

UDC 004.932.2

CLASSIFICATION AND ANALYSIS OF MEDICAL IMAGE SEGMENTATION METHODS FOR CUSTOM-MADE PROSTHETICS

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As a result of the full-scale war in Ukraine, there has been a significant rise in the number of patients with severe injuries and amputations, leading to a sharp increase in the demand for custom prosthetics and reconstructive solutions. In these circumstances, the accuracy of every stage in the creation of a prosthesis becomes particularly important, from obtaining the initial medical data to designing the socket. It is the quality of the digital representation of anatomical structures that determines the effectiveness of subsequent engineering modelling, the comfort of using the prosthesis, and the level of the patient’s rehabilitation.

In this context, medical image segmentation plays a key role as the fundamental stage in the transition from computed tomography data to three-dimensional models. Image segmentation is one of the key stages in the automated analysis of medical data. The main objective of segmentation is to divide an image into separate regions corresponding to different anatomical structures or tissue types. In medical imaging tasks, it enables the identification of the boundaries of organs, tissues or pathological formations for further analysis, measurement of geometric characteristics and the construction of three-dimensional models.

Medical image segmentation methods can be classified according to the principles on which the identification of individual image regions is based. The most common classification is into thresholding methods, clustering approaches, machine learning methods, boundary detection methods, regional methods and deformable models. This classification allows existing approaches to be systematised and the areas of their effective application in the analysis of medical data to be identified. [1]

Threshold segmentation

Threshold segmentation methods are based on classifying image pixels according to their intensity values. In the simplest case, a single global threshold value is used to separate the object from the background. This group also includes multi-level and adaptive thresholding methods, which take into account the more complex structure of the image.

Mathematically, threshold segmentation is described as the transformation of the original image $I(x,y)$ into a binary mask $B(x,y)$ based on a given threshold value T :

$$B(x,y) = \begin{cases} 1, & I(x,y) \geq T \\ 0, & I(x,y) < T \end{cases}$$

in the case of multi-level segmentation, a set of thresholds T_1, T_2, \dots, T_n is used to divide the intensity range into several classes:

$$C_k = \{(x,y): T_k \leq I(x,y) < T_{k+1}\}$$

or CT images, this model is particularly useful, as pixel intensity can be interpreted using the Hounsfield scale, and different tissue types correspond to different density ranges.

The advantages of thresholding methods include their simplicity, high speed and low computational cost. At the same time, they are sensitive to noise and intensity non-uniformity, which is frequently observed in medical images. Consequently, their effectiveness depends to a large extent on the quality of the image pre-processing [2]. Threshold segmentation allows the object to be effectively separated from the background by binarising the image.

Clustering methods

Clustering methods of segmentation are based on grouping pixels into clusters according to their similarity in terms of certain characteristics, such as intensity or textural features. This group includes traditional, hierarchical and partitioning clustering.

Mathematically, image clustering can be formulated as the problem of partitioning the set of pixels $X = \{x_1, x_2, \dots, x_N\}$ into K clusters C_1, C_2, \dots, C_K , where each pixel is described by a feature vector, such as intensity or a set of textural characteristics. For partition-based clustering, in particular the k -means method, the objective function is minimised:

$$J = \sum_{k=1}^K \sum_{x_i \in C_k} \|x_i - \mu_k\|^2,$$

where μ_k is the centre of the k th cluster. A pixel belongs to the cluster whose centre is closest to it:

$$c(x_i) = \arg \min_k \|x_i - \mu_k\|$$

in medical segmentation tasks, this model allows pixels to be automatically grouped; however, the result depends on the choice of the number of clusters and the initial position of their centres.

The main advantage of such methods is the ability to automatically divide an image into several classes without first defining the boundaries of the objects. However, clustering results may be unstable in the presence of noise and may also depend on the algorithm's initial parameters [3].

Machine learning methods

Machine learning and deep learning methods represent a modern direction in the development of medical image segmentation. They enable the automatic detection of complex patterns in data and the classification of pixels based on training examples.

From a mathematical point of view, machine learning methods treat segmentation as a problem of classifying pixels or image regions. For each pixel, a feature vector x_i is formed, and the model performs a mapping:

$$f_{\theta}(x_i) \rightarrow y_i$$

where y_i is the pixel class and θ are the model parameters. In the case of neural networks, the parameters θ are determined during training by minimising the loss function:

$$\theta^* = \arg \min_{\theta} L(y, \hat{y}),$$

where y is the ground truth label, and $\hat{y} = f_{\theta}(x)$ is the model's prediction. For segmentation tasks, pixel-level classification is often used, in which each pixel in the image is assigned to a specific anatomical class. The main limitation of this approach is the need for a large amount of labelled training data.

This group includes both classical machine learning methods and deep neural networks. The latter demonstrate high accuracy in segmentation tasks, but require significant amounts of labelled data and computational resources.

Edge detection methods

Edge detection methods are based on the search for abrupt changes in intensity that correspond to the boundaries between different regions of the image. To this end, operators are used to compute the image gradient.

Mathematically, edge detection methods are based on the analysis of the image intensity gradient. For an image $I(x,y)$, the gradient is defined as:

$$\nabla I(x, y) = \left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y} \right)$$

The gradient magnitude characterises the rate of change in brightness:

$$|\nabla I(x, y)| = \sqrt{\left(\frac{\partial I}{\partial x} \right)^2 + \left(\frac{\partial I}{\partial y} \right)^2}$$

The boundary of the object is defined at points where the gradient magnitude exceeds a specified threshold T_g :

$$E(x, y) = \begin{cases} 1, & |\nabla I(x, y)| \geq T_g \\ 0, & |\nabla I(x, y)| < T_g \end{cases}$$

Thus, contours are defined as regions of abrupt changes in intensity, corresponding to transitions between different tissues or structures.

Such methods allow the contours of objects to be identified; however, they are sensitive to noise and may result in gaps in the contours. In medical images, this is particularly critical, as the boundaries between tissues may be blurred [4].

Thus, the classification of medical image segmentation methods allows for the systematisation of existing approaches and the identification of their strengths and weaknesses. Each of the groups of methods considered has its own characteristics, which must be taken into account when selecting an algorithm for processing computed tomography images.

Having reviewed the main approaches to medical image segmentation, it is advisable to conduct a comparative analysis to identify the advantages, disadvantages and areas of effective application for each method. This allows for a well-founded choice of the approach to be used for processing computed tomography images.

Threshold-based segmentation methods are characterised by high speed and ease of implementation. They do not require significant computational resources and can be effective in cases where there is a sufficiently clear difference in intensity between the object and the background. However, in the presence of noise, heterogeneity or overlapping intensity values of different tissues, such methods can produce significant errors [2].

Clustering methods allow pixels to be automatically grouped without first defining the object's boundaries. This makes them versatile for different types of images. At the same time, they can be sensitive to initial conditions and do not always ensure the accurate determination of objects' geometric boundaries [3].

Machine learning methods, particularly deep neural networks, demonstrate the highest accuracy among modern approaches. They are capable of accounting for complex spatial relationships within an image and adapting to different types of data. However, their application requires significant amounts of labelled data, as well as substantial computational resources, which limits their use in certain practical tasks [5].

Edge detection methods allow for the effective identification of object contours in an image. They are relatively simple to implement, but their effectiveness depends largely on image quality. In the presence of noise or poorly defined edges, results may be unstable [4].

Regional segmentation methods enable the identification of homogeneous regions by analysing the spatial connectivity of pixels. They allow for the extraction of more coherent regions compared to thresholding methods, but require careful parameter tuning and the selection of initial conditions [6].

Deformable models are one of the most flexible approaches to segmentation, as they allow for the accurate description of complex object shapes. They are widely used in medical applications, but require significant computational resources and can be sensitive to the initial contour position [7].

Based on the analysis carried out, it has been established that a combined approach, which combines threshold segmentation and subsequent contour extraction, is appropriate for the task of processing computed tomography (CT) scans. In the first stage, threshold image processing is applied to separate the region of interest from the background, which allows for a rapid reduction in data volume and the identification of key structures [8]. This approach was chosen due to its computational efficiency and sufficient accuracy in the case of CT images, where different tissue types are characterised by differences in intensity.

In the next stage, the boundaries of the detected regions are refined using contour methods, which allows for a more accurate representation of the object's geometry. The use of this specific combination of methods is driven by the need to balance the algorithm's speed with the accuracy of contour detection. Unlike machine learning methods, the proposed approach does not require labelled data or significant computational resources, making it suitable for practical application under conditions of limited resources and variability in input data.

Thus, the chosen approach, based on a combination of threshold segmentation and contour analysis, is well-founded for the task of structure segmentation in computed tomography images and ensures the required level of accuracy whilst maintaining high computational efficiency.

Keywords: medical image segmentation, computed tomography (CT), 3D modelling, custom prosthetics, stump socket, digital anatomical models, medical image processing.

References

- [1]. Xu, Y.; Quan, R.; Xu, W.; Huang, Y.; Chen, X.; Liu, F. Advances in Medical Image Segmentation: A Comprehensive Review of Traditional, Deep Learning and Hybrid Approaches. *Bioengineering* 2024, 11, 1034.
- [2]. Mehmet Sezgin, Bülent Sankur, "Survey over image thresholding techniques and quantitative performance evaluation," *J. Electron. Imag.* 13(1) (1 January 2004).
- [3]. Jain, A.K. (2008). Data Clustering: 50 Years Beyond K-means. In: Daelemans, W., Goethals, B., Morik, K. (eds) *Machine Learning and Knowledge Discovery in Databases. ECML PKDD 2008. Lecture Notes in Computer Science()*, vol 5211. Springer, Berlin, Heidelberg.
- [4]. J. Canny, "A Computational Approach to Edge Detection," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-8, no. 6, pp. 679-698, Nov. 1986, doi: 10.1109/TPAMI.1986.4767851.
- [5]. Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghahfoorian M, van der Laak JAWM, van Ginneken B, Sánchez CI. A survey on deep learning in medical image analysis. *Med Image Anal.* 2017 Dec;42:60-88. doi: 10.1016/j.media.2017.07.005. Epub 2017 Jul 26. PMID: 28778026.
- [6]. O. Serdyuk i N. Stel'makh, «BIOMEDYCHNA VIZUALIZATSIYA TA STRUKTURNA OTSINKA KISTKOVOYI TKANYNY PRY OSTEOINTEHRATSIYI», *Byul. Kyyivs'ka politekh. in-t Ser. instrument. Mak., vyp. 69(1), s. 119–127, Cher 2025. DOI:10.20535/1970.69(1).2025.332029*
- [7]. Ronneberger, Olaf & Fischer, Philipp & Brox, Thomas. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. 10.48550/arXiv.1505.04597.
- [8]. Serdyuk O.V, Stelmakh N.V., “Review and analysis of methods of reconstruction and mathematical description of CT images,” *Scientific notes of Taurida National V.I. Vernadsky University. Series: Technical Sciences*, vol. 35 (74), № 3, pp. 215-221, 2024. DOI: 10.32782/2663-5941/2024.3.1/31

UDC 615.849.11

ROBOTIC MECHATRONIC PLATFORM FOR A HEALTHCARE FACILITY

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A modern medical institution, in particular a clinical one, requires increased efficiency of work, speed of response of personnel to complex challenges, which are characteristic of functioning of complex medical technologies of surgical