Morphological and Watershed Segmentation of C-Spine MRI Images

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Abstract

Segmentation of bony structures plays an important role in image-guided surgery of the spine. In this, a novel approach to the segmentation of vertebral bodies from 2D sagittal magnetic resonance images of the spine is discussed. We would like to show that morphological and watershed segmentation could be used as a powerful segmentation tool in the segmentation of cervical(C) -spine MRI images. The structure, shape and morphology of the bony structures in spine images lend itself to the watershed segmentation.

1 Introduction

Automatic classification of images has always been an important part of pattern recognition. The segmentation and classification of magnetic resonance imaging (MRI) images have always been a challenge. A segmented image is often a very important input to the classification process. Many classification techniques use segmented images as input to the classification process. Certain segments or areas of an image serve as important features that will be used for classification. Important information can be derived from the features that are present in the segmented image. Sometimes there might be a need to extract a certain object from an image to do classification on the object.

In the case of MRI images, the segmentation process can isolate certain structures of the human body like organs and tissue. These objects of interest (OOI) can give vital information for the identification of medical abnormalities (anomalies) and diseases. Segmented objects can play an important role to assist medical practitioners in the diagnosis and treatment of medical problems.

Many segmentation and classification techniques have been implemented on MRI images. The latest techniques include support vector machines (SVMs), neural networks (NNs), statistical methods and threshold techniques.

The goal of this work was to test the performance of the watershed segmentation algorithm on MRI images of the vertebral spine.

2 Segmentation Process

Segmentation is the partitioning of images/volumes into meaningful pieces [1]. Segmentation involves the isolation on a specific region of interest. Segmentation subdivides an image into objects of interest. These objects are often referred to as regions of interest (ROI) or volumes of interest (VOI). In this paper we will only use the term ROI, whether they are 2D or 3D.

Segmentation plays a key role in the identification of objects and features and subsequent classification of images. Objects of interest can be isolated and extracted by the segmentation process. The segmented objects can be used as input features for the classification process. The segmented regions can also be used as inputs to intelligent processes like fuzzy logic systems and neural network systems.

The purpose of image segmentation is:
- Detection or recognition of an object or feature of an object
- Quantifying of the properties of an object, like the size and quantity of the object
- Identification of statistical, morphological and geometrical properties of the object.

There are three types of image segmentation: thresholding, edge-based and region-based.
segmentation (Figure 1). Segmentation techniques can also be classified as statistical segmentation, morphological and region-based segmentation (Figure 2).

Segmentation Classification (2)

Statistical Segmentation  Morphological Segmentation  Region-based Segmentation

Figure 2 Segmentation classification (2)

3 Segmentation in MRI

Segmentation is a key process in the image processing of MRI images. Physical structures like organs, bones and tissues can be isolated in the segmentation process. These regions of interest (ROI) will play a crucial role in further analysis and diagnosis of abnormalities and diseases. Specific objects of interest like tumours, fractured bones, lesions, etc. can be isolated and identified in the segmentation process [2], [3].

Many segmentation techniques have been developed for MRI images. Statistical techniques like expectation/maximization, binary mathematical morphology and active contour models have been implemented. Nearest-neighbour techniques have also been implemented.

Scale-invariant segmentation [4], a combination of expectation-maximization segmentation, binary mathematical morphology and active contour models are also used [5]. A combination of texture based segmentation [6] and neural network classification can also be used.

4 Morphological Processing Theory

A typical image processing system is described in Figure 3. It typically consists of a number of stages, i.e. pre-processing, thresholding, morphological processing, segmentation and classification. Sometimes the thresholding and classification stages are omitted. The focus in this paper will be on thresholding, morphological processing and segmentation.

The method that has been used includes a combination of processes. Thresholding, morphological processing, edge-detection, filtering and the watershed segmentation have been used to yield a segmented image.

PRE-PROCESSING

THRESHOLDING

MORPHOLOGICAL PROCESSING

SEGMENTATION

CLASSIFICATION

Some pre-processing like filtering or histogram equalization needs to be applied on the MRI images to improve segmentation of the raw data.

Morphological Operations

- Erosion
- Dilation
- Closing
- Opening
- Morphological reconstruction
- Extended-minima transform
- Extended-minima transform

The input processing includes morphological operations. Morphology is a broad set of image processing operations that process images based on shapes. Morphological operations that can be used as powerful pre-processing techniques are discussed in the following paragraphs.

Erosion removes pixels from object boundaries. It assigns the minimum value of all the neighbouring pixels in the structuring element to the pixel that is currently evaluated. It can be used on grayscale or binary images. In a binary image, the pixel will be set to zero, if any pixel in the structuring element is zero. The equation for erosion is as follows:

\[
(f \ominus g)(x) = \bigvee_{y \in E} f(y) + g(x - y)
\]

where \(\ominus\) refers to the Minkowski addition [7].

Dilation adds pixels to boundaries of an object. It assigns the maximum value of all the neighbouring
pixels in the structuring element to the pixel under test. In a binary image, the pixel will be set to one, if any pixel in the structuring element is one. In algebra, any transformation which is increasing, anti-extensive and idempotent is called an (algebraic) opening, increasing, extensive and idempotent is called a (algebraic) closing.

\[( f \ominus g)(x) \equiv \bigwedge_{y \in E} f(y) - g(x-y) \quad (2)\]
where \(\ominus\) refers to Minkowski subtraction.

Closing is a dilation operation followed by erosion with the same structuring element. Morphological closing can be used to join shapes and structures and to fill up gaps. It can also be used to fill in basins and valleys in a topological image [8]. The resulting structures can be used as markers.

\[f \mapsto (f \ominus g) \ominus g \quad (3)\]

Opening is erosion followed by dilation with the same structuring element. Morphological opening can be used to remove small objects from an image while preserving the larger objects in an image. An opening removes some peaks and crest lines.

\[f \mapsto (f \Theta g) \oplus g \quad (4)\]

Morphological reconstruction processes one image, called the marker, based on the characteristics of another image, called the mask [9]. Morphological reconstruction can be used to reconstruct the topology of an image.

The regional extrema of a raw image mark relevant as well as irrelevant image features. The h-maxima transformation suppresses all maxima whose depth is lower or equal to a given threshold level \(h\). This is achieved by performing the reconstruction by dilation of \(f\) from \(f-h\) [10]:

\[HMAX_h(f) = R_f^d(f-h) \quad (5)\]

The extended-minima transform calculates the regional minima of the corresponding h-minima transform. Regional minima are connected components of pixels with the same intensity value, whose external boundary pixels all have a higher value. The extended minima are defined by:

\[EMIN_h(f) = RMIN[HMIN_h(f)] \quad (6)\]

The extended-maxima transform calculates the regional maxima of the k-maxima transform. Regional maxima are connected components of pixels with the same intensity value, whose external boundary pixels all have a lower value. The extended maxima \(EMAX\) is defined by:

\[EMAX_h(f) = RMAX[HMAX_h(f)] \quad (7)\]

An important input to segmentation and image classification is the gradient image. The gradient image gives an indication of the level of the gradients (peaks and valleys) in an image. The gradient image can be calculated with the derivative of a Gaussian filter. Gradient images can be used to calculate edges in images. It can also be used as an input to the watershed transforms [11]. The gradient of a function of two variables, \(F(x,y)\) is defined as:

\[\nabla F = \frac{\partial F}{\partial x} \hat{i} + \frac{\partial F}{\partial y} \hat{j} \quad (8)\]

A distance transform can be used to calculate the gradient of an image. The distance transform provides a measure of the separation of points in an image. The distance transform calculates the distance of the current pixel to the nearest non-zero pixel of the input binary image. The distance function \(dist_x\) of a set of \(X \subset Z^2\) associates the distance of each pixel to the background [12]:

\[dist_x \left( p \mapsto \min\{d(q,p) | q \notin X\} \right) \quad (9)\]

The distance function \(d_i\) of a binary image \(I\) is equivalent to that of its set of feature pixels, i.e. pixels with value 1. In addition we put conveniently:

\[\forall p \in D_i, I(p) = 0 \Rightarrow dist_i(p) = 0 \quad (10)\]

The distance transform can be calculated with several distance metrics, for example the Euclidean distance, city block, chessboard and the quasi-Euclidean distance.

An image can be enhanced or modified by applying an image filter. A filter can be applied to emphasize or remove certain features. Image processing operations implemented with filtering include smoothing, sharpening, and edge enhancement. Many different kinds of filters can be applied to an image to enhance to image.
5 MRI Segmentation System

Two systems have been implemented. The flow diagrams of these systems can be seen in Figure 4. The first system will be described in the next section.

5.1 Segmentation System I

The first step is to threshold the image with a fixed threshold. The threshold is calculated with Matlab’s graythresh function. This function uses Otsu’s method [13], calculating a threshold that minimizes the intraclass variance of the black and white pixels.

The next step is to implement a closing function. The bwmorph function in Matlab was used to perform this operation. This function performs a morphological dilation followed by erosion. The operation is implemented 30 times, until the process settles and no more changes happen in the output image.

The next step is to perform a two-dimensional convolution. A Gaussian mask of 10-by-10 pixels is used. Matlab’s conv2 function is used to perform this operation. This operation enhances block-shape structures in the input image.

An erosion operation is then performed on the convoluted image. A disk shape structure with a radius of 5 is used. The disk shape structure is approximated by a sequence of 4 periodic-line structuring elements.

The next step is to threshold the image with a regional minima transform of the H-minima transform. Regional minima are connected components of pixels with similar intensity values, and whose external boundary pixels all have a higher value. This transform is very useful as a pre-process for the segmentation process. The Matlab function imextendedmin is used to do this thresholding.

The next step is to implement a distance transform. This function calculates the Euclidean distance between each non-zero pixel and the nearest non-zero pixel. The Matlab function bwdist is used for this operation. This operation yields a gradient image giving an indication of the distance between objects and neighbouring objects in the image.

The sign of the values of the output image is inverted. Pixels belonging to the background of the image are set to minus infinity.

A median filter is implemented next to remove outliers and noise. This is a non-linear operation that reduces noise significantly, but preserves edges. Matlab’s medfilt2 is used for this operation.

The final step is to calculate the watershed transformation. This function calculates the watershed regions, yielding the final segmented image. We used a modified version of the Vincent Soille watershed algorithm to perform this operation.

5.2 Segmentation System II

This system is much simpler and only consists of a small number of steps:

Figure 4 Flow diagrams of system I and II
The first step is to equalize the histogram of the input image. This step enhances the contrast of the image. It is done with the function `jcontrast`.

The second step is to threshold the image to create a binary image. The Matlab function `graythresh` is used to calculate the threshold. The thresholding is done with the function `im2bw`. All pixels above the threshold is set to one and pixels below the threshold is set to zero. The output of this function is a binary (black-and-white) image.

The next step is to implement a distance transform. This function calculates the Euclidean distance between each non-zero pixel and the nearest non-zero pixel. The Matlab function `bwdist` is used for this operation.

The sign of the values of the output image is complemented. Pixels belonging to the background of the image are set to minus infinity.

A median filter is implemented to get rid of outliers and noise. This is a non-linear operation that reduces noise significantly, but preserves edges. Matlab’s `medfilt2` is used for this operation.

The final step is to calculate the watershed transformation. This function calculates the watershed regions, yielding the final segmented image. A modified version of the Vincent Soille watershed algorithm was used to perform this operation.

## 6 Results

The two systems have been applied to the same C-spine MRI images. The results can be seen in Figure 5 and Figure 6. The objects of system II have been more accurately segmented (see Table 1).

### 6.1 Results of Application to MRI Test Images

Test images have been selected from MRI C-spine images from 9 different patients obtained from Radiology at Kloof Hospital. Ground truth images have been created by manually segmenting the C-spine MRI test images. Binary-segmented images have been created. All the segments in each image have been labelled. Input test MRI images can be seen in the first row of Figure 7. The filled and boundary images of the manual segmentations are in the 2nd and 3rd row respectively of Figure 7.

### 6.2 Numerical Performance

Precision-recall curves were generated and plotted for the algorithm for each segmented image.
Figure 8 Precision-recall curve for a test images

Precision is the probability that a computer-generated boundary pixel is a true boundary pixel. Recall is the probability that a true boundary pixel is detected [14]. The F-measure, which is the harmonic mean of precision and recall, is also calculated.

Table 1 Performance numbers for test images

<table>
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<th>Im No</th>
<th>Precision</th>
<th>Recall</th>
<th>F-measure</th>
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<td>Sys II</td>
<td>Sys I</td>
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Looking at the F-measures in Table 1, System II performed better than System I on all test images.

7 Conclusion

The results show that a combination of morphological functions and the watershed transform can be used to segment the C-spine from the rest of the MRI-image. System II performed better than System I and gives a simple and effective solution for the C-spine segmentation problem.

8 Acknowledgements

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9 References