{x}) = sign\left(\sum_{i=1}^{l} y_i \lambda_i (K(\mathbf{x}, \mathbf{x}_i)) + b \right) \ . \tag{5}$$

In pattern recognition problem several kernels have been applied (Burges, 1998). The kernels for which (3) is verified are all those that satisfy the Mercers's condition (Vapnik, 1995; Williamson et al., 1999). Some commonly used kernels:

$$K(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j + 1)^p \ . \tag{6}$$

$$K(\mathbf{x}_i, \mathbf{x}_j) = \tanh(\mathbf{x}_i \cdot \mathbf{x}_j - \theta) \ . \tag{7}$$

$$K(\mathbf{x}_i, \mathbf{x}_j) = e^{-\|\mathbf{x}_i - \mathbf{x}_j\|^2 / 2\sigma^2} \ . \tag{8}$$

A SVM polynomial classifier of degree p is constructed using (6). (7) results in a particular multi layer perceptron only for some values of θ, and (8) gives a radial basis function classifier. Other valid kernel functions that satisfy Mercer's conditions are (Gunn, 1997):

- Exponential radial basis function:

$$K(\mathbf{x}_i, \mathbf{x}_j) = e^{-\|\mathbf{x}_i - \mathbf{x}_j\| / 2\sigma^2}$$

- Fourier series:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \frac{\sin\left(N + \frac{1}{2}\right)(\mathbf{x}_i - \mathbf{x}_j)}{\sin(\frac{1}{2}(\mathbf{x}_i - \mathbf{x}_j)}$$

- B–splines:

$$K(\mathbf{x}_i, \mathbf{x}_j) = B_{2N+1}(\mathbf{x}_i - \mathbf{x}_j)$$

- Additive kernels:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \sum_l K_l(\mathbf{x}_i, \mathbf{x}_j)$$

- Tensor product:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \prod_l K_l(\mathbf{x}_i, \mathbf{x}_j)$$

3 PROPOSED APPROACH

The learning task here involves classifying patterns that represent left ventricle landmarks on ventriculographycs images.

3.1 Data Source

The images used are sequences of ventriculographics images acquire on patients using a digital flat–panel X–ray system (Innova^{TM} 4100 General Electric Medical System). These images were acquired from Right Anterior Oblique (RAO 30°) direction. Each image with resolution of 420×420 pixels and with each image pixel described by a greyscale intensity value between 0 (black) and 255 (white). Figure 1 shows angiographics images of the left ventricle in RAO incident.

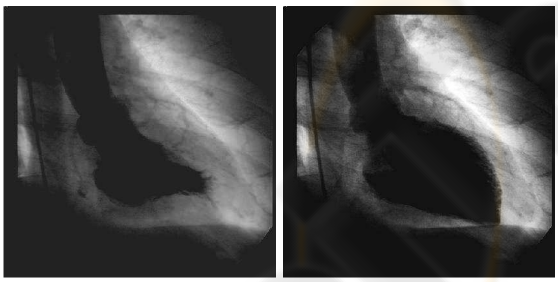

Figure 1: Left ventricle images. Systole phase (left). Diastole phase (right).

3.2 Training Set Selection

American Heart Association (AHA) establishes fifteen anatomical landmarks for the left ventricle shape definition on the angiographic images acquired from RAO 30° direction.

The selected landmarks correspond to apex (AP), the basal regions (BA2, BP3, BP4) and the aortica valve sides (VA, VP). Dataset of landmarks patterns

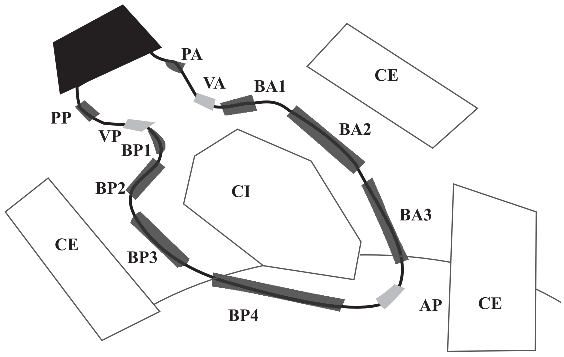

Figure 2: AHA anatomical landmarks.

is constructed from a ventriculographic image sequence. A manually process driven by a cardiologist is applied to locate 31×31 pixel patterns corresponding to each LV landmark. A total of 300 patterns constitutes the landmarks dataset, 50 images of 31×31 pixel for each landmark. Applying a similar procedure, a dataset of 1200 non–landmark images was generated from angiographic images of coronary vessel and kidney. A training set is formed in relation 1:4, by each pattern that represents an anatomical landmark, four non–landmark images are introduced. Class +1 is assigned to identify a landmark and class -1 for the non–landmark.

3.3 Training a Support Vector Machine

In this Section we design a SVM using the library for Support Vector Machines of MatLab 7.0. The idea is to construct a SVM classifier using one of the most popular parametric kernel: Gaussian radial basis function (8).

This implementation considers a unique parameter σ. Additionality, our SVM classifier considers a misclassification tolerance parameter C that penalizing the most undesirables errors. A large value of this parameter corresponding a higher penalty errors.

The SVM is trained using a training set of 1500 patterns (see section 3.2). The training process is used to construct a decision surface that allows to classify the input images as left ventricle landmark or non–landmark.

The bootstrapping step is applied. The decision surface obtained in the training process is used to classify images that do not contain landmarks. The false positive obtained in this process are incorporated to dataset of non–landmark images and used in subsequent training phases. This bootstrapping process helps to characterize and define the non–landmark class in order to obtain the decision surface than better separates the classes. Non–landmark class is abundant and broader in this sense more complex that landmark class.

3.4 The Svm Left Ventricle Landmark Detection Approach

Our landmark extraction problem can be defined as follows: Given a ventriculographic image which is consider as input data, determine where the LV's landmarks in this image are located and return an encoding of their location. Our encoding is to represent each anatomical landmark on the image by means of 31×31 pixel bounding box whose center represents the exact location of the landmark.

This approach detects left ventricle landmarks by exhaustively scanning an image for landmark–like patterns, by splitting the original image into overlapping sub–images and classifying them using a SVM (see section 3.3) to determine the appropriate class (landmark or non–landmark).

4 RESULTS

The training of support vector machine was performed using the MATLAB Support Vector Machine toolbox developed by Gunn (Gunn, 1997) from the Information: Signals, Images, Systems (ISIS) Research Group at the University of Southampton. A SVM classifier was trained considering $\sigma = 0.002$ and $C = 10$.

The landmark detection stage was implemented in MatLab. The support vector obtained in the training stage are used to construct the decision surface that we use to discriminate if each subimage (see section 3.4) of the original image is a left ventricle landmark or non–landmark.

The proposed approach has been tested with ventriculograms acquired at several instants of the cardiac cycle. During the training procedure false positives were not registered. In the landmark extraction phase 100 % of recognition was obtained. In figure 3, results of the left ventricle images landmarks extraction approach for the end–systole to end–diastole ventriculogram sequence are shown.

Validation of the approach is performed by quantifying the difference between the left ventricle landmark location obtained with respect to the left ventricle landmark located by a cardiologist. The error is expressed as the distance between the manual and automatic landmark location. The error obtained (*mean* $\pm$ *standard deviation*) for a sequence of ventriculograms in the RAO view, including 21 images is 2.47 mm $\pm$ 1.61 mm, with a maximum value of 4.84 mm and a minimum value of 1.03 mm.

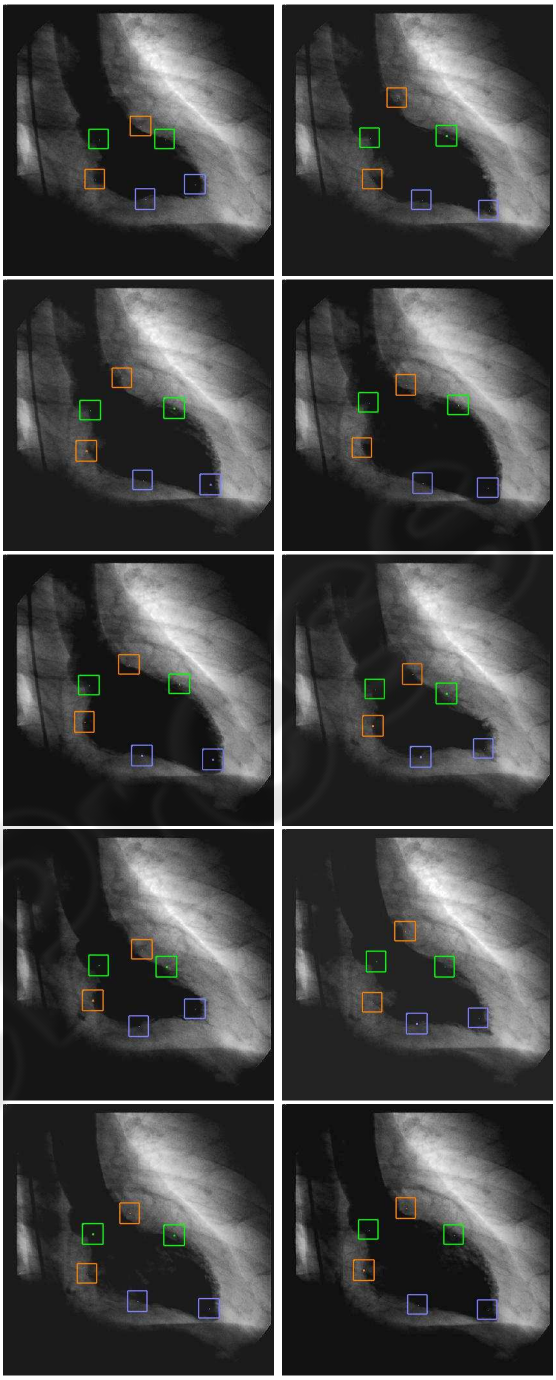

Figure 3: Left ventricle image sequence. Bounding boxes represents the anatomical landmarks obtained.

5 CONCLUSIONS

An automatic approach for left ventricle anatomical landmarks extraction has been implemented. The classification approach does not require any prior knowledge about the ventriculograms and not require some preprocessing of the input data.

A quantitative validation stage is implemented. The estimated landmarks from the detection approach show a good match with the landmarks located by specialist. This application would be a useful tool for detecting the left ventricle landmark in conventional Left Anterior Oblique (LAO) 60° view.

Further research involves incorporation of the proposed classifier to an approach for left ventricle contour detection using deformable models.

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