# A Comparison of X-Ray Image Segmentation Techniques

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***Abstract*—Image segmentation operation has a great importance in most medical imaging applications, by extracting anatomical structures from medical images. There are many image segmentation techniques available in the literature, each of them having advantages and disadvantages. The extraction of bone contours from X-ray images has received a considerable amount of attention in the literature recently, because they represent a vital step in the computer analysis of this kind of images. The aim of X-ray segmentation is to subdivide the image in various portions, so that it can help doctors during the study of the bone structure, for the detection of fractures in bones, or for planning the treatment before surgery. The goal of this paper is to review the most important image segmentation methods starting from a data base composed by real X-ray images. We will discuss the principle and the mathematical model for each method, highlighting the strengths and weaknesses.**

***Index Terms*—image processing, image segmentation, biomedical imaging, digital images, X-rays.**

## I. Introduction

When analyzing objects in images, it is necessary to distinguish the objects of interest from the background. This task can be realized through segmentation. Image segmentation is one of the most challenging issues in image processing domain and it has been an active research area in the last years. Through segmentation we aim to fragment the image in a series of regions, based on the attributes of the image that are approximately constant in each region, but differ significantly from a region to another. Segmentation aims to extract useful information from images in medical imaging applications as well. Actual medical imaging provides perspectives for a major progress in medicine and science, as higher quality images are generated. Medical imaging began with the discovery of Roentgen rays (X-Rays). Then, various image modalities have appeared over the years, each with their own advantages and disadvantages. These are: Magnetic Resonance Imaging (MRI), Ultrasound (US), Computed Tomography (CT), Nuclear Imaging, including Single Photon Emission Computed Tomography (SPECT) and Position Emission Tomography (PET). Among the applications of segmentation in medical imaging we mention the anatomical localization, whose main purpose is to describe anatomic regions of interest. Medical images segmentation has also found applications in studying the anatomical structure, tumors or fractures localizations, diagnosis and treatment planning, computer-integrated surgery, tissue classification, or tumor volume estimation. X-ray segmentation methods have received a considerable amount of attention recently. X-ray segmentation is challenging as X-ray images have a complex nature. They may be also affected by noise, sampling artifacts or spatial aliasing so that the boundaries of the regions of interest to become indistinct or disconnected. X-rays may have various orientations, resolutions, or luminous intensities, depending on the X-ray equipment, that could influence the quality of the segmentation result. Unlike other medical imaging modalities, bone regions in X-rays often overlap with other organs or bones. Another problem to be considered is represented by the joints between bones. When we aim to segment an entire bone structure, the joints need to be considered [1]. Several segmentation techniques have been developed and reported in the literature. However, a perfect method, universally applicable to all kind of images, does not exist. This paper focuses on the comparison of several already existing image segmentation techniques in the case of X-ray images.

## II. Medical Image Segmentation Techniques

General medical image segmentation methods can be categorized into the following classes: classical image segmentation methods (thresholding, regions-based, and edges-based), pattern recognition-based, deformable models, wavelets-based methods, and atlas-based techniques [1]-[4]. To exemplify some of the segmentation technique, we will consider a real X-ray image shown in Fig. 1.

Figure 1. An X-ray image test.

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### A. Classical image segmentation methods

Classical methods include the following segmentation techniques: thresholding, region-based, and edge-based methods.

**Thresholding** is one of the most simple segmentation techniques and involves thresholding the image intensity. There are two classes of thresholding methods [5]: global methods and adaptive methods. In the case of global thresholding, only one threshold is selected for the entire image, while in the case of adaptive thresholding, the local thresholds are selected independently for each pixel (groups of pixels).

Global methods are based on the fact that the image has a bimodal histogram [2]. The object of interest can be separated from the background by comparing the intensity of each pixel in the image with a threshold. Some pixels, whose intensity values are greater than the threshold, are classified as being part of group *A - object of interest* (with an intensity value of 1), and the rest of the pixels as being part of group *B-background* (with an intensity value of 0.

Adaptive methods are based on the fact that a given image is split into a series of sub-images and, for each sub-image, some thresholds are computed. A different approach, called local adaptive thresholding, consists in analyzing the image intensities around each pixel and selecting an individual threshold for each pixel, taking in consideration the degree of the intensity values in its local neighborhood.

Global methods are simple and fast, but are suitable only for images with bimodal intensity distribution (probability distribution with two different modes). Another factor that affects the performance of thresholding is the unequal illumination in the image. In addition, global methods are not useful for multichannel images, since only two classes are generated.

Adaptive methods are more complex than global methods, concerning computations. However, these methods can be successfully used for extracting small regions or objects from a variable background. The adaptive threshold based segmentation operation is used for the test image in Fig. 1 and the result is presented in Fig. 2. Analyzing the resulted image in Fig. 2, we can see that not only the bones are highlighted, but also parts of the flesh. In addition, the bones of the arm are not separated.

An application of thresholding based segmentation is found in digital mammography, with two classes of tissues, healthy and tumorous [6]. This simple operation can be surprisingly effective, also in Computerized Tomography (CT), where the pixel value has real-world significance, [7]. However, most of the medical images do not have bimodal distribution of intensity. Therefore, thresholding algorithms are rarely used in medical imaging.

**Region-based methods** have the purpose of grouping pixels having similar intensities. The most important region-based segmentation algorithms are: region-growing segmentation, and watershed algorithms.

Region-growing algorithm is a simple pixel-based image segmentation method, which involves the selection of pixels (the seeds), and then growing regions around these seeds, using a homogeneity criteria [1]. If the joining pixels have similar image features as the seed, they are integrated into the region. A statistical test is usually used to take the decision.

Figure 2. X-ray image segmentation using thresholding.

The choice of homogeneity criterion is crucial for the success of the algorithm [2]. Some examples of homogeneity criterions are: the difference between the intensity of the pixel and the region mean intensity, or the weighted sum of gradient information and the contrast between the region and the pixel. The process is iterated on, in the same manner as general data clustering algorithms, until a predefined termination condition is reached.

An advantage is that region growing algorithms are fast and can perform accurate segmentations of regions that have the same features but are spatially separated [5]. However, they are sensitive to noises and therefore may produce undesired segments, regions with holes or disconnected regions. Moreover, the seed point is obtained using manual interaction [2].

*Watershed method* (watershed transform) is another region-based method. This method is based on the gray-scale mathematical morphology and it is used for multi component images, [8]. Intuitively, the watershed algorithm can be thought of as a landscape that is flooded by water. The height of the landscape at each point represents the pixel's intensity. The watershed transform computes the image regions which represent the basins and region boundaries (the ridgelines). The image gradient is used as input of the transform, such that the basin limits are situated at high gradient points.

This type of segmentation method is simple and intuitive and has good properties, which make it useful for many image segmentation applications. However, it has several major disadvantages such as: over-segmentation, sensitivity to noise, and it is poor at detecting thin structures and structures with low signal-to-noise ratio, [2].

The bones segmentation by region growing techniques is obtained in [25], in the case of hand-wrist radiographs.

**Edge-based segmentation methods** use edge detectors to find edges in the image. Edge detection has an important role in image processing and computer vision, especially in feature detection and extraction domain. Edges can be viewed as image points, where the luminous intensity of the image changes distinctly along a particular orientation. If the intensity of the images has a strong change, then there is a high probability for an edge at that image position [9].

The classical operators for edge detection are the following: Prewitt, Sobel, Roberts and Laplacian of Gaussian (LoG) operator [10]. Most classical edge detectors are based on the local gradient (the first order derivatives) of the image function. Practically, the difference between these operators is that they use different types of filters for estimating the gradient components and a different way for combining these components [9].

*Prewitt operator* is a discrete operator which estimates the gradient of the image intensity function. It computes the approximations of the derivatives using two 3×3 kernels (masks), in order to find the localized orientation of each pixel in an image. Prewitt differs from Sobel operator only in the filters they use. Prewitt operator used the following filters [9]:

$$H_x^P = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \tag{1}$$

and

$$H_y^P = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}, \tag{2}$$

The local gradient components are obtained from the filter by scaling:

$$\nabla I(u,v) \approx \frac{1}{6} \cdot \begin{bmatrix} (I * H_x^P)(u,v) \\ (I * H_y^P)(u,v) \end{bmatrix} \tag{3}$$

*Sobel operator* computes the approximation of gradients along the horizontal (x) and the vertical (y) directions (2D spatial) of the image intensity function, at each pixel [2], and highlights regions corresponding to edges. Sobel edge detection is implemented using two 3x3 convolution masks or kernels, one for horizontal direction, and the other for vertical direction in an image, that approximate the derivative along the two directions [4].

Sobel operator uses the following filters:

$$H_x^S = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{4}$$

and

$$H_y^S = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}, \tag{5}$$

The two filters are almost identical with the filters used by Prewitt operator, excepting the weighting of the middle row (for horizontal kernel) and column (for vertical kernel): Sobel uses a weighting of 2 and -2, while Prewitt uses a weighting of 1 and-1.

The local gradient components are computed as follows:

$$\nabla I(u,v) \approx \frac{1}{8} \cdot \begin{bmatrix} (I * H_x^S)(u,v) \\ (I * H_y^S)(u,v) \end{bmatrix} \tag{6}$$

An example of X-ray image segmentation using Sobel is presented in Fig. 3. In this case the contour of the hand's skeleton is not perfectly detected, some discontinuities at the top of the fingers' bones can be observed. Moreover, not only the hands' skeleton is detected, but also contours of the hand/arm, which can be observed at the bottom of the image in Fig. 3.

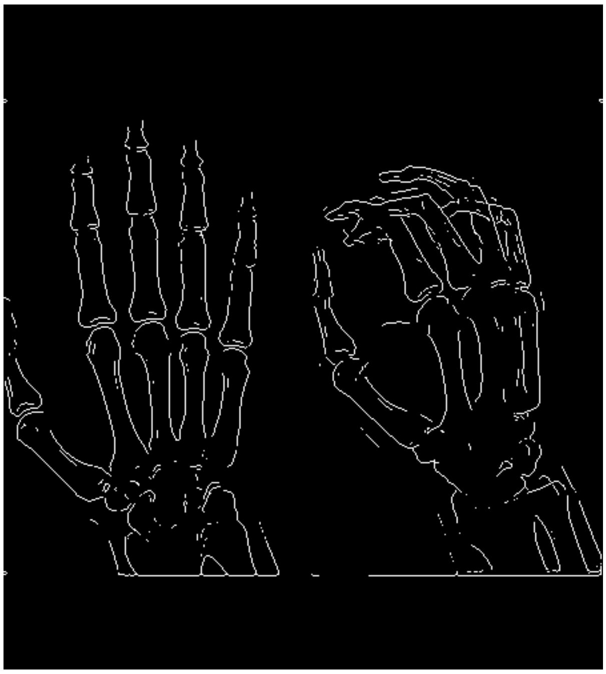

Figure 3. X-ray image segmentation using Sobel.

*Roberts* (Roberts' Cross operator) is one of the oldest edge detector. It is a simple operator that approximates the image gradient along the horizontal and the vertical directions, using discrete differentiation and emphasizes regions corresponding to edges (regions with a high spatial frequency) [39].

The filters used by Roberts detector are:

$$H_x^R = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \tag{7}$$

and

$$H_y^R = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}, \tag{8}$$

The disadvantage of Roberts operator is that it uses filters with a small size. This fact implies the detection of very small edge structures.

*Laplacian of Gaussian (LoG)* operator computes the second-order derivatives of the intensity function for a given image. The image is smoothed using a Gaussian smoothing filter, to reduce its sensitivity to noise, and then the Laplacian filter is applied. The edges obtained using LoG operator, have a more precise localization than the ones detected by applying Prewitt or Sobel [9].

More advanced edge detectors have been proposed in the computer vision literature such as Harris detector or Canny edge detector. *Harris* finds the edges based on the eigenvalues of the Hessian matrix [2]. *Canny* is a very effective edge detecting technique. It detects faint edges, even when the image is noisy, because it is used after a series of preprocessing procedures, such as edge enhancement (Gaussian filtering). Next, the edge strength (magnitude) of the image must be found. This procedure implies the approximation of the image gradient in the x-direction ($G_x$) and in the in the y-direction ($G_y$), using

Sobel operator. The gradient magnitudes are determined using the formula:

$$|G| = \sqrt{G_x^2 + G_y^2} \tag{9}$$

The next step consists in finding the edge direction, as shown in the following equation:

$$\theta = \mathrm{arctag}\left(\frac{|G_y|}{|G_x|}\right) \tag{10}$$

The purpose of the next step, called non-maximum suppression, is to keep only edge-pixels, in the image of the gradient magnitudes, where the gradient has local maxima. Finally, the last step implies thresholding with hysteresis. Two thresholds are used, T1 and T2 and, in the end, the pixels are separated into edge pixels or a non-edge pixels. An example of X-ray segmentation using Canny edge detector is presented in Fig. 4.

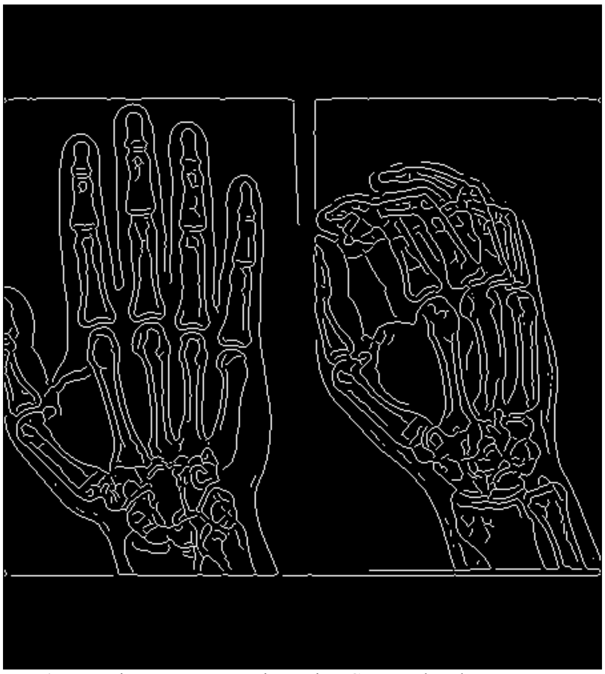

Figure 4. X-ray image segmentation using Canny edge detector.

The disadvantage of edge-based segmentation algorithms is that they are sensitive to noise and tend to find edges which are irrelevant to the real boundary of the object. For example, in Fig. 4 are detected two edge boundaries, one of the flesh and one for the bone. But, usually, only the bone needs to be separated. Another problem that could appear is that the extracted edges could be disjoint and cannot completely represent the boundary of an object. Such a case is shown in Fig. 2. Therefore, some additional processing is needed to connect them to form closed and connected object regions [2].

Edge detection (including Sobel, Prewitt, Roberts or Canny detectors) was used in [14], [23] and [26]. In [40] a computer based automatic tool used for the diagnosis in prosthesed hip has been proposed. One step in the algorithm is the bone and prosthesis segmentation, which is used to produce clinical relevant measurements. The best results for identifying the prosthesis were found using Expectation-Maximaization algorithm and Canny.

### *B. Pattern recognition-based*

Segmentation implies pixels classification, so it is frequently handled as a pattern recognition issue. Pattern recognition techniques include unsupervised methods (clustering) and supervised methods (classification).

**Clustering or cluster analysis** is an unsupervised method and refers to a class of algorithms extensively used for image segmentation. It is a technique for grouping a set of objects into groups (clusters), so that similar objects belong to the same cluster, while dissimilar object belong to different clusters. Various clustering algorithms have been proposed in the literature. Between them we mention: the K-means algorithm, the fuzzy c-means algorithm, hierarchical clustering or the Gaussian mixture approach.

A particular algorithm that can be included in this category is the *mean-shift algorithm*. It was introduced in [11] and searches modes or local maxima of the density function in the features space, defining the clusters. The next step is grouping data in these clusters. The two steps of the mean shift algorithm are: the filtering step, in which the original image is filtered in the feature space, and the clustering step, in which the filtered data points are grouped, using linkage clustering or edge-directed clustering. In the filtering step, the probability density function (*pdf*) of the image is analyzed in the feature space. The density function at point *x* is estimated using the next equation [8]:

$$f(x) = \frac{c}{nh^d}\sum_{i=1}^{n} K \left\| \frac{x - x_i}{h} \right\|^2 , \tag{11}$$

with *n* being the number of points, $x_i$ *( i =1,..,n)* the pixels in the image, *h* the bandwidth, *d* the data dimensionality, *c* a constant, and *K*(-) the density estimation kernel. X-ray segmentation using the mean-shift algorithm is shown in Fig.5.

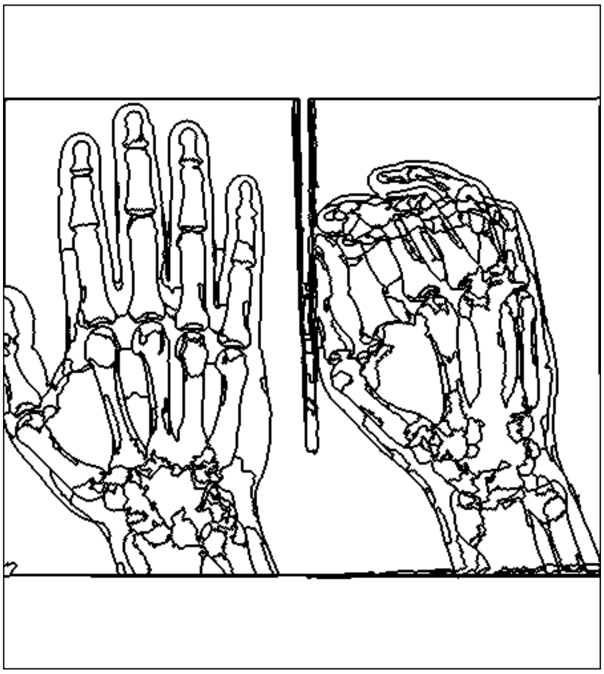

Figure 5. X-ray image segmentation using mean-shift algorithm.

Clustering techniques are effective methods because they are appropriate for multi-band images, for example color images or remote sensing images. The disadvantage of cluster analysis is the fact that the number of clusters must be a priori set [12].

Fuzzy clustering based on fuzzy c-means algorithm was used for segmentation in [16]. In [40] the authors present a new object based segmentation using fuzzy clustering algorithm for an X-ray image having two objects (femur and tibia).

**Classification-based segmentation techniques** are supervised methods. They require a training phase, in which the training data is manually segmented. Based on the training phase results, the test data is automatically segmented. Several classification methods are described in the literature. They can be categorized in: nonparametric classifiers (the nearest-neighbor classifier, the k-nearest-neighbor classifier, the Parzen window) and parametric classifiers (the maximum likelihood and Bayes classifier). In the case of the nearest-neighbor classifier, the pixels belonging to the test data are classified in the same class as the pixels with the closest intensity from the training data. The k-nearest-neighbor (kNN) classifier is the generalized nearest-neighbor classifier. In this case, each pixel is classified in the most appropriate class among its *k* nearest neighbors considering the weighted majority of its neighbors' votes. Parzen windows can be viewed as the generalized kNN algorithm. The algorithm considers all pixels in the voting scheme and assigns their weight using a kernel function. Parametric classifiers assume a probability distribution of data.

The disadvantage of classification algorithms is the lack of spatial modeling. This problem is raised, when images corrupted by intensity inhomogeneities must be segmented. The accuracy of this algorithm largely depends on the selected training samples.

Classification-based techniques were used in [22] where an adaptive fuzzy method was used for lateral skull segmentation. However, classification-based algorithms are generally not effective for X-ray image segmentation, due to the intrinsic properties of X-ray images and also because X-rays are affected by noise and may produce over-segmentation [2].

### C. Deformable models

Image segmentation using traditional low-level methods requires considerable amounts of expert interactive guidance. Many limitations of traditional image processing techniques reduced or even eliminated by using a deformable model. Deformable models are dynamic models based on the idea of moving a curve or shape under the influence of external and internal. Deformable models became very popular and successfully used in image segmentation research areas, after the publication of the paper [13].

**Active contour models (ACM)** or snakes, iteratively deform the model and find the configuration with the minimum total energy. The energy function is the sum of the"external energy", also called the image energy and the"internal energy" in an image.

Representing the position of the snake parametrically by $v(s)=(x(s);y(s))$, with $x$ and $y$ as coordinate functions, and $s\in[0;1]$, the energy of a snake is:

$$E_{snake}=\int_0^1 E_{int}(v(s))+E_{image}(v(s))ds. \tag{12}$$

The internal energy helps to keep the continuity and regularity of the contour/surface. The external energy used to attract contour points to appropriate image features, [7], [14]. The algorithm attempts to minimize the sum of these two energies using a set of Euler equations.

The snake does not perform well with images that have curves or sharp bends in them.

**Level set methods** evolve a contour by handling a dimensional function, the level set function, $\phi(x,t)$. The contour can be obtained from the zero level set, $\Gamma(x,t)=\phi(x,t)=0$. The contour or surface evolution is controlled by the following equation:

$$\frac{\partial\phi}{\partial t}+\nabla\phi F=0, \tag{13}$$

where the speed term *F* describes the level set evolution and $\nabla\phi$ the gradient of $\phi$. By manipulating *F*, we can guide the level set to different areas or shapes, given a particular initialization of the level set function [15].

An edge indication function *g,* used to stop the evolution of the level set, near the optimal solution [16], is computed as:

$$g=\frac{1}{1+\nabla(G_\sigma * I)^2}, \tag{14}$$

where $G_\sigma * I$ represents the image *I* convolved with a Gaussian filter $G_\sigma$. The resulting function *g* is close to zero in the areas of high gradient, and is positive elsewhere.

Another formulation for level set segmentation is:

$$\frac{\partial\phi}{\partial t}=g\,|\nabla\phi|\,(\mathrm{div}(N)+\nu), \tag{15}$$

where *div(N )*approximates mean curvature and $\nu$ is a customable balloon force, [16]. The level set iteration can be terminated once $\phi$ has converged, or after a certain number of iterations.

**Active Shape Models (ASM)** work on shapes, learned from training images, and then they try to locate the shape in a test image. A shape is a collection of points and can be represented by a diagram showing the points, or as an n×2 array, where the *n* is the number of points and 2 represents the x and y co-ordinates of the points. The distance between two points can be computed as Euclidean distance between them. The distance between two shapes can be defined as the distance between their corresponding points.

The first stage in the Active Shape Model comprises of training images to learn the shape that has to be found in the test image. In the training phase, aligning different shapes is important to get the mean shape. Aligning shapes is trying to get all the shapes in the same orientation [14].

There are several advantages in using deformable models for segmentation: deformable models are robust to artifacts and noise, have good performance for images with a small value if the signal-to-noise ratio (SNR), and are easy to interact with, based on user defined forces. In addition, by using the parameterized deformable model, it is easy to obtain a sub-pixel accuracy in segmentation applications [7].

Deformable models have been used for segmenting various types of medical images such as X-rays, MRIs ultrasound images, CTs, or angiographies. They have been used to segment a variety of anatomic structures, such as brain and brain tumors, cellular structures, kidneys, lungs, heart, coronary and retinal arteries, stomach, liver, skull, or vertebra, [5]. Snakes were used in [28] and [29] for extracting the contour of the femur from hip X-rays, in [30] for separating the tibia and femur from knee X-rays, in [31] to extract the contours of teeth, or in [32] to segment the hand bones. Active Shape Models have been originally proposed by the authors of [33] and [34]. In [35], ASM were used for the segmentation of the lumbar and cervical vertebrae, in [36] for femur segmentation or in [37] for pelvis and femur segmentation. Level set methods have been effectively used in [26], where the authors presented a multi resolution level set model for chest X-ray images. In [16], a fuzzy level set algorithm is described. Fuzzy clustering facilitates the level set segmentation. The fuzzy c-means algorithm was used for a first segmentation, and then level set methods were used for increasing the segmentation accuracy, by observing the boundary variation.

### *D. Wavelets based methods*

When dealing with images segmentation, many authors recommend the use of real or complex wavelet transforms. These decompositions capture the directionality, the structure and the dimensions of the objects embedded in the image under analysis. The objective of the statistical segmentation methods is to select a whole set of parameters from the wavelet coefficients of any pixel of the image analyzed and to compute a distance between this set of parameters and a set of parameters which characterizes a specific region of the image. If this distance is sufficiently small, the current pixel will be associated with the considered region. If not, another specific region will be considered. Basically, there are two types of distance which are computed in segmentation applications: the Euclidean distance and the Kulback-Leibler (KL) distance. Generally, the Euclidean distance is used when the set of parameters already mentioned is a features vector. This is a vector composed by some local values of statistical moments computed in a neighborhood centered in the current pixel. For example, the features vector can be formed considering the local mean and the local standard deviation of the current pixel computed in a rectangular neighborhood with size 5×5. The KL distance is computed between two probability density functions (pdf). Both distances require some statistical models of the "segments" of the image under investigation. Different models of the wavelet coefficients were already tested.

The advantage of the wavelets based algorithms is that wavelets decrease the number of performed computations and increase the segmentation speed.

Morphological and wavelet based transforms are used in [24]. In [27], the authors proposed wavelets based approach for tooth segmentation. The multi resolution has been used in [26] for lung segmentation.

### *E. Atlas based methods*

Atlas-based segmentation methods represent a powerful tool in medical imaging, used in detection and diagnosis of diseases. These methods involve a reference image (the atlas), which contain relevant information about anatomical structures (location, shapes, relationships between structures), obtain by manual segmentation or provided by an expert.

The method has three stages: the first stage, registration, in which the image is compared to each atlas image, the second stage implies the selection of the atlas, that best matches the original image and the third stage, the local refinement of the chosen atlas image(aligning of the atlas and the target as accurately as possible) [2].

The most frequently applied transformations in the first stage are the similarity transformation, the affine transformation (linear transformations) or low-order polynomial (non-linear transformation). The transformation can be performed manually, semi-automatically or automatically. From the automatic methods belong the following algorithms: the Iterative Closest Point (ICP) based algorithm, the optical flow-based algorithm, or optimization-based algorithms (gradient descent, Levenberg-Marquardt, simulated annealing). The methods used for local refinement are highly complex since the methods in this stage focus on the details of the atlas and the target image [2]. Two major approaches used for local refinement include: local deformation, which deforms the atlas locally and fits it to the target image accurately and pixel classification, which separates the pixels into several groups, and each corresponds to an anatomical part [2].

Atlas-based segmentation methods are similar to classifiers, with the difference that they are implemented in the spatial domain and not in the feature space of the image.

An important advantage of atlas-based segmentation is their use in clinical practice, for computer aided diagnosis. They are often used for measuring an object’s shape or to detect morphological differences between patients groups. However, they are time-consuming.

Atlas based segmentation techniques usually have been proposed for heart and especially for brain segmentation, but also for femur segmentation in [38].

### *F. Knowledge-based techniques*

Another class of segmentation methods is knowledge-based. The algorithm is supposed to be trained using some domain specific rules, and the best way of representing them is **ontology**-based. In [17] the authors proposed an application to determine thoracic structures based on ontologies. The method consists of several hierarchies, especially meant for image segmentation: radiograph entity, features and landmarks. The ontology is centered on radiography entities. The authors of [18] proposed a knowledge-based approach for analyzing and segmenting lung boundaries in chest X-rays. The approach is based both on knowledge derived from both model and image, with the purpose of spatially constraining the extraction of a given anatomical structure. The authors proposed modeling methods for normal and pathological changes in the anatomy. The Canny operator is applied the at multiple resolutions.

**Artificial Neural Networks (ANNs)** can be used for X-ray image segmentation. The use of ANNs for medical image segmentation simplifies the process when dealing with complex images. Feed-forward (associative) and feedback (auto-associative) networks have been used for image segmentation. The most used ANN for segmentation in medical imaging is the feed forward neural network. The advantage is that the segmentation using feed forward neural networks produces less noisy images.

In [19] the authors used Back Propagation Networks and Counter Propagation Networks to separate the bone from the thigh in the image, and to identify irregularities. In [20] the authors used ANNs for chest X-ray segmentation. In [21] the authors propose a rule-based system for X-ray image segmentation.

**Bio-inspired algorithms (BIAs)** represent an innovation in biomedical image segmentation techniques. These algorithms are inspired from the behavior of natural systems and are used for optimization.

BIAs can be divided in three categories of algorithms: Evolutionary Algorithms (EAs), Swarm Intelligence (SI) and Ecology Inspired Algorithms (EIAs).

*Evolutionary Algorithms (EAs)* are the most well-known BIA. They are stochastic optimization algorithms, based on the genetic adaptation of organisms [41]. EAs include: genetic algorithms (GA), genetic programming (an extension of GA), Differential Evolution, Evolutionary Strategy and Paddy Field Algorithm. A detailed description of these algorithms is given in [41]. Among them GAs are the most popular in image segmentation. Radiographic image segmentation methods, using GAs, have been proposed in [42] and [43].

*Swarm Intelligence (SI)* [44] is a new and in developing model in bio inspired computing. SI is based on the social behavior of organisms [41]. Swarm Intelligence comprises a series of algorithms such as: Particle swarm optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony Algorithm (ABC), Fish Swarm Algorithm (FSA), Intelligent Water Drops Algorithm (IWD), Bacterial Foraging Optimization Algorithm (BF0), Firefly algorithm, Group search optimizer (GSO), and Shuffled frog-leaping algorithm (SFLA) [41]. Among them PSO, ABC and ACO, were successfully used in image processing. PSO simulates the behavior of flocks of birds, groups of fishes or insects, ACO is inspired by the behavior of ant colonies in finding their way to the food, and ABC is inspired by the behavior of swarms of honey bees.

In [44] the authors show that Swarm Intelligence (the ACO and PSO algorithms) can improve the performance of clustering based image segmentation. In [45] a new segmentation method for dental X-rays, based on SI is proposed. In [46] the authors compared two clustering algorithms, one based on PSO and the second based on ABC for MRI images. In [47] the ACO algorithm was used for segmentation and edge detection in mammograms and microtomographies. The authors of [48] proposed an edge detection technique, using ACO and Artificial Neural Networks, for biomedical images.

*Ecology Inspired Algorithms (EIAs)* include Biogeography-Based Optimization (BBO), Invasive Weed Optimization (IWO) and PS20. BBO is based on the mathematical modeling of the geographical distribution of plants and animals (for example migration or mutation). BBO algorithm has been used recently in image segmentation as well. The authors of [49] proposed a BBO based approach for image segmentation.

## III. CONCLUSIONS

In this paper we described a series of approaches that have been published in the recent literature, concerning medical images segmentation. We provided an overview regarding the implementation of each segmentation method, highlighting advantages and disadvantages. The evaluation of these segmentation techniques can be done, in terms of: performance, sensitivity to noise, computational complexity, or the necessity of training phase. The most accurate techniques are the most complex and time consuming. We realized the classification starting with the most simple and fast methods and we increased the computational complexity and the processing time with each presented method.

Thresholding is one of the most simple segmentation techniques. The disadvantage of thresholding methods is that they can be applied to a single-band image, such as a gray-scale image or a single band of a multi-band image.

Region based methods have shown to be very useful and efficient segmentation techniques in image processing. However they have over-segmentation tendency, require manual initialization and are sensitive to noise.

Clustering technique can be used for multi-band images, but the number of groups must be established first. Classification-based algorithm requires a training phase.

Deformable models are less sensitive to noise than the other techniques presented in this chapter, which make them suitable for complex medical image segmentation problems.

Atlas-based methods use prior knowledge in order to perform segmentation, but they are time-consuming.

Generally, thresholding, edge-based, region based, and classification-based algorithms can solve simple medical image segmentation problems. For complex medical images, which cannot be handled robustly by general segmentation methods, deformable models and atlas-based segmentation methods are the most appropriate. Another solution is to combine two or more segmentation techniques. As future work, we intend to combine a classical image segmentation technique for an initial segmentation and then to apply a deformable model in order to increase the segmentation accuracy.

Bio-inspired algorithms are among the most powerful algorithms used for optimization. Recently, BIAs have proven efficiency in handling computationally complex problems. So, another idea is to use a bio-inspired optimization technique, for example to determine the input parameters, before applying a classical segmentation algorithm.

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