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LEVEL SETS AND COMPUTATIONAL INTELLIGENCE ALGORITHMS TO MEDICAL IMAGE ANALYSIS IN E-MEDICUS SYSTEM

Tomasz Rymarczyk
Netrix S.A., Research and Development Center, Związkowa Str. 26, 20-148 Lublin

Abstract. *In this work, there were implemented methods to analyze and segmentation medical images by using topological, statistical algorithms and artificial intelligence techniques. The solution shows the architecture of the system collecting and analyzing data. There was tried to develop an algorithm for level set method (LSM) applied to piecewise constant image segmentation. These algorithms are needed to identify arbitrary number of phases for the segmentation problem. The image segmentation refers to the process of partitioning a digital image into multiple regions. There is typically used to locate objects and boundaries in images. There was also shown an algorithm for analyzing medical images using a neural network MLP.*

Keywords: segmentation, image analysis, level set method

ZBIORY POZIOMICOWE I ALGORYTMY INTELIGENCJI OBLICZENIOWEJ DO ANALIZY OBRAZÓW MEDYCZNYCH W SYSTEMIE E-MEDICUS

Streszczenie*. W artykule zostały zaimplementowane metody do analizy i segmentacji obrazów medycznych przy użyciu algorytmów topologicznych, statystycznych i technik sztucznej inteligencji. Rozwiązanie przedstawia architekturę systemu do gromadzenia i analizy danych. Opracowano algorytmy oparte na metodzie zbiorów poziomicowych (MZP) jako odcinkowo stałą segmentację obrazu. Algorytmy te są potrzebne do identyfikacji dowolnej liczby faz dla problemu segmentacji, która odnosi się do procesu dzielenia cyfrowego obrazu w różnych regionach. Metoda używana jest zwykle do lokalizacji obiektów i brzegów w obrazach. W pracy przedstawiono również algorytm do analizy obrazów medycznych z wykorzystaniem sieci neuronowej MLP.*

Słowa kluczowe: segmentacja, analiza obrazów, metoda zbiorów poziomicowych

Introduction

This paper presents the architecture of the system collecting data and analyzing medical images. The picture understanding is the process of actually interpreting those regions/objects to figure out what's actually happening in the image. This may include figuring out what the objects are, their spatial relationship to each other. It may also include ultimately making some decision for further action. Medical images are pictures which make it possible to visualize the inner part of the body of an organism. There are used in the clinical diagnostic. Such images can make it possible to analyze a specific function performed in a specific area. Level set methods are the numerical techniques which can follow the evolution of interfaces. These interfaces can develop sharp corners, break apart, and merge together.

In medical clinical research and practice, imaging has become an essential part to diagnose and to study anatomy and function of the human body. The proposed algorithms have been used to real pictures with promising results in the medical images segmentation. The level set methods have natural flexibility to create various shapes. The segmentation gives good results, because the region borders accurately locating the object edges. An increasing numbers of iteration the quantitative results are better but it is not the principle [4, 18].

The application can use the following data sources:

- Electrical Impedance Tomography,
- DICOM,
- Images,
- Databases.

In medical clinical research and practice, imaging has become an essential part to diagnose and to study anatomy and function of the human body. The architecture of such the medical system was projected in the Figure 1.

The e-Medicus system consists:

- artificial intelligence algorithms,
- segmentation algorithms
- the framework,
- agents,
- topological algorithms,
- databases,
- visualization systems,
- the user interface.

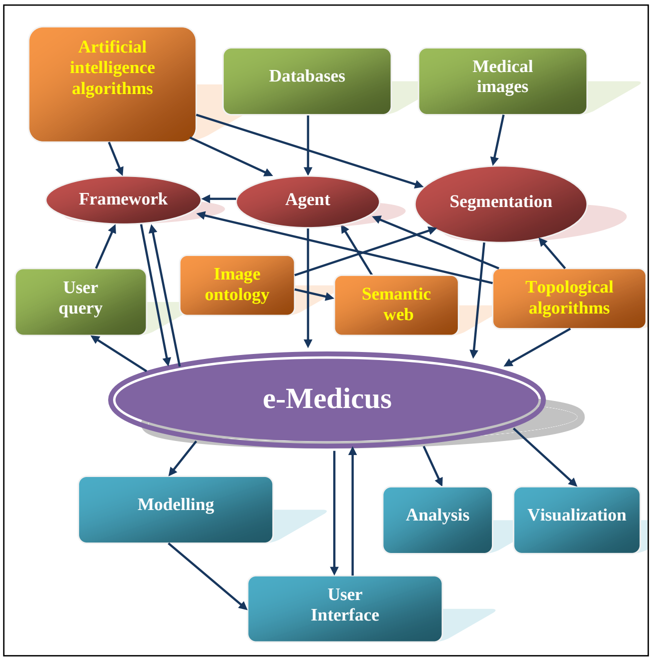

Fig. 1. The architecture of the e-Medicus system

1. Electrical Impedance Tomography

In medical research there was noted that among the healthy tissue and the diseased there are differences in electrical properties. Electrical impedance tomography can be used in some fields of medical diagnostics, such as gastroscopy and lung ventilation. Completed research allow to analyze changes resistance in the chest during the two physiological processes. In the first case, the observed resistance changes in the breathing cycle. The amount of air in the lungs, which is a poor conductor of electric current changes during breathing, at the same time so the resistance of the body. The second physiological process can be observed resistance changes caused by heart work. Blood is a good conductor of electricity and thus can easily visualize changes in blood volume in the selected plane chest.

Figure 2 shows the image reconstruction on the basis of numerical simulation of the measurement data using the level set method.

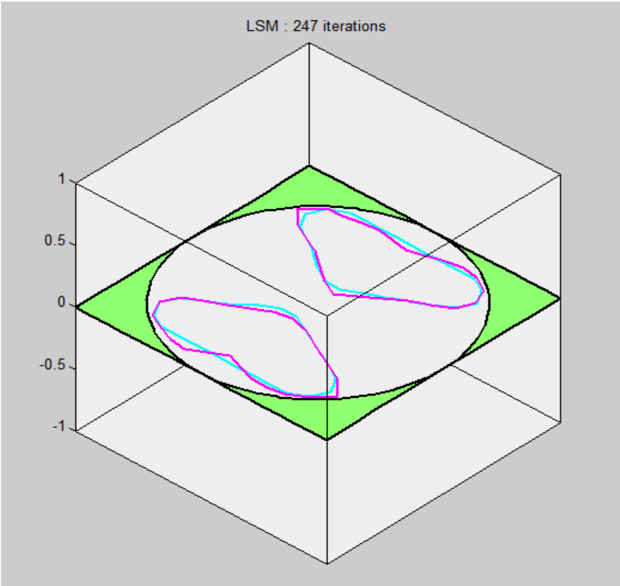

Fig. 2. Image reconstruction in the lung using the level set method - after 247 iteration (pink line – reconstructed image, aquamarine color- original objects)

2. Diagnosis and Segmentation

The image segmentation refers to the process of partitioning a digital image into multiple regions. There is typically used to locate objects and boundaries in images. The level set method is a powerful tool for representing moving or stationary interfaces. There was used the idea of the variational formulation for geometric active contours. There was used to the problem minimization in image processing to compute piecewise-smooth optimal approximations of the given image. The proposed algorithm has been applied to real pictures with promising results in the image segmentation. The level set method tracks the motion of an interface by embedding the interface as the zero level set of the signed distance function. The motion of the interface is matched with the zero level set, and the resulting initial value partial differential equation for the evolution of the level set function. The idea is merely to define a smooth function $\phi(x,t)$, that represents the interface as the set where $\phi(x,t) = 0$. The motion is analyzed by the convection the ϕ values (levels) with the velocity field.

For more than two phases was introduced the multiple level sets idea by Vese and Chan. The algorithm set formulation and algorithm for the general Mumford-Shah minimization problem in image processing, to compute piecewise-smooth optimal approximations of a given image [9-11, 22].

The problem can be easily generalized to the case where the domain contains more than two materials.

$$F(s,C) = \omega L(C) + \eta \int_{\Omega}(s_o - s)^2 d\Omega + \int_{\Omega\backslash C} |\nabla s|^2 d\Omega \quad (1)$$

The process for minimization of the functional is the following:

$$\frac{\partial\phi}{\partial t} = \delta_{\varepsilon}(\phi)\left[\omega\nabla\cdot\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - \eta_1(s_o - c_1)^2 + \eta_2(s_o - c_2)^2\right] \quad (2)$$

where coefficients c_1 and c_2 are mean values of points in the picture.

The formulation of the variational level set method consists of an internal energy term that penalizes the deviation of the level set function and an external energy term that drives the motion of the zero level set toward the desired image features. When flat or steep regions complicate the determination of the contour, the reinitialization is necessary. This reinitialization procedure is based by replacing by another function that has the same zero level set. Variational formulation for geometric active contours that forces the level set function to be close to a signed distance function, and therefore completely eliminates the need of the costly reinitialization procedure [12-17, 19].

The resulting evolution of the level set function is the gradient flow that minimizes the overall energy functional:

$$P(\phi) = \int_{\Omega}\frac{1}{2}(|\nabla\phi| - 1)^2 dxdy \quad (3)$$

An external energy for a function $\phi(x, y)$ is defined as below:

$$E(\phi) = \mu P(\phi) + E_m(\phi) \quad (4)$$

where

$P(\phi)$ – internal energy, $E_m(\phi)$ – external energy.

Denoting by $\frac{\partial E}{\partial \phi}$ the Gateaux derivative of the functional **E** receiving the following evolution equation:

$$\frac{\partial\phi}{\partial t} = -\frac{\partial E}{\partial\phi} \quad (5)$$

In the image segmentation active contours are dynamic curves that moves towards the object boundaries. Denoting letter I as an image, and g be the edge indicator function defined by:

$$g = \frac{1}{1+|\nabla G_{\sigma} * I|^2} \quad (6)$$

where G_{σ} is the Gaussian kernel with standard deviation σ.

The process for minimization of the functional E is the following:

$$\frac{\partial\phi}{\partial t} = \mu\left[\Delta\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right] + \lambda\delta(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + \omega g\delta(\phi) \quad (7)$$

The formulation of the variational level set method with Mumford-Shah model is following:

$$F(\phi, C_1, C_2) = \int_{\Omega}\frac{1}{2}(|\nabla\phi| - 1)^2 dxdy + \omega\int_{\Omega}|\nabla H(\phi)|\, d\Omega +$$
$$+\lambda_1\int_{\Omega}(u_o - c_1)^2 H(\phi)\, d\Omega + \lambda_2\int_{\Omega}(u_o - c_2)^2(1 - H(\phi))\, d\Omega \quad (8)$$

3. Thorax analysis

Medical image segmentation is an essential technique. Among the many available methods it is impossible to identify the ultimate method in medical applications. In the level set method there is provided the algorithm with parameters. So it isn't fully automatic. The user has to type in a number of parameters and every time the parameters are changed, the output of the algorithm changes, meaning that we have to spend a lot of time to tell the algorithm what exactly it is that we want to find on the picture, and after several tries, it will do, what we want it to do, but this solution is not perfect (Fig 3). The downside is that it does not perform well with medical images.

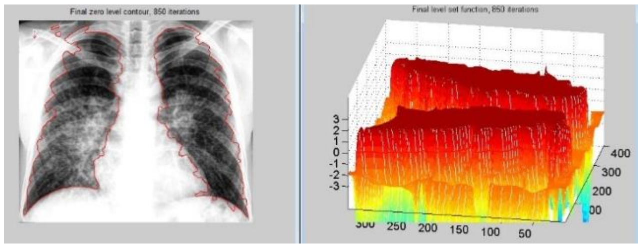

Fig. 3. The image reconstruction by the variational level set method

Souleymane Balla-Arabé, Xinbo Gao and Bin Wang introduce a fast and robust level set method for image segmentation using fuzzy clustering and lattice Boltzmann method [2]. Using: Fuzzy c-means, image segmentation, intensity inhomogeneity, lattice Boltzmann method, level set equation, partial differential equation. Considering the current pixel to be inside or outside of the active contour. Using modified fuzzy C-means objective function which also takes into consideration the shading image due to the intensity inhomogenity. In this method, using a modified FCM objective function, was formed a new fuzzy external force. The image reconstruction of chest by the fast and robust level set method is presented in Figure 4.

Fig. 4. The image reconstruction by the fast and robust level set method

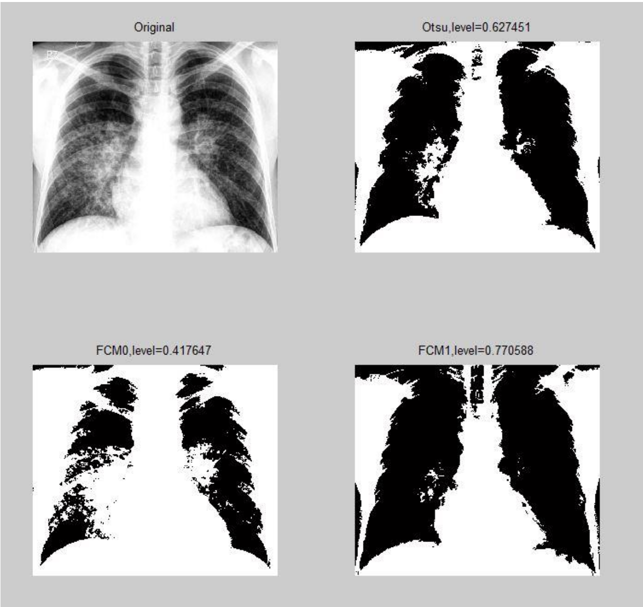

Fig. 5. FCMThresholding - sarcoidosis

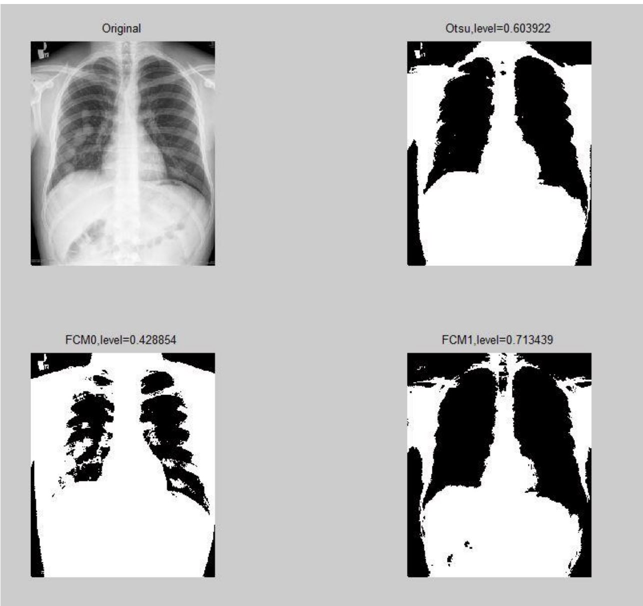

Fig. 6. FCMThresholding - metastasis

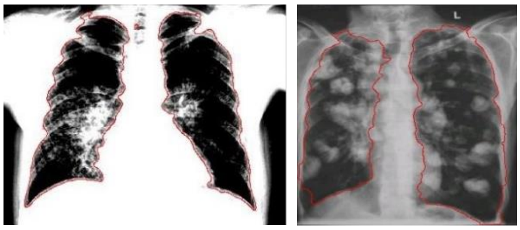

Fig. 7. Sarcoidosis on the left image, metastasis on the right one, the contour function is a result of the level set function

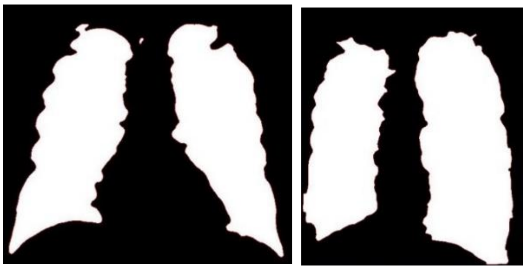

Fig. 8. The divides an image into two areas – black and white, where white area is the area that we are interested in for further analysis

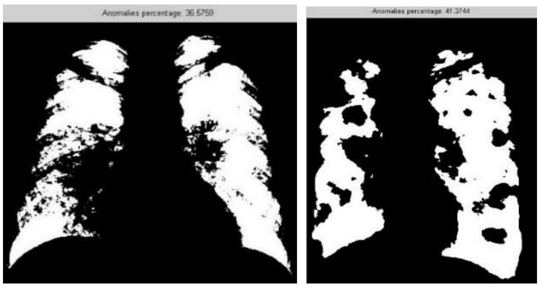

Fig. 9. Final results, we get an estimated percentage of anomalies present on the area of interest; results are visible on the top of every image, where image on the left shows sarcoidosis results, and image on the right shows metastasis

The fuzzy c-means thresholding is the simplest method of segmentation available, and yet it performs perfectly. Images obtained by running this algorithm are created in well under a minute, and the results are easy to see with a naked eye, even to a person who has never seen a medical image before. It is very easy to notice the difference between a healthy lung x-ray and one that has any changes in it. The main advantage of this method is that it barely required any computing power, thus the resolution of an input image becomes irrelevant. There have chosen two chest x-rays, one with sarcoidosis and one with metastasis (Fig. 5-9).

4. Pigmented skin lesions

Skin surface microscopy rules were formed in 1920 by Saphier, but just from 90' this method is widely used by dermatologists as most popular, easy and noninvasive techniques for in-vivo observation of the pigmented skin lesions. Using the simple epiluminescence microscope (dermatoscope) it gives the possibility to evaluate pigmented structures within epidermis, the dermoepidermal junction and the superficial dermis. The standard evaluation procedure is based on 2 basic steps developed by Braun-Falco. The first step should be identification of the lesion as melanocytic or non-melanocytic [1, 3, 6, 7, 20–23]. In case of the identification of the melanocytic lesion next step should be classification as benign, malignant or "suspicious" (Fig. 10).

Currently the most commonly used method for screening and the fast evaluation of the melanocytic lesions is ABCD rule, which according to Nachbar showed 92% specificity, 91% sensitivity and 80% of diagnostic accuracy in evaluation of malignant melanoma. It bases on evaluation of lesion in 4 aspects: A – Asymmetry, B – Borders, C – Colours, and D – Differential structures (tab. 1).

Figures 11 presents the image segmentation by using the level set algorithm (the pigmented skin lesions).

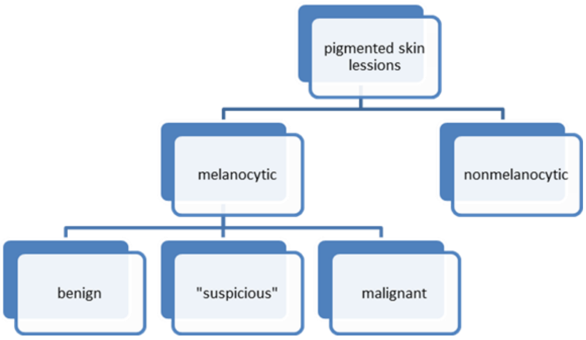

Fig. 10. The two-step procedure for the classification of pigmented skin lesions

Table 1. ABCD rule parameters description

Parameter		Description	Values	TDS weight factor
A	Assymetry	Complete symmetry, asymmetry in 1 or 2 axis	0-2	1,3
B	Borders	8 segments, 1 point for abrupt cut-off of pigment	0-8	0,1
C	Colours	1 point for each color: white, red, light brown, dark brown, black, blue-gray	1-6	0,5
D	Differential structures	1 point for every structure: pigment network, structureless areas, dots, globules, streaks	1-5	0,5

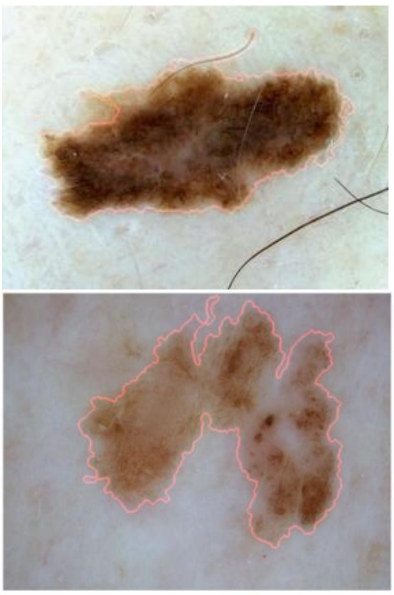

Fig. 11. The medical image analysis by Level Set Method with the Mumford-Shah model (looking for areas with specific characteristics)

5. Dental images

Segmentation presented in this chapter is an attempt of such a classification pixel in the image to the appropriate groups to receive separate areas as a result and thus to locate the disease states of soft tissue around the teeth. Object recognition using statistical methods can be divided into two categories: unsupervised classification methods and the methods of supervised classification. In the first case, belonging data to the classes is determined by the largest similarity of the classified pixels. In the second case, there is known training set that already contains information about belonging data to classes. The work proposes k-mean algorithm, k-nearest neighbour algorithm and Bayesian algorithm. The Euclidean metric was used to measure the distance between points in the first two algorithms.

Although, this algorithm as an example of supervised classification has a learning set, it does not have a classical learning stage, but only a recognition stage, which relies on calculating the distance between classified point and all the points in training set. Then, the smallest distance is selected e.g. there are selected k points which lie closed to the classified point. Finally, this point is included to the group, to which most of its neighbours were included (Fig. 12 and 13).

Fig. 12. The original image

Fig. 13. The segmentation result on 4 clusters using k-nearest neighbour with euclidean distance

The Bayesian algorithm based on Bayesian's Theorem is another method used to classify objects. Also in this case, the number of classes M is known in advance and is usually fixed by specialist from the area, on which the classification refers to. In turn, the allocating of objects x to classes takes place in an unambiguous manner. Because they can be described with plenty of features, before the applying the algorithm it must be first selected only those that are significant in terms of the classification [5, 8].

This algorithm, for $j = 1, \ldots, M$, is determined by the formula:

$$P(J = j \mid X = x) = \frac{P(X=x \mid J=j)P(J=j)}{P(X=x)} \quad (9)$$

where $P(J = j)$ is the probability distribution of classes, $P(X = x \mid J = j)$ is the probability distribution features in these classes and $P(X = x)$ is the probability distribution all features. The decision function has the form:

$$\Leftrightarrow P(J = i \mid X = x) = \max_{j=1,2,\ldots,M} \frac{1}{N\sqrt{2\pi}} \sum_{i=1}^{N_j} h_j exp\left\{-\frac{(x=x_{j,i})^2}{2}\right\} \quad (10)$$

for $i = 1,2,\ldots, M$.

Another algorithms are neural networks MLP (Multi Layer Perceptron) to detect changes periapical on digital dental images. There were used a collection of 160 images. In order to recognize changes on periapical dental digital image there was created neural network MLP with eight inputs and one output. Number of inputs describes the number of descriptors, while the number of outputs is determined by obtaining one of two responses: find or not find a change of the apical. The network has one hidden layer. As a result of learning there was achieved 98% effectiveness. The object was described by eight coefficients: surface area, ratio Feret, sphericity factor, compactness, the beads and shredding. In addition, two other factors: the coefficient of compactness and circularity convex there were used to describe the isolated areas, based upon the convex shells of these areas. The convex hull algorithm there was recovered by Graham. Designated descriptors were subjected to a process of normalization.

Figure 14 shows the medical image analysis – Neural Networks: (a) original picture, (b) searched object, (c) segmentation – Bayes algorithm.

6. Conclusion

In medical clinical research and practice, imaging has become an essential part to diagnose and to study anatomy and function of the human body. The proposed algorithms have been used to real pictures with promising results in the medical images segmentation. The level set methods. statistical algorithms, and the artificial intelligence algorithms have natural flexibility to create various shapes. The segmentation gives good results, because the region borders accurately locating the object edges. In the level set methods an increasing numbers of iteration the quantitative results are better but it is not the principle. There was also shown an algorithm for analysing medical images using a neural network MLP, which detects changes in apical. For the verification the method there were used dental images. There was achieved high efficiency of the learning network. In this work there were developed and implemented effective algorithms to segmentation, machine learning, analysis and compare medical images.

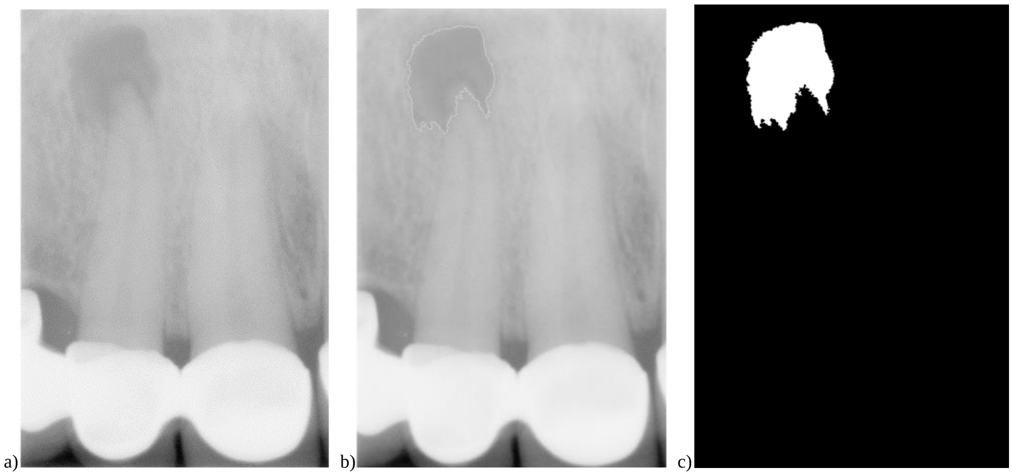

Fig. 14. The medical image analysis – Neural Networks: (a) original picture, (b) searched object, (c) segmentation – Bayes algorithm

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Ph.D. Eng. Tomasz Rymarczyk
e-mail: tomasz.rymarczyk@netrix.com.pl

Director in Research and Development Center Netrix S.A. His research area focuses on the application of non-invasive imaging techniques, electrical tomography, image reconstruction, numerical modelling, image processing and analysis, process tomography, software engineering, knowledge engineering, artificial intelligence and computer measurement systems.

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