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Implementation and evaluation of segmentation algorithms according to multimodal imaging in personalized medicine

Abstract: Multimodal imaging is gaining in importance in the field of personalized medicine and can be described as a current trend in medical imaging diagnostics. The segmentation, classification and analysis of tissue structures is essential. The goal of this study is the evaluation of established segmentation methods on different medical image data sets acquired with different diagnostic procedures. Established segmentation methods were implemented using the latest state of the art and applied to medical image data sets. In order to benchmark the segmentation performance quantitatively, medical image data sets were superimposed with artificial Gaussian noise, and the mis-segmentation as a function of the image SNR or CNR was compared to a gold standard. The evaluation of the image segmentation showed that the best results of pixel-based segmentation ($< 3\%$) can be achieved with methods of machine learning, multi-threshold and advanced level-set method - even at high artificial noise (SNR< 18). Finally, the complexity of the object geometry and the contrast of the ROI to the surrounding tissue must also be considered to select the best segmentation algorithm.

Keywords: contextual methods; image segmentation; machine learning; medical images; radiology;

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1 Introduction

The segmentation of images is a key task in many image especially in medical image processing procedures and in the applications of machine vision (Computer Vision). In diagnostics segmentation methods for the recognition of organic structures or organs to detect pathological tissue or to measure the area or volume of segmented regions. Planning and control during surgery is a main application in interventional medicine.

Furthermore, individually adopted diagnosis and therapy concepts for each individual is gaining importance due to the current demographic development. This development is noticeable, in particular, in the field of medical-imaging procedures, like radiology or nuclear medicine. A better understanding of diseases and therapeutic procedures can be gained through various imaging methods, e.g. SPECT and PET in nuclear medicine or CT and MRT in radiology. Hereby the computer-assisted image segmentation and classification of tissue structures is an elementary task continuously undergoing further development and improvement.

Although hardware phantoms are an established way to evaluate these algorithms [1], they do not replace comprehensive tests using patient data obtained in the clinical routine. The aim of this study is the evaluation of established segmentation methods on image test data sets of the human brain and torso, acquired using different medical imaging modalities.

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2 Methods

2.1 Image segmentation algorithms

The segmentation methods examined in this study cover region-based, histogram-based, model-based and machine learning approaches. In particular, the following algorithms have been implemented in MATLAB R2015b: adaptive multi-thresholding method, marker-controlled watershed transformation (code adopted [2]), region-growing method (code adopted from [3]), advanced level-set model, algorithms from machine learning (k-Means [4], kNN [5]).

While executable code was available for most of these algorithms, which can be further adapted and improved, the adaptive multi-thresholding and advanced level-set model had to be redesigned. All tested algorithms were applied to medical images as described in **Figure 1**. After a DICOM import the images were evaluated in origin and with an artificially superimposed Gaussian noise (kernel with increasing variance from 0.0005 to 0.0025 increment 0.0005). All segmentation algorithms were applied to with and without noise. The result of automated segmentation was compared with a manual pixel-by-pixel segmentation as a gold standard (see **Figure 2**). To allow a quantitative evaluation, the segmentation results were evaluated by calculation of the "segmentation performance" p, defined as the number of correctly segmented pixels in comparison to the golden standard.

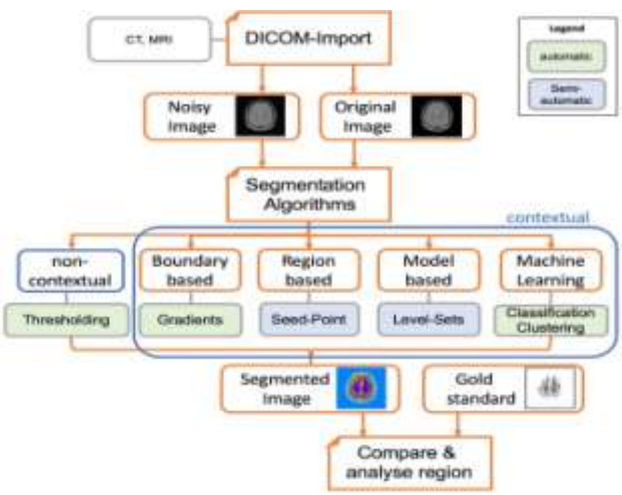

Figure 1: Flow-Chart of the image processing steps.

2.1.1 Adaptive multi-thresholding algorithm for image segmentation

For the adaptive multi-thresholding algorithm it is assumed, that the image contains N different objects and a background which can be delimited by these objects. When plotting the intensities of all pixels in a histogram, all pixels located in the vicinity of one histogram peak are highly probable to belong to the same object. The pixels in the valleys of the distribution are assigned to the class "non-classifiable", since they cannot be assigned to a specific region. The adaptive multi-thresholding approach can be separated in three major implementation steps:

A. Detection of the histogram peaks: The peaks of the histogram are detected by the hill-clustering method of Tsai and Chen [6]. which is based on a hill-climbing algorithm [7].
B. Optimum fitting of the histogram: In the next step, a polynomial function is fitted to the histogram using a least-squares fitting procedure. To improve the polynomial fit, background bins, with a high relative background proportion in the overall image, can be suppressed in the histogram.
C. Determination of the local minima: The determination of the local minima performed by the method of the discrete derivatives or optionally by by the method of the golden search algorithm according to [8], as described in [9].

2.1.2 Advanced level-set model

A level-set is a function $\Phi(\vec{x},t) = const.$ of the pixel coordinates $\vec{x} = (x,y)^T$ and the iteration time t. The user indicates the initial Level-Set $\Phi(\vec{x},t_0 = 0) = const.$ The zero-level-set encloses the object to be segmented and separates it from the surrounding. Subsequently, the optimization problem is solved by means of an iterative adaptation process solving the following differential equation:

$$\frac{\partial \Phi}{\partial t} = \mathbf{V}|\nabla\Phi| = \mathbf{0} \qquad (1)$$

with the speed-function V. To solve eq. 1, the DRLSE (distance regularized level set evolution) algorithm based on the existing implementation of [10] is used in an adopted manner to merge many closed single-contours $\vec{K}_i(t)$ to a combined-contour $\vec{K}(t) = \sum \vec{K}_i(t)$. The solution of eq. 1 is generally given as:

$$\frac{\partial \Phi}{\partial t} = \underbrace{\mu \cdot \mathrm{div}\left(d_p|\nabla\Phi|\nabla\Phi\right)}_{\text{distance regulation}} + \underbrace{\lambda \cdot \delta(\Phi) \cdot \mathrm{div}\left(g\frac{\nabla\Phi}{|\nabla\Phi|}\right)}_{\text{area regulation}} + \underbrace{\alpha \cdot g \cdot \delta(\Phi)}_{\text{edge regulation}} \qquad (2)$$

with $g = 1/(1 + |\nabla G \cdot I_{in}|^2)$, $G =$ Gaussian kernel, $d_p =$ Potential-function, $\delta(\Phi) =$ Dirac-function. The parameters μ, λ and α can be used to weight the three terms in eq. 2. The edge regulation with the indicator g is particularly important as with this term the gray value gradient can be regulated.

2.2 Medical image test data sets

The segmentation methods were evaluated using the following three medical test data sets (see **Figure 2**):

A. Test image 1: CT thoracic image, from which both lungs are to be segmented.
B. Test image 2: CT thoracic image from which pathologically altered tissue is to be segmented.
C. Test image 3: Proton density-weighted MRI image of the brain from which the white substance is to be segmented.

Clinical images were chosen to evaluate the segmentation with various challenges in terms of contrast, intensity variations and complexity of geometry. Test image 1 contains bright regions within the target object (lung wings), which should be segmented and do not belong to the target structure. In test image 2 a circular or elliptical object is to be segmented. Although the geometry of the target object is rather simple, it is difficult to distinguish from the surrounding tissue as it features highly variable intensity. Especially challenging is the decrease towards the object edge. Test image 3 provides a challenging segmentation problem as the adjacent white and gray matter feature a low difference in contrast. In addition, the geometry of the anatomical structure is very complex.

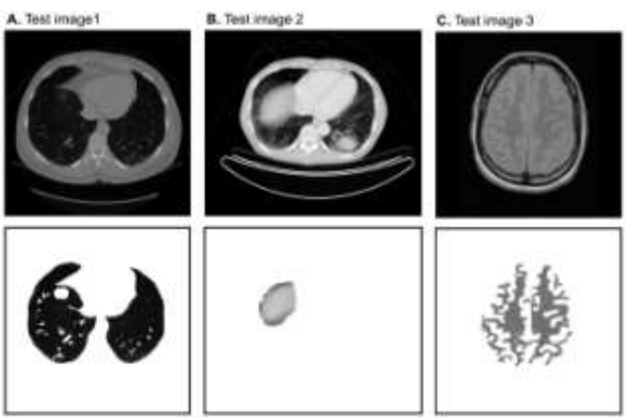

Figure 2: Illustration of the three test images (top) and manual segmentation of the target structures (gold standard) (bottom).

3 Results

Compared to the gold standard, the best segmentation results in test image 1 was done by the region-growing and the advanced level-set method which fulfil the requirement not to segment the bright regions in the lung tissue. For both methods, even with high noise levels, i.e. small SNR and CNR, the segmentation result remains almost constant ($p < 3\%$). The correlation coefficient between SNR/CNR values and the segmentation result attains only small values (c < 0.2). The result is independent of the noise level, for both methods.

In test image 2, the advanced level-set approach shows the best segmentation results. Even with high noise levels, i.e. small SNR and CNR, the segmentation result remains acceptable ($p < 10\%$). The segmentation performance correlates with the SNR and CNR (c > 0.88).

Table 1 and **Figure 3** show the performance p of the segmentation methods for test image 3 in detail. The following segmentation methods achieve acceptable results: multi-thresholding method, kNN classifier, k-mean clustering, and watershed method. In a direct comparison, the multi-thresholding method is preferable, since it has a low mis-segmentation even in the strongly noisy state. The correlation coefficient between SNR/CNR values and the segmentation result attains values c < 0.5. Although, good results are archived, with the kNN classifier and k-means clustering, many pixels are extracted at the wrong location (e.g. the edge of the skull). The region-growing method, on the other hand, provides good segmentation results, also in the non-noisy state. If the noise is increased, the CNR values decrease sharply but the homogeneity criterion can still distinguish between the gray and white substance. Finally, the target region is ultimately segmented a little too large. The level-set method detects too few pixels because the initialization function is not applicable to the small regions.

In general, there is no strong connection between the mis-segmentation and the image noise for all segmentation methods.

Table 1: Performance p of the segmentation methods for test image 3 with no noise and max. noise level ($\sigma^2 = 0.0025$).

Segmentation Method	**No Noise** SNR= 20, CNR= 5	**Noise level 5** SNR= 17, CNR= 2
Watershed	92.16	88.77
Region-Growing	99.22	84.16
Multi-Thresholding	98.24	88.17
Advanced Level-Set	67.05	54.65
kNN	96.56	85.46
k-Means	97.22	90.85

4 Discussion

In summary, it can be said that no omnipotent segmentation method exists. The target object geometry and the image contrast (CNR) play a decisive role when choosing an appropriate segmentation method. Especially complex, non-contiguous anatomical structures proved challenging to most algorithms and were only correctly segmented using level-set approaches. Here, the initial level-set must be positioned in the form of a start contour on each region, which can be complicated in case of many individual, non-connected regions. In addition, the start contour requires a minimum number of pixels to segment a region.

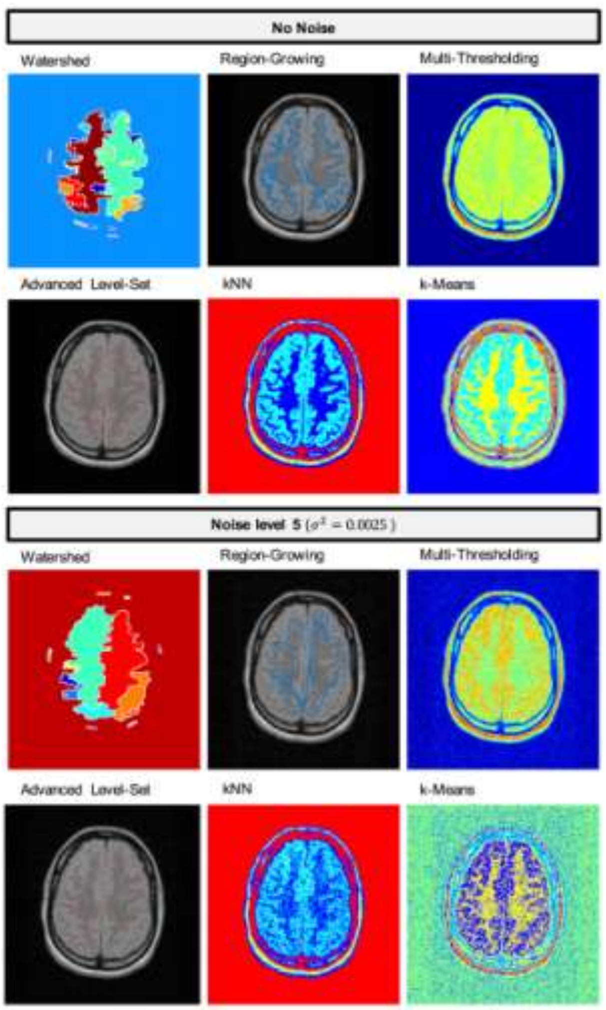

Figure 3: Illustration of the segmentation results for test image 3 (no noise and maximum noise level).

Holes or notches in the object topology could not be segmented correctly by some segmentation methods (e.g. region-growing) The contrast between the target region and neighboring regions also has a strong influence on the result. In the region-growing method, for example, the result is strongly dependent on the choice of the homogeneity criterion. The multi-thresholding method detects multiple peaks in the histogram and therefore assigns the pixels of one inhomogeneous region to more than one class.

All in all, great care should be taken when choosing segmentation algorithm for a certain task. Image contrast and geometrical features of the target structure have to be considered before appointing a method for the given problem.

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