

# Computer-aided Detecting of Early Strokes and its Evaluation on the Base of CT Images

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*Abstract*—This paper presents an easy way of finding strokes on computer tomography images. By calculating a cohesive rate (CR) of suspicious pixels on a series of CT images there is a possibility of calculating a general probability of a stroke. In a difficult case there is always an opportunity to generate a graph of all stroke probabilities interposed on the original image. It is a very helpful tool for specialists and neurologists working in emergency situations . Supported by grant N518 022 31/1338 (Ministry of Science).

### I. INTRODUCTION

A STROKE is a rapidly developing loss of brain functions due to a disturbance in the blood vessels supplying the brain. This can be due to ischemia (lack of blood supply), or due to a hemorrhage which is caused by a blood vessel that breaks and bleeds into the brain. The most common kind an is ischemic stroke. It is /found in about 85% of all the patients with strokes. This kind of disease is very serious and without suitable treatment it leads to death or long term disability.

The availability of treatments, when given at an early stage, can reduce stroke severity. Early diagnosis of acute cerebral infraction is critical due to the timing of thrombolytic treatment.

The clinical diagnosis of an ischemia stroke is difficult and it has to be supported by brain imaging. There are new effective methods for detecting strokes based on the images, but in most cases, a CT remains the most important and the most popular brain imaging tool. It is vital that no longer than 3 hours elapse between diagnosis and action planning that the appropriate treatment is given. During the initial 3 hours the area's ischemia CT attenuation decreases by 2-3 HU (Hunsfield Unit)[1]. The distinction of the colors on the CT images is so small that even a neurologist with great experience cannot see it.

After a few days damaged tissue is very noticeable, but it is too late for effective treatment. Because of the great importance of an early detection of the stroke, many authors presented various approaches to that problem [2-4].

The aim of this paper is to present a self-constructed, effective algorithm to support ischemic stroke detection based on CT images.

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#### II. Algorithm

The proposed heuristic algorithm analyzes a series of CT images of a brain. As a result algorithm generates graphs of the suspicious areas of the brain. Parts of the brain tissue which have the biggest probability of a stroke are highlighted. There is also a possibility to generate a full graph which contains the probabilities of a stroke in a colorful version. The algorithm also calculates a general probability of a stroke. Calculation are based on the patient's CT images. The method is based on a few important statements.

The first of them is about colors which represent the area of the probable stroke's location. According to [2] the area of ischemia CT attenuation decreases by 2-3 HU which means that the suspicious part in the CT image are a little darker than the common tissue of the brain.

The second statement is that strokes have a volume. It gives a possibility of seeing a stroke on more than one image.

The next statement is that strokes are solid structures. The lack of blood supply on the CT image looks like a large, solid and rounded figure.

The probability of a stroke happening on both sides of the brain is almost zero. The algorithm uses this fact and assumes that a stroke can be found only on one side of the brain[1].

The stroke detection contains four main stages.

#### A. Preprocessing

An image has to be prepared by separating the brain tissue from the scan, finding a symmetry of the brain and selecting suspicious points of the CT image where a stroke can be found. Preprocessing is extremely important because it shows significant features of the analyzed case.

Firstly, non-brain tissue must be removed from a CT image. It may be done through region growing. The skull surrounding the brain has an uninterrupted, rounded shape and on image it has a white color. That is why extraction of the brain tissue can be done by using simple figure filling algorithm (e.g., Smith's algorithm[5]). The starting point for extraction algorithm is the center of image and the filled colors have to be other than white (the skull is represented by a white color).

With this information the suspicious pixels are easily found. According to statements and experimental study colors which may represent a stroke are in range  $K \in \langle C_{\max} - g; C_{\max} \rangle$  where g is a precision property.

Searching the symmetry line of the brain is a really important step. It can be found by rotating the image and looking for two parallel straight lines with the smallest distance between them. The  $J_R$  and  $J_L$  contain pixels which are on the right and left side of the brain.

Using the previous calculation suspicious areas of pixels can be found. Taking into consideration the symmetry line and points which have colors from the range K, two subsets  $T_R \subset J_R$  and  $T_L \subset J_L$  are created.

## B. Cohesive rate(CR)

The main part of the algorithm is to calculate the cohesive rate of suspicious pixels. CRs value represents the summary relative locations of one suspicious pixel to the rest of them. It is the key to this algorithm. CR is defined by a formula:

$$\forall p \in T_V(cohesive_{rate}(p) = \sum_{i=1}^{T_V} (1/distance(p, p_i)))$$
 where

V={R,L}. The distance means distance in Manhattan's metric. Value  $P_{max}$  is set as maximum cohesive rate from both  $T_V$  subsets. According to statements the stroke is a solid structure which means that CR gets high values for stroke pixels.

#### C.Probability of a stroke

The algorithm calculates a general probability of a stroke for a series of CT images by taking under consideration the single scans stroke risk.

For selected  $k \in (0, 1)$  calculate number of pixels  $U_V$  which cohesive rate is from range (k  $P_{max}$ ;  $P_{max}$ ) and are in set  $T_V$ , where  $V = \{R, L\}$ . *k* is a kind of a sensitivity property. A bigger k causes a bigger probability of a stroke. On the other hand a minor k causes a lesser probability of a stroke

According to statements and taking into consideration that stroke is only on one side of the brain the probability of a stroke for left and right side can be calculated by a formula:  $P_V=U_V/(U_R+U_L)$ , where  $V=\{R,L\}$ . The formula which describes calculations uses the information about number of selected pixels generated is previous step. Using this calculations it is easy way to estimate general stroke risk.

Simply taking all  $P_R$  and  $P_L$  for a series of CT images and calculating average values of them gives the probability of a stroke for left  $P_{AVGL}$  and right  $P_{AVGR}$  side of the brain.

General probability of a stroke for a series of CT images

is defined by a formula: 
$$P = \frac{|P_{AVGR} - P_{AVGL}|}{|P_{AVGR} + P_{AVGL}|}.$$

#### D. Visualization

Visualization [6] is the final step which is not necessary but extremely important in difficult cases. There are two types of visualization. The first is to generate an original image with selected pixels by sensitivity factor. The second type shows all suspicious pixels but the color of the pixels depends on the CR for that point. For this one there is no need to specify sensitivity property.

### III. EXPERIMENTAL STUDY

Experimental tests were performed to verify the efficiency of the algorithm for the various values of parameters g and k. Tests were carried out on 23 CT images specially selected to represent different positions of the stroke in the brain as well as images of a healthy brain. Among the images chosen there are 3 series of scans and the rest are single representations. Results were very optimistic. First tests revealed the potential of the algorithm, the marking was clear and accurate. Sometimes it seemed to show details that were not noticeable in the original image. After comparison of processed images of a healthy brain and one with a stroke the difference was obvious even for someone with no experience in this kind of analysis.

All of the strokes were pointed correctly with their placement and size. As an example 3 CT images were chosen (Fig. 1) and tested with different parameters. The first pair presents a healthy brain. To show how it works in different cases other two pairs of the images show a brain attacked by the disease.

Every presented case contains a table with algorithm results for the various sensitivity and precision Parameters. There is also a figure of visualizations for each factor combination. The shortcuts used in the tables mean:

*I. g – precision factor,* 

*II.k* – *sensitivity property,* 

 $III.U_L$  – number of selected pixels on the left side

 $IV.U_P-$  number of selected pixels on the right side

 $V.CR_L$  – maximum cohesive rate for the left side

VI.CR <sub>R</sub>-maximum cohesive rate for the right side

Fig 2. shows screenshots of a healthy brain with different parameters values set. For different factors the algorithm calculates the probability of a stroke. All of the calculated values are combined in Table I and for all of the different values set the probability is very low. It is because cohesive rates for left and right side are almost equal which leads to a conclusion that there are no suspicious areas.

Following images in Fig. 3 and Fig. 4 are very difficult for neurologists to analyze. Strokes are hard to notice because the difference between pixels representing the stroke and normal tissue is very small. This algorithm helps to separate the stroke by finding even a small change between pixels and calculating cohesive rate. Table II and III show calculated values due to differently set parameters. Unlike previous analysis these two cases show high probability of a stroke in every combination of the variables. There are certain adjustments that make the probability go high, even up to 1,00. In both cases the algorithm has highlighted the suspicious areas and clearly announced that a stroke has been found in the image.

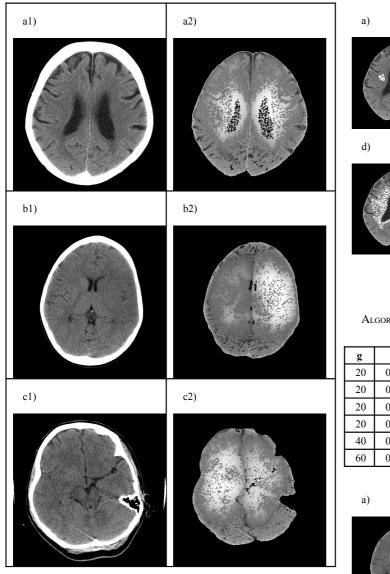


Fig. 1 Pairs of original (left) and fully visualized (right) CT images.

TABLE I. Algorithm results for the various sensitivity and precision factor  $% \mathcal{A}^{(1)}$ FOR HEALTHY BRAIN

| g  | k    | UL   | UR   | CRL | CR <sub>R</sub> | Fig  | Probability |
|----|------|------|------|-----|-----------------|------|-------------|
| 20 | 0,95 | 178  | 212  | 55  | 54              | 2.a) | 0,09        |
| 20 | 0,90 | 433  | 527  | 55  | 54              | 2.b) | 0,10        |
| 20 | 0,80 | 1194 | 1238 | 55  | 54              | 2.c) | 0,02        |
| 20 | 0,70 | 1918 | 1892 | 55  | 54              | 2.d) | 0,01        |
| 40 | 0,90 | 744  | 893  | 70  | 69              | 2.e) | 0,09        |
| 60 | 0,90 | 1058 | 1410 | 79  | 79              | 2.f) | 0,14        |

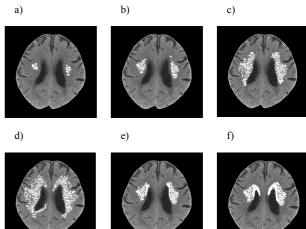


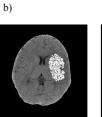
Fig. 2 Visualization for Table I - healthy brain.

TABLE II.

Algorithm results for the various sensitivity and precision factor FOR FIRST DIFFICULT CASE

| g  | k    | $\mathbf{U}_{\mathrm{L}}$ | UR   | CRL | CR <sub>R</sub> | Fig  | Probability |
|----|------|---------------------------|------|-----|-----------------|------|-------------|
| 20 | 0,95 | 0                         | 778  | 58  | 76              | 3.a) | 1,00        |
| 20 | 0,90 | 0                         | 1637 | 58  | 76              | 3.b) | 1,00        |
| 20 | 0,80 | 0                         | 2952 | 58  | 76              | 3.c) | 1,00        |
| 20 | 0,70 | 687                       | 3877 | 58  | 76              | 3.d) | 0,70        |
| 40 | 0,90 | 0                         | 2492 | 65  | 90              | 3.e) | 1,00        |
| 60 | 0,90 | 0                         | 2622 | 69  | 92              | 3.f) | 1,00        |

d)



c)

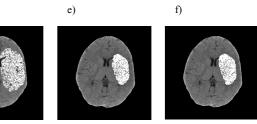


Fig. 3 Visualization for Table II - stroke on the right side.

TABLE III. Algorithm results for the various sensitivity and precision factor for second difficult case

| g  | k        | UL       | UR       | CRL | CR <sub>R</sub> | Fig  | Probability |
|----|----------|----------|----------|-----|-----------------|------|-------------|
| 20 | 0,9<br>5 | 788      | 0        | 60  | 50              | 4.a) | 1,00        |
| 20 | 0,9<br>0 | 161<br>8 | 0        | 60  | 50              | 4.b) | 1,00        |
| 20 | 0,8<br>0 | 280<br>9 | 234      | 60  | 50              | 4.c) | 0,85        |
| 20 | 0,7<br>0 | 359<br>6 | 136<br>7 | 60  | 50              | 4.d) | 0,45        |
| 40 | 0,9<br>0 | 208<br>4 | 0        | 94  | 80              | 4.e) | 1,00        |
| 60 | 0,9<br>0 | 218<br>7 | 0        | 97  | 86              | 4.f) | 1,00        |

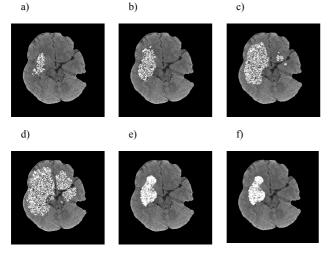


Fig. 4 Visualization for Table III - stroke on the left side.

For the sensitivity factor set to 0.9 and precision property to 20, average probability of a stroke in 8 series has been calculated and it is 0,70%. Standard deviation for these cases is 0,20. It is because some of the CT images contains very dark strokes and for precision property set to 20 it is hard to find it. Changing it to 60 or higher gives better results.

#### IV. CONCLUSIONS AND DISCUSSION

The presented method gives satisfying results. The quality of results given by the algorithm and its performance can be set by the sensitivity factor and the precision parameter. The optimal values were found experimentally by analyzing series of CT images. The best settings are 0.9 for the sensitivity factor and 20 for the precision parameter. The precision parameter is most important for the performance of the method and has a minor influence on quality which can be changed by adjusting the sensitivity factor. Although both parameters can be set manually, it is better to use their optimal settings or to change them only in difficult cases to estimate the volume of a stroke

The presented test sets do not include series. It is because it will take up much space. The series were tested on 11 people with strokes and on 15 healthy people and results were very optimistic. The probability for different cases were from 0.6 to 0.95 for CT images with a stroke and 0.0 to 0.5 without a , stroke, the sensitivity factor having been set at 0.9 and precision property at 20.

Another interesting option is that a cohesive rate graph can be displayed and it can be useful for additional analysis of the brain. There is an example of the graph in this paper shown in grayscale instead of a colored one. In the colored graph the highlighted areas have different colors and intensity. Colors are specially chosen to attract human eyes. Red represents the areas which have the biggest probability of being a stroke, green marks the areas with medium danger and blue is reserved for the less suspected parts of the brain. Thanks to this color palette the graph shows a general view of the brain tissue separated from any distractions from the original image.

There are possibilities to improve this algorithm. Better optimalization can be done by rewriting it in Assembler. There is also an idea to use folds analysis by using the fact that in the area where the stroke is the folds are smaller or not noticeable. The changes proposed here can be very useful to improve the algorithm effectivness and performance.

New discoveries can bring new facts to light about the anatomy and characteristic of a stroke. They can also improve the method by taking them into consideration if possible. There is no possibility for a computer program to replace a good specialist but it can be useful for faster diagnosis because it shows by means of a number the probability of a stroke.

#### V. References

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