

Comparison of Kernel Based Classifier for Prostate Segmentation and Cancerous gland identification in Magnetic Resonance Imaging.

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Abstract — Prostate carcinoma, the second most common cause of cancer death among American men, is not invariably lethal. A heterogeneous disease, it ranges from asymptomatic to rapidly progressive systemic malignancy. The prevalence of prostate cancer is so high that it could be considered a normal age-related phenomenon. Conventional MRI of the prostate relies on morphologic changes within the prostate to define the presence and extent of cancer. Segmentation of the prostate gland in Magnetic Resonance (MR) images is an important task for image guided prostate cancer therapy. In this paper we propose the automatic segmentation and cancerous tissue detection using the SVM classification as the automated approach remove the observer variability and results are reproducible.

T2 - weighted MRI has shown high sensitivity in prostate cancer localization, although performance varies with the patient population studied.

Index Terms — Support Vector Machine, Magnetic Resonance Imaging .

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) plays an increasingly important role for treatment of prostate cancer. MRI is used to support biopsies, radiation therapy, or planning of surgeries. Automatic segmentation of the prostate in MR images can greatly enhance the clinical workflow. Although the contrast between soft-tissue organs in MR images is better than in Computed Tomography scans, accurate delineation of the prostate's border remains difficult even for the human observer. An additional challenge for automatic segmentation is that MR image acquisition does not provide standardized image intensities. Moreover, MR images may be corrupted by artifacts such as large intensity variations within a single image.

In this paper, we propose an automatic segmentation algorithm for prostate segmentation in T2-weighted MR images. The object detection algorithm, for detecting the prostate in MRI scans is used. Post detection of the prostate, finding the particular prostate volume using the equation (i) [2] remains the main area of interest. The prostate volume

deals with the numeric value which can be applied to the Classification technique.

$$\text{Prostate Volume} = AP \times CC \times \text{Trans} \quad (i)$$

Where AP: anterior-posterior
 CC: cranial-caudal
 Trans: transverse dimensions

Support vector classification and Probabilistic- Support Vector Machine results are then compared depending upon the Accuracy (Acc), AUC (area under curve). Probability prediction performance are evaluated by computing the relative entropy and alignment error (Err_{AI}) [2]. The results decides to find the better classification technique for the T2 weighted MR images.

II. METHODOLOGY

A. Inhomogeneity correction.

This phase deals with the image Normalization and Rescaling as the variability in MR images. Image Normalization is often done by shifting the mean intensity to zero and scaling the intensities such that standard deviation equals to one. For more robust normalization, we use the median image intensity I_{med} and the median absolute deviation MAD_I as an estimate for mean and standard deviation, respectively. The MAD_I is defined by

$$MAD_I = \text{median}_v |I(v) - I_{med}|^2, \quad (1)$$

Where $I(v)$ denotes the image intensity at position v . For normal distribution data.

B. Region of interest Detection and feature extraction.

Identification of region of interest (ROI) in the image that contains the prostate is the next task. We slide the detection window of fixed size through the image and compute for each image defined by current detector position whether it contains the prostate or not. The tissue within the prostate's bounding box itself is relatively homogenous and does not contain features that are expressive enough for reliable classification,

hence we use a variably larger bounding box for the feature extraction[4]. The feature in the form of the prostate volume discussed in eq.(i) is used to calculate density measure which then serves the input for the classifiers.

C. Classification.

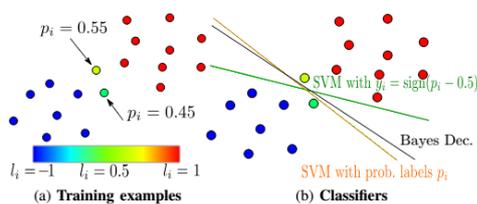
Image classification aims at assigning to each pixel, or to each region of interest (ROI) extracted from image, a label associated with a class of object that can possibly be present in the analyzed scene. In this paper we use the two classification technique such that the better results can be identified. The first classification deals with the support vector machine and the other is the probabilistic variant of the support vector machine known as the Probabilistic SVM.

III. CLASSIFICATION FORMULATION

This study extends the widely used support vector machine (SVM) two-class classification problem [1]. This supervised classification algorithm is based on the maximum margin principle. It has good generalization ability, is very effective in high dimensional feature space and the learning phase associated with the minimization of a convex cost function guarantees the uniqueness of the solution. Our main contribution is a SVM inspired formulation of the learning problem allowing to take into account class labels through a hinge loss cost function as well as class probability estimates using ϵ -insensitive cost function together with a minimum norm (maximum margin) objective. This formulation, referred to as Probabilistic SVM (P-SVM) in the following, shows a dual form leading to a quadratic problem similar to the classical SVM formulation, and allows the use of a representer theorem and associated kernel. It hence can be efficiently solved by adapting existing flexible SVM solvers.

Suppose that we are given a training dataset of n samples $\{(x_1, y_1), \dots, (x_n, y_n)\} \subset X \times Y$, where X denotes the feature space (in the following practical examples, $X = \mathbb{R}^d$ where d is the number of features per sample) and Y represents the two-class labeling, $Y = \{-1, +1\}$. The SVM, introduced by Vapnik [6], aims at constructing a separating hyperplan, of the form :

$$\{ x \in X | w^T x + b = 0 \}, \quad (1).$$



maximizing the margin between the data of the two classes. The associated pattern recognition problem is defined as :

$$\begin{cases} \min_{w \in \mathbb{R}^d, b, \xi_i \in \mathbb{R}} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i, \\ \text{subject to} \\ y_i (w^T x_i + b) \geq 1 - \xi_i, & i = 1, \dots, n \quad (3) \\ 0 \leq \xi_i, & i = 1, \dots, n \quad (4) \end{cases}$$

which combines a minimum norm (maximum margin) objective function (3) and good classification constraints (4). Slack variables $\xi_i \geq 0$ (4) correspond to the distance to the margin of possibly misclassified samples x_i . Parameter C (3) is the associated cost coefficient that weights the classification error.

Note that examples located on or inside the constructed margins, for which $\alpha \neq 0$, are called "support vectors". When the classification problem is nonlinear, SVM can be easily adapted thanks to the "kernel trick". The basic idea is to introduce a nonlinear mapping function $\phi : x \rightarrow \phi(x)$ that maps the data to a higher dimensional space \mathcal{H} , where the data is linearly separable. Then, expression (5) becomes :

$$f(x) = \sum_{i=1}^n a_i y_i \langle \phi(x_i), \phi(x) \rangle + b. \quad (5)$$

Note that when the problem is solved in its dual form, only the scalar product $\langle \phi(x_i), \phi(x_j) \rangle_{\mathcal{H}}$ has to be computed. In practice, we do not need to define explicitly the mapping function ϕ but only the kernel function defined as $k(x_i, x_j) = \langle \phi(x_i), \phi(x_j) \rangle_{\mathcal{H}}$. The kernel k must be a positive definite function satisfying Mercer's condition and \mathcal{H} is the associated Reproducing Kernel Hilbert Space (RKHS).

IV. PROBABILISTIC PROBLEM FORMULATION

We present a new formulation derived from the classical SVM two-class classification problem, which allows accounting for uncertain labels during the training step while constructing an accurate probabilistic discrimination function. This approach is referred to as P-SVM in the following where P stands for "probabilistic"[1]. We introduce the problem in a linear context, but we can easily extend the formulation to non-linearly separable datasets using kernels.

Let X be a feature space. We define $(x_i, \ell_i)_{i=1 \dots m}$ the training dataset of input vectors $(x_i)_{i=1 \dots m} \in X$ along with their corresponding labels $(\ell_i)_{i=1 \dots m}$, the latter of which being :

- class labels : $\ell_i = y_i \in \{-1, +1\}$ with $i = 1 \dots n$ for the n training samples that are assigned to any of the two classes with certainty,
- real values : $\ell_i = p_i \in [0, 1]$ with $i = n + 1 \dots m$ for the m - n training samples for which the class label ling is more ambiguous.

Probability p_i , associated to point x_i , is an estimated conditional probability for class +1 : $p_i = p(x_i) = P(Y_i = 1 | X_i = x_i)$. We aim at constructing the optimal maximal margin hyperplane

$$\{x \in X | f(x) = w^T x + b = 0\} \quad (6)$$

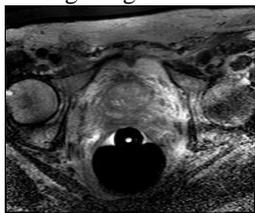
- class membership for binary labeled data $(x_i, y_i)_{i=1 \dots n}$ (in classification),
- conditional class probability for uncertain labelled data $(x_i, p_i)_{i=n+1 \dots m}$ (in regression).

Let η be an estimate of the uncertainty in the probabilistic labelling. To avoid dealing with undefined cases, we constrain labels $\{p_i\}_{i=n+1 \dots m}$ of samples $\{x_i\}_{i=n+1 \dots m}$, to belong to $[\eta, 1-\eta]$, even if it means re-labelling data

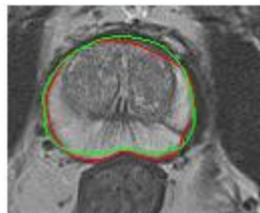
V. EXPERIMENTAL SETUP

In order to experimentally evaluate the proposed method for handling uncertain labels in SVM classification, we simulate different MRI images for above mentioned methodologies. We compare the classification performances and probabilistic predictions of the SVM and P-SVM approaches.

The above mentioned techniques are applied on the following image :



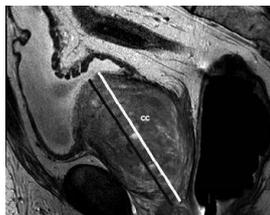
a) Prostate MRI image



b) Prostate detection.



c) Prostate volume detection



d) Ellipsoid method for volume.

Fig 2. Prostate Detection and volume calculation.

When the prostate volume using above method is being provided to the SVM classifier with a set of 30 MRI images[7]. The result obtained shows that the Probabilistic SVM supersedes the classification as compared to the normal SVM [2] with respect to the Accuracy (A_{CC}) and (AUC).

VI. CONCLUSION AND FURTHER WORK

The proposed method aims at learning a prediction function that will both discriminate samples and be able to

predict class probabilities. The approach can be easily extended to other kind of prediction for the cancerous prostate detection. The P-SVM provides the better results as compared to the Standard two class SVM, with better cancerous tissue estimation rate. We proposed the method of prostate detection using the volume calculation which can be more enhanced using the shape identification using multi-atlas or patch based voxel weighing. The classification can also be compared with the Fuzzy SVM and the Hidden Markov Classifier.

VII. REFERENCES

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