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Modified Heuristic Clustering Algorithm to Avoid Cardiac Arrest

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Abstract: Studies have proven that the blockage that may occur in the blood vessels is a direct cause of cardiac arrest and myocardial arrest, so it is necessary to use the results of the application of radiological examination methods of the heart and large blood vessels - X-ray images, ultrasound, MRI. Therefore, the paper proposed a segmentation method based on a new approach to calculating a continuous and accurate membership function using the (Heaviside and Polynomials) function, in order to extract distinct regions in the images, making the analysis process effective and obtaining an accurate diagnosis, as the results proved that the proposed method highlights the important parts of the cardiovascular images more clearly compared to by traditional methods.

Keywords: *CT scans and MRI Images, Heuristic clustering algorithm, Partition coefficient, Partition entropy, Dice sorensen similarity coefficient.*

1. Introduction

Currently, mortality statistics, formed by groups of diseases, shows that mortality due to cardiovascular diseases (CVD) is higher than from infectious and oncological diseases [1].

According to the World Health Organization (WHO), in 2022, 17.9 million people died from cardiovascular diseases worldwide (32% of global mortality), In turn, ischemic stroke is directly related to a number of pathologies, mainly cardiovascular, the presence of which significantly increases the risk of strokes. The main ones are cerebral atherosclerosis, atrial fibrillation, myocardial infarction and other cardiovascular diseases (CVD) [2].

It is new to mention that the heart is surrounded by many problems, many of which are related to arterial blockage, where blood clots narrow the arteries, making it more difficult or stopping blood flow through them. This could cause a heart attack.

Difficulties in diagnosing in conditions of limited time, as well as limited diagnostic capabilities when examining a patient, the lack of prompt exchange of information with leading specialists and obtaining their advice. In this case were used enhancement and clustering methods in these works [3, 4, 5, 6, 7, 8, 9]. Many clustering techniques are still striving to reach accurate results to highlight areas in which the disease is concentrated, and it has been noted that previous work is closer to specializing in the segmentation of certain medical images and its results become less accurate with the increase in the diversity of images and different diseases [10, 11, 12, 13].

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When using fuzzy methods based on the use of qualitative information, to formalize these methods, one of the main issues is the construction of the membership function. Despite the fact that various methods and approaches are currently presented in world literature, they are all aimed at building an organic function in each of the distinct periods of changing arguments.

Such a description of the membership function leads to the need to consider its parts when solving problems of modeling, optimization, control and decision-making depending on the change in the argument. A typical example is L-R numbers. In this regard, an attempt is made in the work to propose a form of representation of the membership function, free from the above disadvantages, i.e., do not use it at every interval, but go to a single form of notation. The following is the outline of the paper, section 2 of this paper provides a full description of the proposed membership function and hash algorithm. Section 3 will present the results and describe the analysis to assess the accuracy of the results of the proposed model. The final section contains details of the conclusion of the work presented in this paper.

1. Proposed Method

2.1 Membership Function Configuration

Currently, the main problem of information (data or images) clustering algorithms was who to calculate membership function. The most commonly method used to create fuzzy membership are triangular shape [14]. i.e., those that can be specified by a triple of numbers $\breve{N} = \langle A, B, C\rangle$ $(A < B < C)$.

Where (*A*, *C*) – carrier of a fuzzy number, *B* – his high. In this case, the left and right parts of the membership function are straight lines. If the membership function of a fuzzy number $\breve{N}$ given by the expression.

(1) $$\mu_N(x) = \begin{cases} f_L(x), & x \in (A, B) \\ f_R(x), & x \in (B, C) \\ 0, & otherwise \end{cases}$$

Where $f_L(x), f_R(x)$ – some monotonic functions, and $f_L(B) = f_R(B)$=1, who such numbers are called triangle numbers (L-R)-type [2]. Trapezoidal fuzzy numbers of (L-R)-type are defined in a similar way [3], given by the set,

$\breve{N} = \langle A,\ B_L,\ B_R, C\rangle$ $(A < B_L, B_R < C)$, where (B_L, B_R) is the stability interval, and the membership function is given by the expression

(2) $$\mu_N(x) = \begin{cases} f_L(x), & x \in (A, B_L) \\ 1, & x \in (B_L, B_R) \\ f_R(x), & x \in (B_R, C) \\ 0, & otherwise \end{cases}$$

Further in the text, only triangular numbers (L-R)-type are considered, since the developed provisions are similarly applied to trapezoidal fuzzy numbers. In this paper, the membership function of a triangular fuzzy number $\breve{N} = \langle A, B, C\rangle$ it is proposed to set in (3).

(3) $$\mu_N(x) = f_L(x)H(x - A)H(B - x) + f_R(x)H(x - B)H(C - x)$$

Where $f_L(x), f_R(x)$

- functions, respectively, of the left and right parts of the function $H(x)$ is the unit Heaviside function [16, 17, 18].

In the case of trapezoidal fuzzy numbers, the membership function will look like in (4).

(4) $$\mu_N(x) = f_L(x)H(x - A)H(B_L - x) + (x - B_L)H(B_R - x) + f_R(x)H(x - B_R)H(C - x)$$

Functions $f_L(x), f_R(x)$ here and below for triangular fuzzy numbers should satisfy the conditions in (3).

(5) $$\begin{cases} f_L(A) = 0; \\ f_L(B) = 1; \\ f_R(B) = 1; \\ f_R(C) = 0. \end{cases}$$

Equion. (3) and (4) can be changed by imposing additional conditions on the equality to zero of the derivatives of the functions $f_L(x)$ and $f_R(x)$ at points *A*, *B*, *C*. There are four options for these conditions:

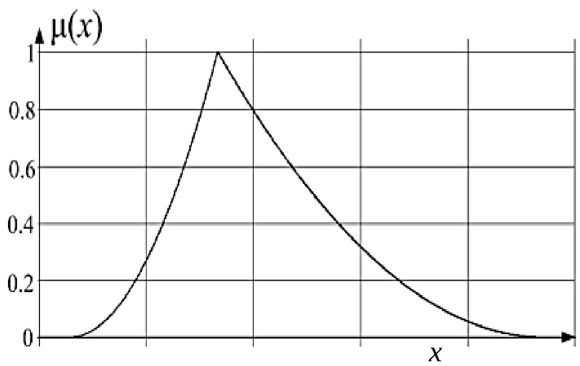
(6) $$\begin{cases} f_L'(A) = 0; \\ f_R'(C) = 0. \end{cases}$$

(7) $$\begin{cases} f_L'(B) = 0; \\ f_R'(B) = 0. \end{cases}$$

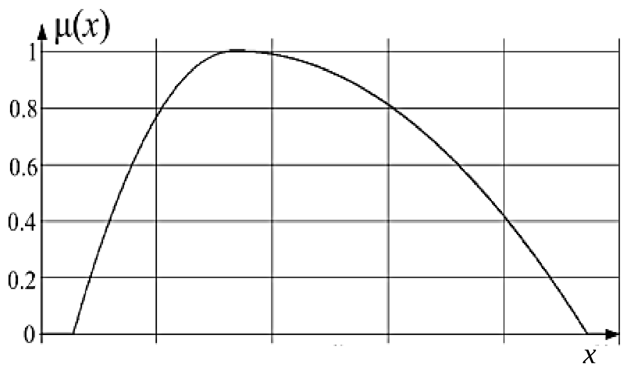
(8) $$\begin{cases} f_L'(A) = 0; \\ f_R'(C) = 0. \end{cases}$$

(9) $$\begin{cases} f_L'(B) = 0; \\ f_R'(C) = 0. \end{cases}$$

The appearance of membership functions of triangular fuzzy numbers, taking into account conditions as in (6) and (9), is shown in Fig.1.



(a)



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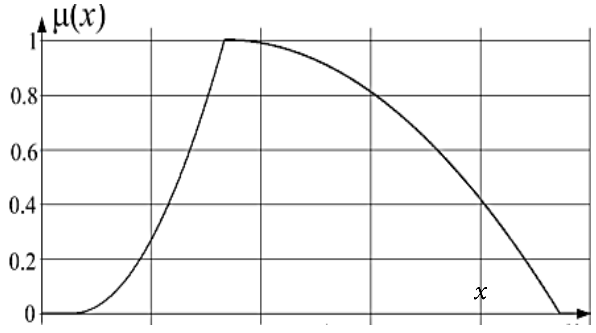
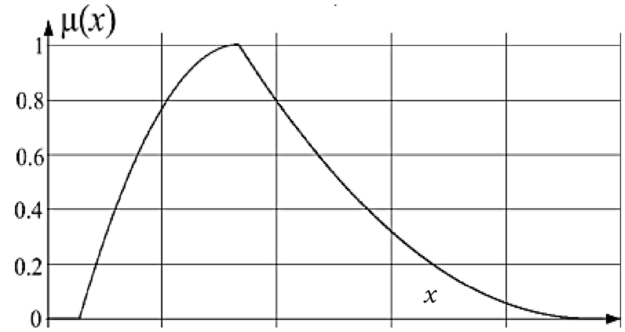


(c)



(d)

Figure 1. Forms of Membership Functions with Additional Conditions

Solving the system of equations composed of condition (5) and one of the conditions (6) – (9), one can uniquely express the coefficients of the functions $f_L(x)$, $f_R(x)$ in terms of the values A, B, C.

This property of the proposed membership function can be used in our clustering algorithm.

1.2 Clustering Algorithm

As part of the modification of the solution of the clustering problem based on heuristics, an algorithm for solving the clustering problem based on the new approach of membership function has been developed. the main parameters of which are:

α – Threshold difference of items combined into fuzzy clusters α∈ [0,1]; u – minimum number of elements in a fuzzy cluster A^l, l=1, …, c; w – the maximum number of elements in the area of intersection of any two fuzzy clusters.

Our algorithm for solving the clustering problem contains the following sequence of steps.

Step 1: For some difference threshold set by the researcher α, α ∈ [0,1] build I_α - α- level fuzzy dissimilarity relation I using (3) in accordance with the following condition.

(10)
$$\mu_{I\alpha} = \left\{\begin{matrix} 0, \mu_l(x_i, x_j) \le \alpha \\ 1, \mu_l(x_i, x_j) > \alpha \end{matrix}, I, j=1,\dots,n; \right\}$$

Step 2: Calculate internally stable sets for the constructed dissimilarity relation I_α.

Step 3: Select a cluster A^l, l=1, …, c, for given parameters u and w from the set I of internally stable sets.

Step 4: For a cluster A^l, l=1,…, c, find a point its center, and construct a membership function μ_{li} that satisfies the following condition:

(11)
$$\mu_{li} = \left\{\begin{matrix} 1, x_i = \tau^l \\ 0, \mu_l(x_i, \tau^l) = \max \mu_l(x_i, x_j) \end{matrix}, i, j=1,\dots,c. \right\}$$

Step 5: Build Matrix C_{cxn}=μ_{li} fuzzy cover C={A^1, …, A^c}, whose elements are degrees of similarity $\mu_{li}(x_i,\tau^l)$,i=1, …,n, l=1,…,c set elements X={x_1, ..., x_n} with centers τ^l,…,τ^c clusters A^1, …, A^c according to Eq.(12).

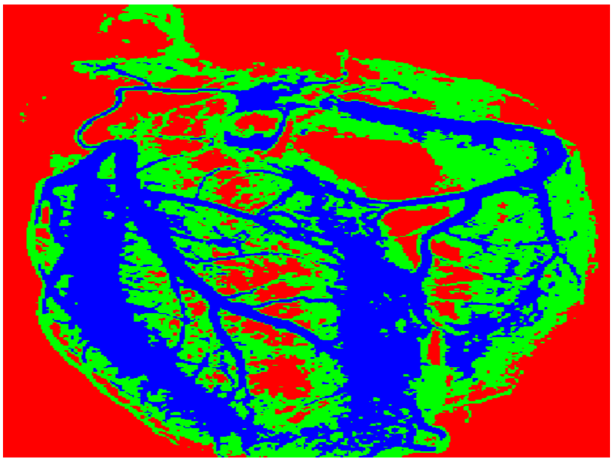
(12)
$$\mu_{li} = \frac{\mu_l(x_i,\tau^l)}{max\mu_l(x_i,x_j)}, i, j = 1, \dots n, l = 1, \dots c$$

and the algorithm terminates.

3. Results and Analysis

For the purpose of applying the proposed method we used the results of coronary angiography following are the results of implementing the method proposed in the paper, which makes it possible to clearly distinguish coronary heart vessels as shown in the Fig. 2 and Fig. 3. Both figures contain the original image, a segmented image using standard fuzzy c-means, and image segmented using proposed method. We will notice that there is a vast difference in the results obtained from the proposed method compared to the standard method.

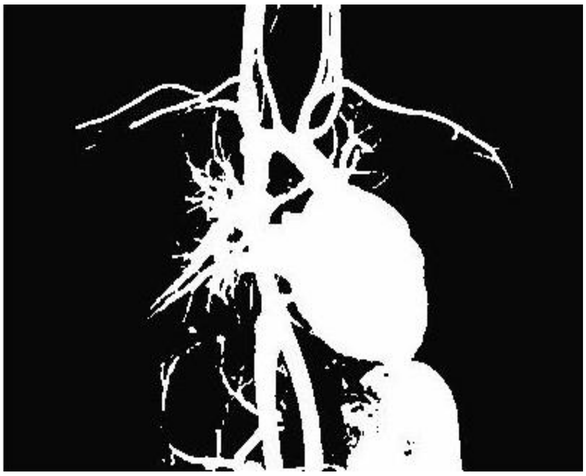
(a) (b)



(c)

Figure 3. (a) Cardiac coronary angiography (original image) (b) Segmentation based on Standard Fuzzy C-means (c) Segmentation based on proposed method

(a)



(b)

(c)

Figure 4. (a) Cardiac coronary angiography (original image) (b) Segmentation based on Standard Fuzzy C-means (c) Segmentation based on proposed method

To evaluation of the quality of the proposed method we will use the coefficient partitioning [19, 20] as in (13) and Entropy partitioning [21, 22] as in (14).

$$F_c = (P) = \frac{1}{n}\sum_{l=1}^{c}\sum_{i}^{n}\mu_{li}^2 \quad (13)$$

$$H_c = (P) = \frac{1}{n}\sum_{l=1}^{c}\sum_{i}^{n}|\mu_{li} * ln\mu_{li}| \quad (14)$$

These indicators have the following properties:

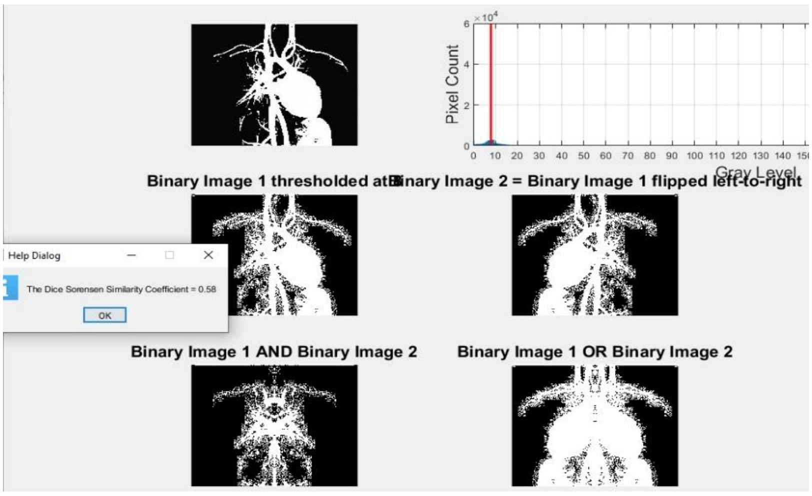
1. In the case when the resulting partition is clear, i.e., μ_{li} takes values on the two elements set $\{0,1\}$, characterizing the membership of the *i* elements to the *l* cluster, $F(p) = 1\ and\ H_c(P) = 0$.

2. In the case when the resulting partition is the least $\mu_{li} = \frac{1}{c}$ for all *i*=1, ..., n and *l*= 1, ..., c, the indicators take the values $F(p) = 1$ and, accordingly, $H_c(P) = \ln(c)$. Thus, the range of partitioning coefficient values is determined by the inequality $1/c \le F_c(P) \le 1$, and the range of partitioning entropy values is determined by the inequality $0 < H(P) < \ln(c)$. The main purpose of using the partitioning factor F(P) and the partitioning entropy H(P) is to find the most appropriate number of clusters in the fuzzy partitioning $P*$. The following Table 1 shows that the heuristic fuzzy segmentation produced (HFS) the best results compared to the fuzzy c means, and the F(P) and H(P) values proved it.

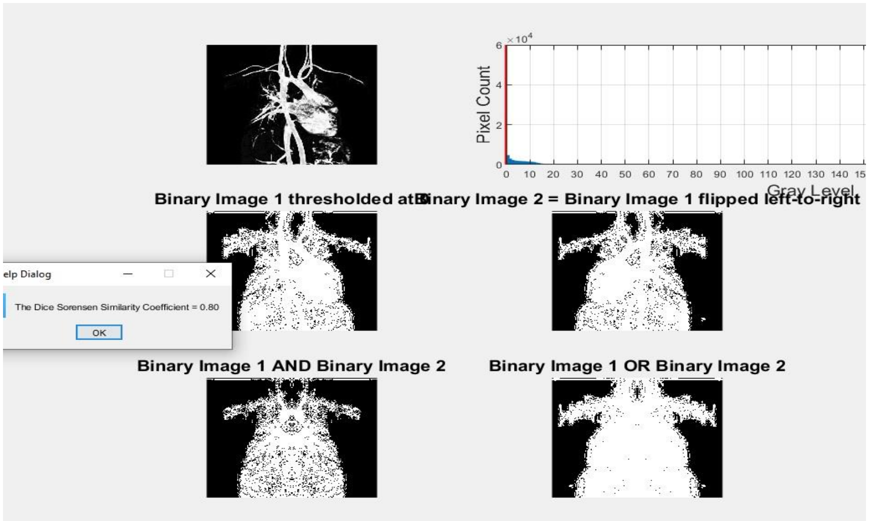
Table 1. Values of F(P) and H(P) for FCM and HFS Methods

Segmentation Method	F(P)	H(P)
FCM	0.214343	1.543343
HFS	0.687571	0.211502

We note that the value of F(P) and H(P) for HFS method are close, and this indicates that the elements of the same cluster are somewhat similar, also the value of Dice Sorensen Similarity Coefficient (Dice) [23, 24, 25] can also be taken into account, as a measure of the degree of overlap between the clusters to determine the accuracy of the algorithm, where, when we used the proposed algorithm, we got a drastic change in the value of (Dice) as shown in Fig. 5 and Fig. 6, respectively.

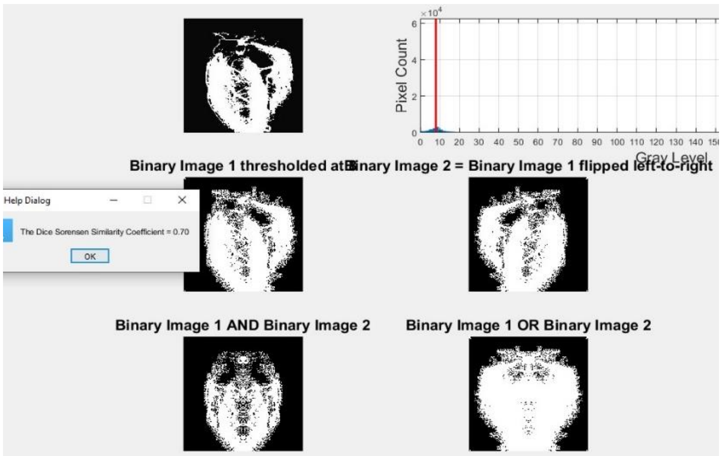


(a)

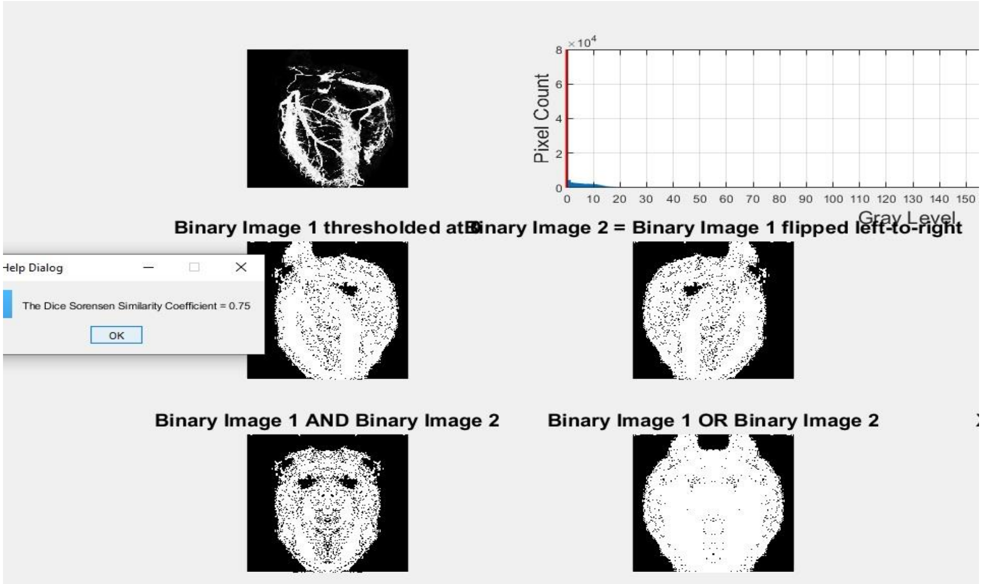


(b)

Figure 5. (a) Dice value for FCM method (b) Dice value for HFS method



(a)



(b)

Figure 6. (a) Dice value for FCM method (b) Dice value for HFS method

4. Conclusion

We conclude that not all collection techniques have the ability to deal with all the details of medical images, especially coronary images, which are difficult to extract blood vessels and highlight the blockages that fall within them, because they contain very fine details. Also, the evaluation of the algorithm's work depends not only on the time factor, but on the accuracy of its work and its ability to extract important details in the image.

As we can note from the results obtained, the fuzzy c-mean method tries to extract certain parts of the blood vessels and lose other parts and become as if they were part of the background of the image.

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