# HEMATOMA VOLUME DETECTION AND ESTIMATION FROM CT IMAGES

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***Keywords:*** *hematoma, image segmentation, volume calculation, CT image processing*

***Abstract:*** *The paper presents techniques for the detection of brain hematoma segmentation and volume calculation for images obtained from MRI and CT scans. We will survey a few semi-automatic detection techniques and a method for calculating the volume of the hematoma. The methods presented here are: Region Growing, Watershed and GVF Snake. Our purpose is to highlight which one of these methods is the quickest and brings up the most satisfactory results to be implemented and used in medical imaging applications. Also, we will conclude that our method for computing the volume of hematoma region is superior to the current methods.*

***Cuvinte cheie:*** *hematom, segmentare de imagini,calcularea volumului, procesarea imaginilor CT*

***Rezumat:*** *În acest articol vă prezentăm comparativ câteva tehnici pentru detecția volumului hematomului intracerebral, segmentarea acestuia precum şi calculul de volum pe imagini obținute din scanările MRI şi CT. Pe parcursul lucrării vor fi trecute in vedere câteva tehnici de detecție semi-automată , precum şi o metodă de calcul de volum a hematomului. Metodele prezentate sunt: Region Growing, Watershed şi GVF Snake. Scopul acestei lucrări este să evidențieze care din metodele propuse mai sus este cea mai rapidă şi cu cele mai satisfăcătoare rezultate pentru a putea fii implementată şi utilizată în aplicații de imagistică medicală. De asemenea se va concluziona asupra faptului că aceste metode calcul al ariei (volumul) regiunii cu hematom sunt net superioare metodelor curente de măsurare a hematomului.*

**SCIENTIFIC ARTICLE PREDOMINANT THEORETICALY**

Hematoma detection by image processing is an important step towards the application of a specific treatment and also, it allows physicians to visualize its form. Images used are mostly provided by a CT scan. One of the most important steps in processing the image is the segmentation process (1, 2, 3). Segmentation is the operation that decomposes the image in disjunctive fragments that are correlated with the exposed objects or areas. The segmentation will highlight and extract distinct objects or regions, which satisfy a certain criteria of uniformity or other elements of interest. As a mathematical definition of an *f* image segmentation process, is the complete partitioning of *f* into an ensemble of disjoint nonempty and connected areas, each of them satisfies a certain criterion *C.* Choosing a specific segmentation technique is related to several aspects of the proposed image for analysis and to user requirements. There are two types of segmentation (4): complete and partial. Complete segmentation generates a set of disjoint regions uniquely corresponding to objects from the image. To achieve a complete segmentation is necessary to cooperate with the superior processing levels, the artificial intelligence that uses industry specific knowledge. In partial segmentation, the image is divided into disjoint regions that are homogeneous relatively to some property such as brightness, color, reflectivity, and context.

Hematoma volume determination is of real importance in the clinical examination and treatment of a patient. Manual segmentation of brain hematoma using MR Imaging is a demanding and challenging task. A semi-automatic segmentation method called Region Growing is proposed in (5), in order to segment the brain hematoma using CT images. This method can successfully segment a hematoma whose parameters where set correctly. Important issues related to fundamental aspects of image segmentation methods, such as initialization (6), convergence (7), the ability to solve problems on the topological changes, stopping criteria and excessive segmentation must be considered.

Segmentation using deformable models deals with the image information and external constraints to guide the evolution of the so called snake model. Gradient Vector Flow (8, 9) solves largely the weak convergence problem by amplifying the image gradient in order to increase the radius of snake's capture (6, 7). Another segmentation method, the Watershed transformation, treats the image as a 3D surface, but can lead to an excessive segmentation. However, in order to overcome this inconvenience, methods have been developed combining watershed segmentation with GVF (10).

## 2. Segmentation techniques suitable for medical images

### 2.1. Local filtering.

It is the simplest method of segmenting an image and is based on the choice of gray levels, called segmentation thresholds that will allow the identification of the image regions (3). Typically these thresholds are chosen as suitable to the local minima of the histogram. The original image *f* builds an image of labels *g*, according to a transformation of the form:

$$g(m,n) = \begin{cases} E_0, & 0 \le f(m,n) < T_{K-1} \\ E_K, & T_{K-1} \le f(m,n) < L \end{cases}$$

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Article received on 28.02.2011 and accepted for publication on 21.06.2011
ACTA MEDICA TRANSILVANICA September 2011; 2(3)298-301

### 2.2. Region growing

Region growing technique detects a region by identifying the neighboring pixels in the image that have similar gray level as the starting point (4). Recursive algorithm ensures the expansion of the region in four directions (to the four neighboring pixels), if their intensities fall within [*m-t, m + t*], where *m* is the average intensity of the region, and *t* is a threshold value entered by the user. Another parameter to be set by the user is the starting point that can be entered by clicking the mouse on the image or by directly specifying its coordinates. The purpose of the method consists of a binary copy of the processed image, where a 1 represents a pixel of the object and a 0 indicates a pixel belonging to the background. The process stops when each pixel of the image was assigned to a class. The method has two basic steps: selecting the start points (initial points), called germs or seeds, and the effective growth of the regions. The final number of regions is equal to the number of germs initially selected for growth. In principle, it is desirable that each individual object in the image found to be marked by a germ. If inside an object are more germs, for each of them will be developed a region, which leads to an undesirable artificial segmentation of the object. This shortcoming can be corrected through a stage of fusion of the adjacent regions that have similar properties.

### 2.3. Deformable active contours ("Snakes") - Gradient Vector Flow (GVF)

Known in literature under the name of "snakes", the active deformable contours are mathematical models of semi-elastic wires (11). They can be used to segment the objects in two-dimensional images (with a closed curve form) or three-dimensional (closed surface form). Compared to the techniques using high pass filtering, contours extraction of objects by the above procedure has the advantage of greater robustness to noise (13). Besides, the technique provides continuous closed curves, eliminating the need for further unification of edges. Initialized in the proximity of an object, the active contour tends to approach its edges. Its final position is the expression of a compromise between the external forces that draw the outline to the discontinuities of the image and the internal forces whose role is to maintain the unity of the curve (elasticity forces) and to not allow the breaking of it (rigidity forces).

The limitations of the active contours are given by the necessity of initialization in the proximity of the object (capture area), in order to allow it the convergence to the right solution. Given the limitations of and the impossibility of tracing all the object details, the classical variant of the active contours does not always provide the best results. Increasing the working area of by the convolution with Gaussian two-dimensional functions can be done only within certain limits, otherwise the image details can be lost. As a result, a number of options have been proposed to improve the performance. Thus, by the addition of external pressure forces which tend to dilate or contract the active contour will increase the range (13). These forces are calculated as the gradient negative of a Euclidean distance map (distance potential forces). Neither this method allows an accurate tracking of all object details.

Other solutions for removing these limitations were proposed in (8). These are based on the use of an external force field, $V(x,y)=[u(x,y),v(x,y)]$ calculated to ensure minimizing of the functional energy. Using this force field (called "gradient vector flow") provides increased capture range and tracking ability of active contours.

### 2.4. Watershed

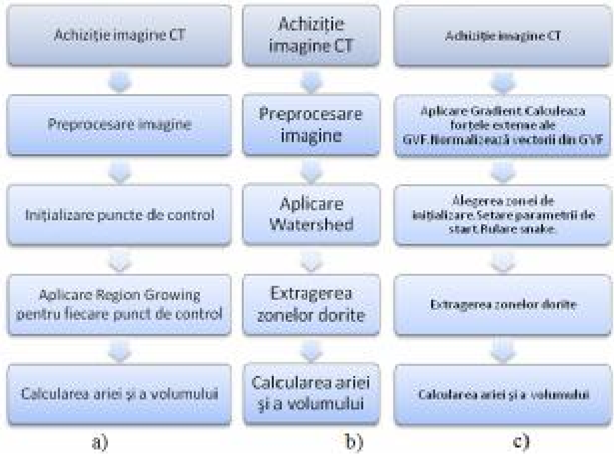
A technique similar to active contours is Watershed (4, 14). An image with gray levels can be seen as a topographic relief form, where a pixel gray level is interpreted as a relief elevation. A drop of water that starts flowing on a topographic relief flows along a route to reach a local minimum. Intuitively, the basin of one relief corresponds to the adjacent watersheds.

## 3. A new technique for extracting and computing the hematoma volume

### 3.1. Tresholding. Region Growing

As was previously presented, one of the methods used for brain tumor segmentation is Region Growing. The user must choose the starting points "seeds" and the algorithm starting from those points will detect the surrounded area. When using this technique, problems arise due to DICOM format images obtained from a CT acquisition

**Figura nr. 1. Processing steps:a) Region Growing; b) Watershed; c) GVF Snake.**

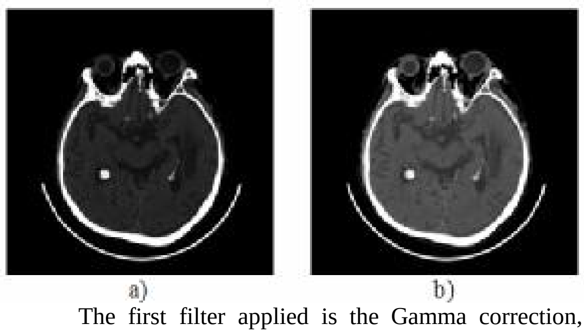



Although the images obtained from CT scans have a high-resolution, CT can introduce a lot of unwanted artifacts:

- Strip artifact (Streak) - these artifacts are seen especially in the material that blocks X-rays - metal or bone.
- Partial volume artifact - This area appears as "unclear" in the sharp edges.
- Ring artifacts - the most common mechanical artifact
- Noise artifacts - this is caused by poor signal to noise. May occur for example when X-ray power can't penetrate deep parts of the body.
- Movement artifact- may occur because the patient moves during image acquisition.

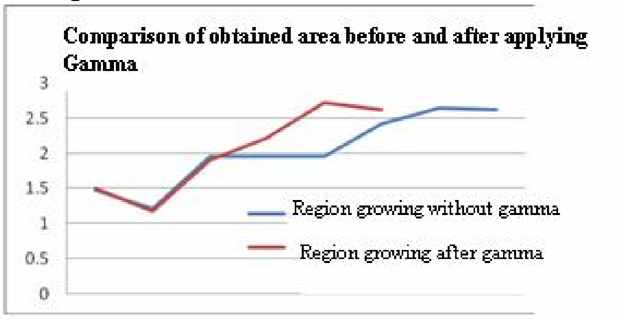
To remove unwanted elements that are influencing the quality of image processing, the algorithm will first do a pre-processing stage. This step will remove the artifacts, especially noise from the image**.**

**Figure no. 2. Pre-processing step a) Initial image; b) image after gamma filter**



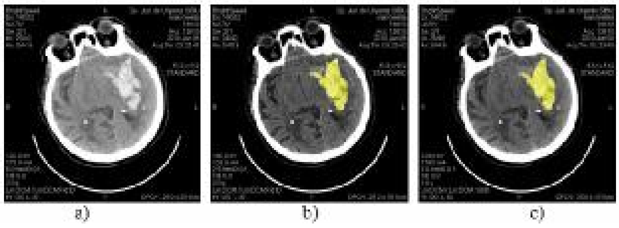

The first filter applied is the Gamma correction, a nonlinear operation that changes image brightness. When processing images from a CT, the hematoma appears as a white spot. Applying this filter ensures that the surround of the hematoma is ignored, the general area containing much noise. The results of this technique have generally the effect of decreasing the area of hematoma, as can be seen in the following graph.

**Figure no. 3 Area modification according to the gamma filtering**




The next step is to eliminate the noise. We will apply a median filter followed by a Gaussian filter, aimed to eliminate the "salt and pepper" noise. In the case of a low contrast image this technique must be used carefully, because it could introduce artifacts that will affect the hematoma detection.

**Figure no. 4. Results of noise filtering a) initial image; b) segmented image without gamma filter; c) segmented image with gamma filter**




After the preprocessing stage, we have applied the region growing algorithm. The basic idea of this image segmentation method is a simple. It starts with a group of pixels and examines all their neighbors. If one of them meets a certain criterion, it is added to the formed group of pixels. The process is continued till no more pixels are added to the region (see Figure 4). The major problem is defining the homogeneity criterion and the recursivity, which may require resources from the processing system.

The user will select some starting points within the hematoma but not part of the same area of hematoma (hematoma may be scattered in several areas of the brain), providing the seed points. Based on these points, the algorithm compares the value of the pixels with their neighbors using a similarity measure. If the metric is below a threshold set by the user, the current pixel is added to a queue of processed pixels and thus eliminating his future processing. When no more pixels are left unprocessed, the algorithm ends.

The next step is to extract contours from the obtained groups of pixels. After detection of the corresponding hematoma regions, we will calculate the area of each region using the following formula:

$$(\sum Nr) * A_{AreaOfPixel} * D_{DistanceSlice}$$

It does a sum of all pixels in the region and multiplies the value with the corresponding pixel area. The result is multiplied by the distance between tomography slices computing the hematoma volume. This technique is superior to the one proposed in (16), which calculates the volume by choosing a slice site hematoma that has the greater range, measuring the height and width of the area and approximating as an average-sized slice for this value. Although in many cases the value offered by this algorithm delivers satisfactory results, there are situations when due to the hematoma nature or its form, this approach has serious limitations. In figure 4b – 4c we presents cases were we successfully applied the region growing technique.

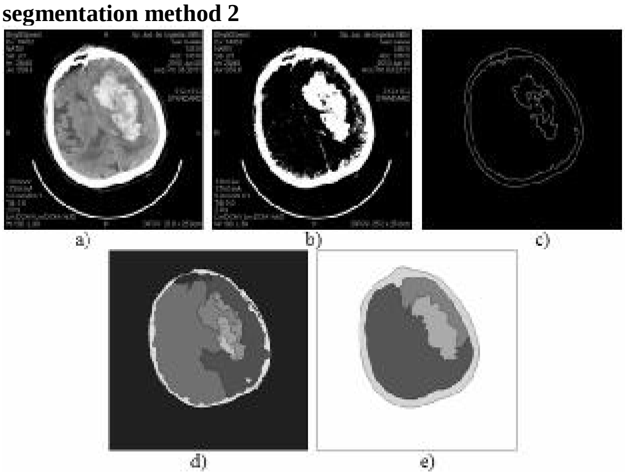
The main advantage of the proposed method is the processing speed and good results. We also noted the possibility of eliminating various types of noise in processed images, leading to increased detection. Note that the presented method may require more computing power due to recursive method of growing region. There are various ways to improve it, among them, the definition of Regions of Interest (ROI).

**3. 2. Segmentation using Watershed**

As stated in the previous chapter, during the segmentation algorithm is very important to pre-process, because image noise may adversely affect the result quality. It is therefore necessary to apply filters for image smoothing, which aim to mitigate noise and small fluctuations in image intensity. In this respect, we have applied a median filter with variable window. To validate a segmentation scheme we have tested two techniques: automatic segmentation and then manually selecting areas of hematoma, and manual selection of starting points from which to start Watershed segmentation algorithm.

For the first implementation of the algorithm, we have made an initial binary segmentation: if the value of the selected pixel is above the selected threshold then the pixel value will be 255 otherwise 0. The next step is to apply a filter to detect edges. We have used a canny filter, based on gradient image calculation. In addition, this technique maximizes the signal/noise ratio for accurate detection, good localization of edge points and minimizes the number of positive responses to a single edge.

**Figura nr. 5. Segmentation steps. a) original image; b) binarized image; c) after applying Canny filter; d) watershed segmentation method 1; e) watershed segmentation method 2**




Starting from these detected contours, a Watershed segmentation method is employed. One may note that due to image quality, the Watershed algorithm may produce image "over-segmentation". Another limitation is the large number of parameters required to be initially set by the user. Some predefined values cannot be used because each captured image may differ in brightness, artificial artifacts, etc.

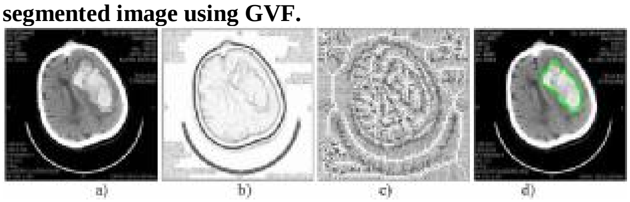
In order to overcome these disadvantages, we have tried a similar approach like in the Region Growing algorithm. We have defined for each hematoma area some checkpoints that will be the starting points for the Watershed algorithm. The results are superior compared to the previously presented method (see Figure 5d-5e). Also, this processing method can produce over-segmentation due to artifacts as it can be seen in Figure 5d.

Compared with the first technique presented, Watershed improves hematoma detection zone. The main disadvantage of the method is that each algorithm produces a local minimum region normally leading to an over-segmentation. The detection algorithm solves the problem, but the result is like a puzzle. One way to deal with this problem is the hierarchical interpretation of regions.

**3.3. Segmentation using Gradient Vector Flow – Snake**

By far the most accurate algorithm is the Gradient Vector Flow segmentation. Xu and Prince have proposed it in (8, 9) using a static external force field to gain a significantly better convergence in minimums. The method generates a field of external forces that will be used by the following Snake iteration. An important disadvantage is the complexity of the method that computes the GVF field. Another disadvantage is given by smoothed edges, especially in the case of two neighboring contours.

**Figure no. 6. Segmentation of a hematoma using GVF. a) Original image; b) Gaussian filter σ=1; c) GVF arrays; d) segmented image using GVF.**




The first step for GVF segmentation was applying a gradient filter and a Gaussian filter of $\sigma=1$. The next step was to calculate the external force vectors and the normalization of the GVF. We have used standard parameters $\mu=1$ and the number of iterations set to 80, resulting the GVF vectors shown in Figure 6c.

The last step in the segmentation framework was the snake iterations. The algorithm, as it can be seen from figure 6d, provides the best detection compared to the other two methods, but is computation time is prohibitive. The GVF enhance the concave object extraction capability. However, it has to suffer from the computing conditions and sensitivity to noise.

## CONCLUSIONS

Comparing all three methods with manual segmentation, we note that GVF detects the best areas of interest, the second algorithm is Watershed and Region Growing is on the last place. However, due to execution time and difficult to boot, the GVF algorithm can’t be implemented in a commercial application. Watershed segmentation was a running time close to Region Growing but suffers from the fact that in some cases, because of image noise and imperfections, it creates an over-segmentation. Region growing algorithm has the worst results, but on the other hand excels in a fast initialization and execution. The differences between him and the manual segmentation are on average less then $5mm^2$.

For further developments we would try to combine GVF and Region Growing algorithm as follows: Region Growing is executed to detect the approximate area of hematoma, to set a ROI area (not to calculate the GVF for all image) and then apply segmentation GVF. Theoretically this should improve the speed performance of segmentation. We will also study the results obtained with other methods, such as Otsu's method and Mean Shift.

**Tabel no. 1. Values obtained for each segmentation method. The values are in square cm**

| Imagine | Manual segmentation | Region Growing | Watershed | GVF Snake |
|---|---|---|---|---|
| 1 | 1371.00 | 974.50 | 1108.50 | 1183.00 |
| 2 | 2596.00 | 2134.50 | 2136.50 | 2398.12 |
| 3 | 3178.00 | 2638.50 | 2926.50 | 2564.20 |
| 4 | 3975.00 | 3890.50 | 4148.00 | 3937.85 |
| 5 | 4850.00 | 4649.50 | 4696.00 | 4867.97 |
| 6 | 6387.00 | 6003.00 | 6213.50 | 6283.02 |
| 7 | 6694.00 | 6171.50 | 6048.50 | 6789.44 |
| 8 | 9789.00 | 9256.00 | 9460.50 | 9603.75 |
| 9 | 11645.00 | 10619.50 | 11202.50 | 12422.76 |
| 10 | 12530.00 | 11939.00 | 12134.00 | 12583.37 |

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