Two-Dimensional Signal Analysis Methods and Applications in Medicine

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Abstract. This PhD thesis introduces novel two-dimensional signal analysis methods, focusing on image segmentation, as well as on applications in medicine. The proposed methods utilize textural and intensity information, based on the active contour approach. Textural information is exploited following scalar and vector active contour approaches, which are associated with alternative balances between computational cost and detail of texture representation. Moreover, the novel variable background active contour model (VBAC) is proposed. The formulation of VBAC model ensures that image regions enter selectively into the calculations of model equation terms, so that regions adding to inhomogeneity are excluded. An optimization framework based on genetic algorithms is developed for the automatic search of active contour parameters. Finally, the potential of boundary features, which are extracted from the detected contours, for malignancy risk assessment of thyroid nodules is investigated. The proposed methods are applied on standard image sets (VisTex, Brodatz, Berkeley), as well as on sets of thyroid ultrasound (US) images for the delineation of thyroid nodules, leading to higher quality segmentations than state-of-the-art segmentation methods. Future perspectives include applications in various domains, such as content-based image retrieval, face recognition and remote sensing.

Keywords: Image Analysis, Segmentation, Active Contours, Texture, Medical Imaging.

1 Introduction

The human visual system is an excellent mechanism for the extraction of high-level information from images of the surrounding environment; however it lacks the computational power, which is required for the analysis of a large amount of visual data, the performance of complex calculations and the extraction of precise quantitative information. The increase of the available computational power allows the development of efficient image analysis models, which utilize elements of human visual perception, as well as two-dimensional signal analysis methods.

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Image analysis with its closely related research areas of image processing and computer vision, have been associated with various applications including medical imaging, remote sensing, industrial automation, medical jurisprudence, telemedicine, proteomics, genomics, pattern recognition, robotics and content-based image retrieval.

A crucial step, along with image representation, in a wide range of image processing, image analysis and computer vision methods is image segmentation, which refers to partitioning an image to different regions that are homogeneous with respect to intensity, color or texture. The most representative class of image segmentation applications is in medical image analysis, for the detection of the boundaries of anatomical structures of interest. However, the inhomogeneity of medical images, as well as the existence of sampling artefacts, distortion and noise, make the boundaries of the anatomical structures fuzzy and disconnected, complicating the segmentation task. The early low-level image processing methods, which utilize local intensity information, are susceptible to the existence of noise and inhomogeneity. This fact imposes manual interventions so as to correct the end result. The research challenge lies in the utilization of region-based information, so as to facilitate the automated and precise detection of the boundaries of anatomical structures of interest and the extraction of malignancy risk indicators.

In this work, novel image segmentation methods are proposed, which are based on the active contour approach and utilize textural as well as intensity information. An optimization framework based on genetic algorithms is developed for the automatic search of active contour parameters. The proposed methods are applied on standard image sets (VisTex, Brodatz, Berkeley), as well as on sets of thyroid ultrasound (US) images for the delineation of thyroid nodules, leading to higher quality segmentations than state-of-the-art segmentation methods. Moreover, they are applicable on US images provided from different US imaging devices or the same device with varying settings. It should be noticed that, to the best of our knowledge, this work is the first on image segmentation of thyroid US images. Finally, the potential of boundary features for malignancy risk assessment of thyroid nodules is investigated.

Various aspects of this work have been published [1]-[4] or submitted [5] in 5 peer-reviewed international journals, in the peer-reviewed proceedings of 8 international conferences [6]-[13], in the peer-reviewed proceedings of 3 national conferences [14]-[16], and in 1 poster announcement in a national conference [17].

2 LBP-guided Active Contours

Two LBP-guided active contours have been formulated, namely the scalar-LBP active contour (*s*-LAC) and the vector-LBP active contour (*v*-LAC). These active contours combine the advantages of both the LBP texture representation [18] and the Chan-Vese active contour model [19], and result in high quality texture segmentation. *s*-LAC avoids the iterative calculation of active contour equation terms derived from textural feature vectors and enables efficient, high quality texture segmentation. *v*-LAC evolves utilizing regional information encoded by means of LBP feature vectors. It involves more complex computations than *s*-LAC but it can achieve higher segmentation quality. The computational cost involved in the application of *v*-LAC can be reduced if it is preceded by the application of *s*-LAC. The experimental evaluation of the proposed approaches demonstrates their segmentation performance on a variety of standard images of natural textures and scenes.

The underlying idea of *s*-LAC is to encode the spatial distribution of the most discriminative $LBP_{P,R}$ values of an input image into gray-level intensities so as to produce a new image that satisfies the assumption of approximately piecewise constant intensities. This is the basic assumption of the Chan-Vese model [19], which is subsequently applied on the new image. As this approach avoids the iterative calculation of active contour equation terms derived from textural feature vectors, *s*-LAC can be more efficient than other active contour approaches. Figure 1 illustrates a schematic representation of the algorithm step by step, as applied on a composite image of the Brodatz collection [20]. A more detailed presentation of the algorithm steps is provided in [3].

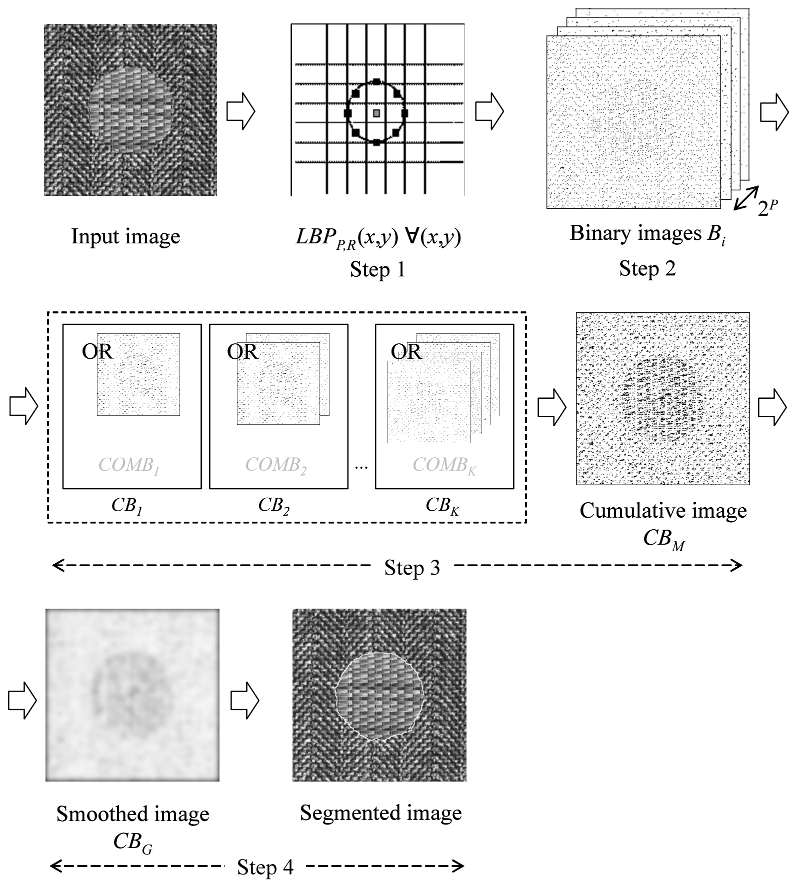

Fig. 1. Schematic representation of the steps of the *s*-LAC algorithm and images generated at each step. The input image is Brodatz D17D55. The binary, the cumulative, and the smoothed images have been inverted for illustrational purposes.

As in the case of s-LAC, v-LAC is formulated acknowledging that texture is undefined at the single pixel level and it is always associated with an image region. It utilizes vectors $Di(x, y)$, i=1,2,…,b, where each component $Di(x, y)$ corresponds to the i-th bin of the LBP distribution, and b is the number of bins comprising each distribution. $Di(x, y)$ encodes the textural properties of k×k-pixel image regions centered at pixel (x, y).

Aiming to incorporate the regional information encoded by means of LBP distributions into the energy functional defined in [19], we consider the replacement of the original vector which represents the image components at a single pixel, with $Di(x, y)$. Moreover, motivated by Ojala et al [18] in which the log-likelihood statistic is suggested as an accurate similarity measure for LBP distributions, we incorporate $(1 - D^i(x,y)\log(c_+^i))$ and $(1 - D^i(x,y)\log(c_-^i))$, where c_+^i, c_-^i are the average values of Di inside and outside the curve C, respectively.

These considerations lead to the derivation of a new energy functional:

$$F'(C,\bar{c}_+,\bar{c}_-) = \mu \cdot length(C) + \int_{inside(C)} \frac{1}{b}\sum_{i=1}^{b} \lambda_i^+ (1 - D^i(x,y)\log(c_+^i))dxdy + \int_{outside(C)} \frac{1}{b}\sum_{i=1}^{b} \lambda_i^- (1 - D^i(x,y)\log(c_-^i))dxdy \quad \textbf{(1)}$$

where $\mu, \lambda_i^-, \lambda_i^+$ parameters.

The Euler-Langrange formulation of (1) is:

$$\frac{\partial\varphi}{\partial t} = \delta\ (\varphi)[\mu \cdot div(\frac{\nabla\varphi}{|\nabla\varphi|}) - \frac{1}{b}\cdot\sum_{i=1}^{b} \lambda_i^+ (1 - D^i(x,y)\log(c_+^i)) + \frac{1}{b}\cdot\sum_{i=1}^{b} \lambda_i^- (1 - D^i(x,y)\log(c_-^i))] = 0 \quad \textbf{(2)}$$

where φ is the level set function, implicitly representing curve C.

The experimental evaluation of s-LAC and v-LAC on textures and natural scenes, acquired from standard databases, showed that s-LAC enables efficient, high quality texture segmentation by avoiding the iterative calculation of the active contour equation terms derived from LBP feature vectors. Moreover, the experiments showed that s-LAC is robust to illumination changes, a capability mainly associated with the LBP texture representation, whereas it allows the segmentation of regions with non-stationary textures. These capabilities are also valid for v-LAC, which although computationally more demanding, it can lead to higher segmentation quality than s-LAC, especially if the distance between the LBP feature vectors is measured by means of the log-likelihood statistic.

The convergence times of s-LAC observed for the available images, range between

3 and 4 seconds depending on the complexity of the target boundaries. Although *v*-LAC outperforms *s*-LAC in terms of segmentation quality, its computational requirements raise up to an order of magnitude for the particular experimental setup with convergence times ranging between 40 and 60 seconds. *v*-LAC segmentation can be accelerated by successively applying both *s*-LAC and *v*-LAC, which reduces the required time up to 20 seconds, whereas the individual overlaps obtained for the segmentation of the composite texture images are approximately the same with the ones obtained with *v*-LAC.

It has been shown that the proposed LBP-guided active contours compete state of the art active contours in texture segmentation, resulting in a comparable or better segmentation performance than various texture segmentation approaches [21]-[24], with less computational effort. More details on the formulation and the experimental evaluation of *s*-LAC and *v*-LAC can be found in [3],[8],[10].

Figure 2 illustrates example segmentation results obtained by the application of *s*-LAC and *v*-LAC.

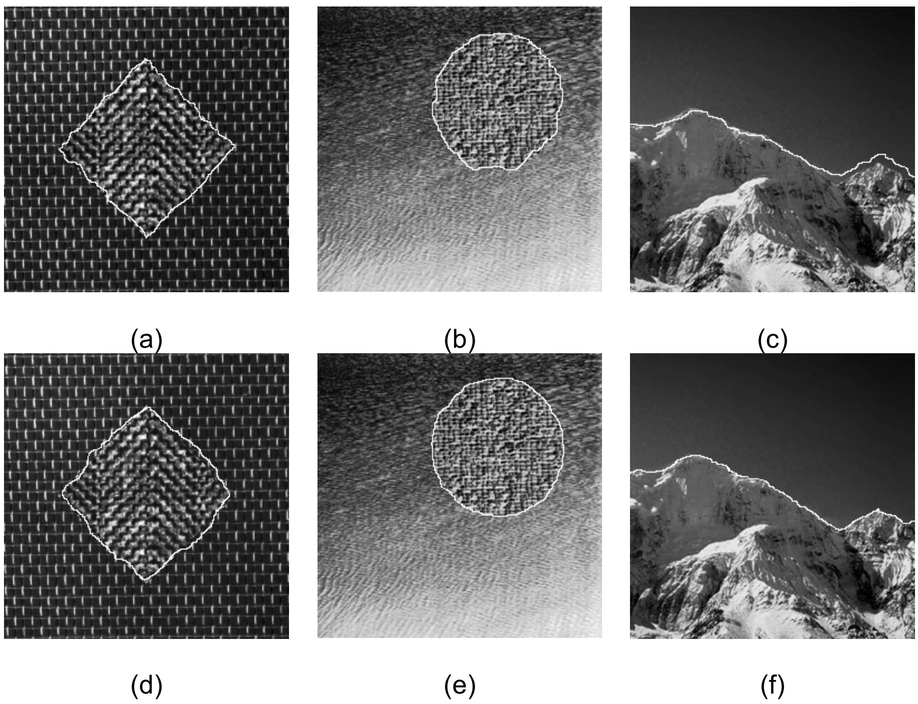

Fig. 2. Example segmentation results obtained by the application of: (a-c) *s*-LAC, and (d-f) *v*-LAC.

3 Thyroid US Image Segmentation

A novel level set active contour model, which is based on the Chan-Vese model [19], is proposed for the delineation of nodules in thyroid US images. The proposed model is called variable background active contour (VBAC) and introduces variable background regions, to reduce the effects of intensity inhomogeneity, which is attributed to noise, tissue texture and calcifications. Thus, VBAC achieves more accurate delineation of the thyroid nodules as well as faster convergence than Chan-Vese model.

The application of VBAC is limited to hypoechoic nodules, whereas the malignancy risk of isoechoic nodules, although lower, is considerable as well [25]. The joint echogenicity-texture (JET) model is proposed so as to extend the capabilities of VBAC for the delineation of isoechoic nodules by exploiting the topological adaptability of the level-sets used in its formulation. JET is an active contour model that co-evaluates regional image intensity and textural information encoded by LBP distributions. Figure 3 illustrates example segmentation results obtained by the application of VBAC (Fig. 3a-3c) and JET (Fig 3d-3f) on thyroid US images, containing hypoechoic and isoechoic nodules, respectively.

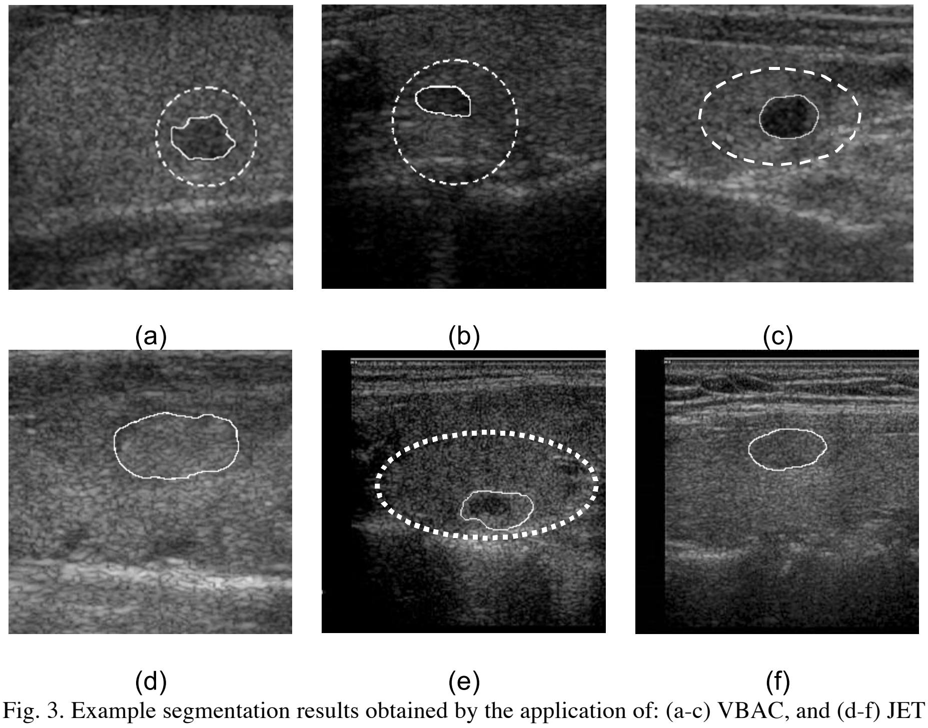

Fig. 3. Example segmentation results obtained by the application of: (a-c) VBAC, and (d-f) JET on thyroid US images, containing hypoechoic and isoechoic nodules, respectively.

Details on the mathematical formulation of VBAC and JET can be found in [1],[6],[7],[14],[15],[17] and [4], respectively.

4 Optimization Framework Based on Genetic Algorithms

A naive approach to tuning the active contour parameters for segmentation of images acquired from an US imaging device is the exhaustive search of all possible solutions in a discretized parameter space. Such an approach can lead to optimal parameter values but it is time consuming, to an extent that it could be prohibiting for medical application on routine basis. Also, many researchers in the field of active contour applications commonly employ empirical approaches to parameter tuning [19]. However, such approaches lack scientific foundation, lead to suboptimal solutions, and require specialized technical knowledge and experience, that could hardly be found in a physician's background.

These considerations lead to the development of a parameter tuning mechanism based on genetic algorithms (GA), capable of searching for the optimal active contour parameters automatically, without requiring technical skills. Figure 4 illustrates a flowchart of the proposed framework in the case of the VBAC model.

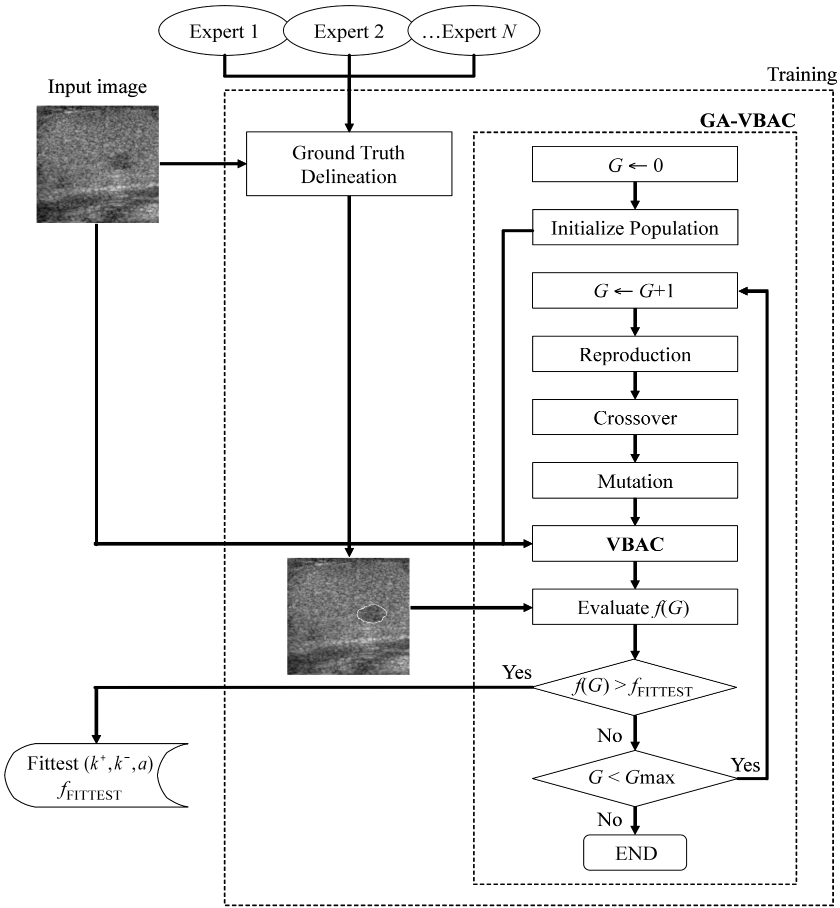

Fig. 4. The GA-VBAC framework.

The total training time of the GA-VBAC framework is 18.9 h, which is justified considering the population size and the maximum number of generations used in the experiments. It should be noted that: (a) if one had to follow the naive approach of exhaustive search in the parameter space, the execution time required would be almost 700 times more, and (b) the GA-VBAC framework has to be applied only once, for training. The resulting set of optimal parameters may be applied for the delineation of thyroid nodules in other thyroid US images acquired from the same US imaging device with the same settings. Details on the proposed optimization framework can be found in [2],[13].

5 A Classification Approach for Malignancy Risk Assessment of Thyroid Nodules in US Images

The development of the proposed thyroid US image segmentation methods was motivated by the results of clinical research, demonstrating that blurred or irregular nodule boundaries correlate with thyroid malignancy risk [25]. The quantification of the irregularity of nodule boundaries derived by these segmentation methods could be valuable for malignancy risk assessment. In this light, a classification approach is proposed, based on boundary features and local echogenicity variance (LEV). The latter provides valuable information for the discrimination of high-risk nodules with blurred boundaries from medium risk nodules with regular boundaries.

The optimal classification performance was achieved with the use of the SVM classifier. Figure 5 illustrates the ROC curve obtained. The associated AUC is 0.95, which is 2% higher when compared to the AUC obtained by using *k*-NN classifier, whereas it is derived that for specificity equal to 0.80, the obtained sensitivity is 0.98. Details on the proposed classification approach can be found in [5].

6 Conclusions

In this PhD thesis, novel image analysis methods have been proposed and applied on standard image sets, as well as on thyroid US images. The developed ideas lead to satisfying solutions of various issues in image segmentation, whereas they bring research one step closer to the objectification of the diagnostic process by utilizing explicit image features that encode visual information about thyroid nodules. This is important especially in the case of follow-up diagnosis where the validity of conclusions drawn by the comparison of subsequent nodule delineations depends on the delineation accuracy. Future perspectives of this work include:

1. Generalization of the entropy function utilized in *s*-LAC and *v*-LAC, so as to be applicable on images of multiple textures.
2. Derivation of additional information from video frame sequences for the identification of thyroid nodules.

3. Embedment of the proposed methods into an integrated medical decision support system combining heterogeneous information from various sources for identification and automated assessment of thyroid nodules.

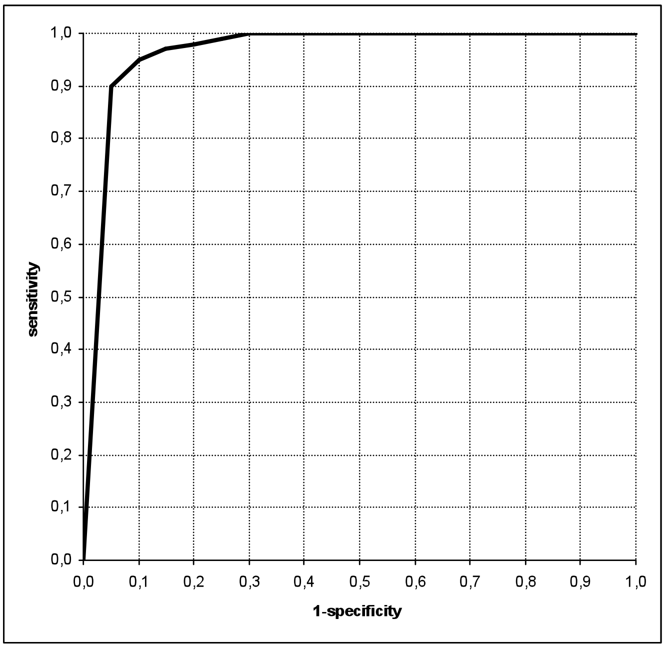

Fig. 5. ROC curve obtained by SVM utilizing the combination of all boundary features.

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