AUTOMATIC ARTERY LOCALISATION IN US IMAGES

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Abstract: In the paper, a novel robust method for localization of common carotid artery (CCA) in longitudal scan in B-mode ultrasound image is proposed. The method is based on a local analysis of image and its further classification with support vector machine (SVM) classifier. The classification inaccuracies are eliminated by further utilization of RANSAC algorithm, which will adjust the final localization of artery. The proposed algorithm is important for full automation of noninvasive measurements of artery parameters in B-mode images such as intima-media thickness (IMT).

Keywords: Digital Image Processing, B- mode Ultrasound Image, Artery, SVM, RANSAC, IMT

1. INTRODUCTION

Nowadays, the automated analysis of biomedical images is an important task, due to the increasing number of medical images being used in medical praxis. In many cases, the manual processing of the data is impossible due to the vast number of data available. Therefore, the automatic processing is necessary. Human factor is limiting especially in the case of processing of large databases. One of the cases, where the full automation of measuring process is suitable, is the measurement of static and dynamic parameters of arteries [1], such as lumen diameter (LD), artery stiffness (AS), or intima media thickness (IMT). The results of such measurements can be used for the prediction of patient's risk of cardio-vascular events [2]. Nowadays, such measurements are performed manually but the main effort is to automatize them.

The measurement process typically consists of two subsequent steps – the detection of the artery (localization in an ultrasound image) and subsequent segmentation of artery wall. Nowadays, the issue of segmentation (the second step) is quite well explored and this step is fully automated. But still many measurement systems are not fully automated; often the localization step in most cases requires the interaction with operator. To achieve the fully automatic system it is required to automate both steps.

In this paper a novel robust method for initial artery localization (the first step in measurement system) in B-mode ultrasound image is proposed. The proposed method has been designed to be capable to initialize the subsequent segmentation methods. The localization method is fully automated and over existing methods it is even capable of processing not ideally captured arteries.

The article is organized as follows. Related work is presented in the second chapter. Third chapter is focused on the proposal method for artery localization, where the particular sections describe basic components that were used. Results are summarized in chapter four and the last chapter concludes the paper and suggests possible directions of future research.

2. RELATED WORK

As mentioned above, artery localization is the initialization step before the main segmentation and measure (for example measure of IMT) step. Nowadays, some systems for IMT measurement are still only semi-automatic (the initialization step is manual [3]) and thus not suitable for batch data processing. The next problem of such methods lays in their inaccuracy (different segmentation results) caused by different initialization by various operators. These problems show the importance of automation of the artery localization.

Several automated methods for artery localization exist, but the most of them are very simple [4]. Often, the localization methods are unable to localize non-ideally captured arteries (for example the CCA cut is not depicted horizontally in the image or it is curved). In such case the localization of artery fails and it is impossible to start further segmentation step, thus the measurement could not be performed. In many implementations, the segmentation step is very robust but the simple localization process degrades the whole measurement method. This problem shows the importance of the designing of the robust localization methods as the proposed one.

The proposed method is, unlike the above mentioned methods, fully automated (needs no interaction with user), and more robust against image capture problems. Proposed method is absolutely independent on the rotation of the artery in the image, and moreover the proposed method is capable of localization of slightly curved artery.

3. PROPOSED METHOD OF CCA LOCALISATION

The block diagram of proposed method for CCA localization in longitudal scan is depicted in Fig. 1. This method starts with classification of pixels in input image (Fig. 2 (a)) on the basis of the local features in the image. The SVM classifier [5] classifies the pixels into one of two categories: (a) the "artery pixels" (Fig. 2 (c) – white pixels), (b) "other pixels" (Fig. 2 (c) – black pixels).

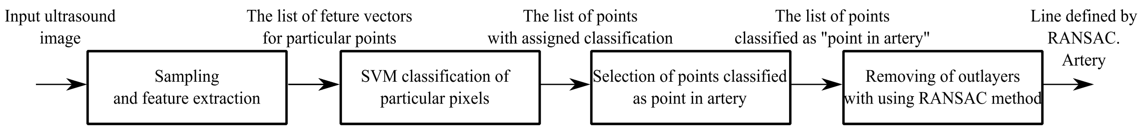

Fig. 1: Block diagram of the proposed artery localization method.

In further processing, only points classified as the "artery pixels" are considered (Fig. 2 (c) – white points, Fig. 2 (d) – highlighted points). Some points in the image are misclassified as the "artery pixels", either because of classifier inaccuracy or due to the similarity of the tissue with the artery tissue. Therefore, further processing is important in which only real artery pixels are selected. With respect to the linear or slightly bended character of CCA in longitudal scan, the RANSAC algorithm [6] has been used. By using RANSAC, it is possible to find the most suitable set of points lying in the ideal linear constellation and it is possible to suppress the influence of misclassified points. The localized artery, which can be seen in Fig. 2 (e), is the result of the proposed approach.

3.1. INPUT DATA SET OF IMAGES

The set of 57 B-mode ultrasound images, captured by Sonix OP, have been used for this experiment. All images depict the CCA in longitudal scan (Fig. 2 (a)) of different volunteers and they were scanned with different ultrasound station settings (frequency, depth, gain) and different rotation of the probe. For each input image, an appropriate mask has been created to define the artery position in input image (Fig. 2 (b)). These images and masks have been used for training and testing (evaluation) purposes and therefore the set of images was divided into two disjunctive groups – training and testing set. The training data set has been used for training the SVM classifier and the testing set has been used for the performance evaluation of the proposed method.

3.2. SVM CLASSIFIER

The SVM classifier has been used for classifying the pixels into one of two categories: (a) the “artery pixels” (Fig. 2 (c) – white pixels), (b) “other pixels” (Fig. 2 (c) – black pixels). The classification was performed on the basis of image local features obtained from the neighborhood of particular pixels. The selection of suitable features is crucial for classifier performance. It is important to select such features which are distinctive for both classes. The features were selected according to our experience – the mean value in the neighborhood, standard deviation, median value, center of the mass, maximal intensity, minimal intensity, and others.

The SVM classification is a process of fitting an optimal separating hyperplane between two or more classes [7], [8]. During the training process, only the training samples that lie at the edge of the class border (the support vectors) are considered. All of the other training samples have no influence on the parameters of hyperplane. Described basic approach to SVM classification may be extended with using a nonlinear decision surfaces. This approach uses the nonlinear mapping into the high dimensional space, where the linear hyperplanes can be used for classification more effectively. The radial basis function (RBF) is one of the wieldiest kernels which were used for nonlinear mapping. In this paper, the RBF extension was also tested and its accuracy was evaluated.

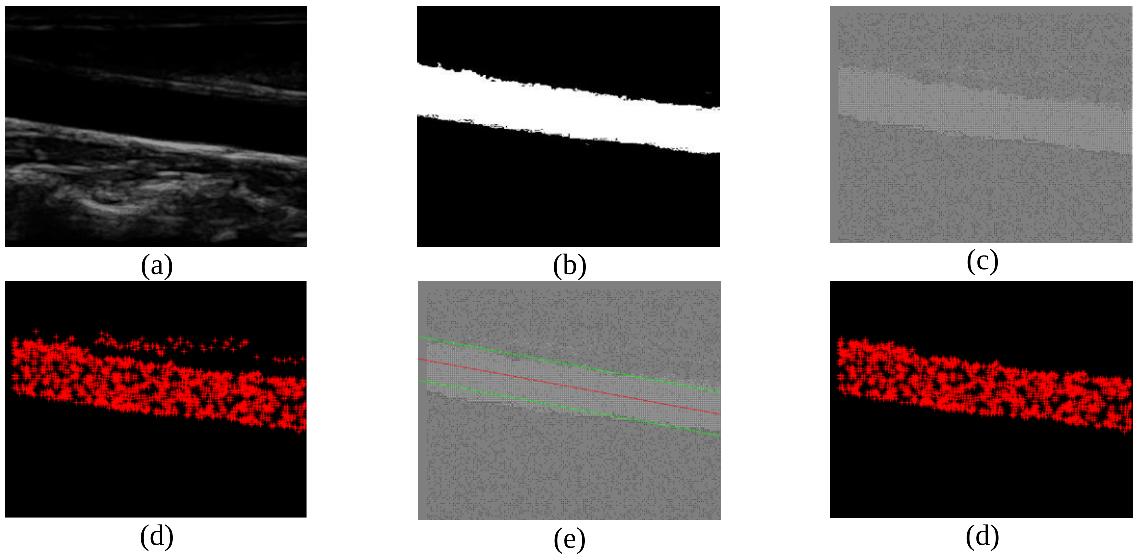

Fig. 2: (a) Example of the original image, (b) a mask defined for training and testing purposes only, (c) pixel classification by SVM with radial basis function used as nonlinear maping kernel, (d) all pixels classified as “artery pixels“highlighted, (e) line searched by RANSAC, (f) final artery points with no outliers.

Classification with SVM classifier

The classifier was separately (outside of the proposed method) tested on the disjunctive testing set. Particular pixels in images from the training set were classified and the results were compared with a ground truth defined by an expert in appropriate masks. The accuracy of the classifier is summarized in result section in Tab. 1.

In the proposed method, the classification is performed on the basis of pixel analysis in input image. For the speed optimization, not all pixels in image are classified, but with respect to next processing, only a subset containing randomly chosen pixels is formed and the pixels within are classified. The probability of selection of a pixel is 0.2 – this means that approximately each fifth pixel will be selected and classified.

The SVM classifies pixels to above mentioned two categories. Unfortunately not only pixels in artery are classified as “artery pixels”, but due to the classifier inaccuracy or the similar echogenity some other pixels are misclassified as "artery pixels, thus the further processing by using RANSAC has to follow.

3.3. RANSAC ALGORITHM

The RANSAC algorithm [6] was used to remove outliers – the points misclassified as the "artery pixels". Such points are often isolated or they form small clusters, but they never create the compact clusters comparable with the main cluster formed by correctly classified "artery pixels". This is the main presumption, which led to utilization of RANSAC.

RANSAC is an iterative algorithm, which separates the set of points into two categories – inliers, outliers. The inliers are the points which satisfy the condition specified by RANSAC and the searched model (the line model is used in our implementation). Points selected as inliers are essentially the points of the localized artery.

The RANSAC algorithm:

1. Repeat steps a) – d) for selected number of iterations:
   a) Select two points and construct line $\mathbf{p}$ through these points.
   b) Compute the distances $d(\mathbf{x}_i, \mathbf{p})$ from this line $\mathbf{p}$ for all points $\mathbf{x}_i$.
   c) All points, which satisfy the criterion $d(\mathbf{x}_i, \mathbf{p}) < t$ are inliers (t threshold).
   d) If the actual number of inliers is greater than the temporary highest number of inliers, than the model and the temporary number of inliers is saved and the algorithm continues.
2. Interpolate line through all inliers in saved model.

The performance of RANSAC algorithm was improved by using the implementation inspired by [6]. In this implementation the number of iterations N can be reduced according to Eq. 1 during the algorithm step 1d) if the better model is found.

$$N = \frac{\log(1-p)}{\log(1-(1-\epsilon)^s)}, \tag{1}$$

where the probability constant p [6] is commonly chosen as 0.99. The parameter s is the number of randomly choose points, in our linear model $s = 2$. The parameter ϵ evaluates the probability, that the selected point is outlier

$$\epsilon = 1 - \frac{number\ of\ inliers}{number\ of\ all\ points}. \tag{2}$$

4. RESULTS

4.1. SVM ACCURACY

The testing data set was used for the measurement of the SVM classifier accuracy. The testing set contains 30 images with particular masks (described in detail in section 3.1).

The utilization of classic SVM and its extended version that uses the nonlinear mapping by RBF was tested and both variants were mutually compared. With using classic SVM classifier the accuracy was 80.73%. Extended version of classifier achieves better accuracy – 91.22%. The higher accuracy of classifier makes the further RANSAC processing easier. The comparison of different SVM classifier in the form of confusion matrix is summarized in Tab. 1.

Tab. 1: confusion matrix (a) classic SVM, (b) radial basis function

	class. false	class. true
Pred. false	42.2%	6.4%
Pred. true	12.9%	38.5%

(a)

	class. false	class. true
Pred. false	52.7%	6.4%
Pred. true	2.3%	38.6%

(b)

4.2. RANSAC APPLICATION RESULTS

By using RANSAC, the whole localization achieved the assumed results – the outlier was eliminated and the artery was localized correctly in 28 of 30 images in test set. Such a good results were obtained due to high accuracy of SVM classifier and thus the low amount of misclassified pixels.

5. CONCLUSION

In the paper, a novel method for CCA localization in longitudal scan in B-mode ultrasound images is proposed. The method is designed to suppress the drawbacks of comparable methods – incorrect localization of non-horizontally displayed arteries or curved arteries. In proposed implementation, the SVM classifier was used, and it was extended by using RBF nonlinear mapping function in order to increase its accuracy. In this application, the accuracy of SVM with RBF was 91.22% on independent testing set.

The proposed method was tested on training set and the artery was correctly localized in all images. Moreover, the used testing database contains a lot distinctive images, which tested the proposed algorithm very well.

In future, the RANSAC algorithm can be extended by using general curve model – not only line model. With such extension, the proposed algorithm is expected to be more robust and can localize even more bended arteries.

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