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SALUD, CIENCIA Y TECNOLOGÍA

**ORIGINAL**

# A novel multithresholding algorithm for segmentation of the MRI images

## Un nuevo algoritmo multiumbral para la segmentación de imágenes de resonancia magnética

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## ABSTRACT

Segmentation is a crucial stage in picture evaluation techniques. Brain magnetic resonance imaging has been accurately segmented, extensively studied because the use of these types of methods allows the detection and recognition of a wide range of disorders. Thresholding is a simple and effective method for segmenting images. But depending on how many thresholds are employed for segmentation, thresholding-based techniques tend to cost more to compute. As a result, metaheuristic algorithms are a crucial tool for multilevel thresholding that aid in determining the best values. Using a novel cuckoo search (NCS) algorithm, we have suggested a method for segmenting MRI images that is more efficient. Three different objective functions (Otsu's method, Kapur entropy, and Tsallis entropy function) were utilised by comparing the output of the projected strategy with the Cuckoo Search (CS) algorithm.

**Keywords:** Segmentation; Brain Magnetic Resonance Imaging; Metaheuristic Algorithms; Innovation Technology.

## RESUMEN

La segmentación es una etapa crucial en las técnicas de evaluación de imágenes. La segmentación precisa de imágenes de resonancia magnética cerebral se ha estudiado ampliamente porque el uso de este tipo de métodos permite detectar y reconocer una amplia gama de trastornos. El umbralaje es un método sencillo y eficaz para segmentar imágenes. Pero dependiendo de cuántos umbrales se empleen para la segmentación, las técnicas basadas en el umbral tienden a ser más costosas de calcular. En consecuencia, los algoritmos metaheurísticos son una herramienta crucial para el umbralado multinivel que ayudan a determinar los mejores valores. Utilizando un algoritmo de búsqueda cucú (NCS), hemos sugerido un método más eficiente para segmentar imágenes de resonancia magnética. Se utilizaron tres funciones objetivo diferentes (el método de Otsu, la entropía de Kapur y la función de entropía de Tsallis) comparando el resultado de la estrategia proyectada con el algoritmo de búsqueda del cuco (CS).

**Palabras clave:** Segmentación; Resonancia Magnética Cerebral; Algoritmos Metaheurísticos; Tecnología De La Innovación.

## INTRODUCTION

The current field that is extending its literature and growing pretty quickly is computational intelligence and optimization. The majority of applications have finite amounts of time, money, and resources, so it is crucial to develop the best possible solutions to make the most of them. However, in the actual world, it can be very challenging to locate the best answers to many optimization issues. Some issues, like the travelling salesman problem, are NP-Hard problems. These NP-hard issues typically lack any effective solutions. Most of the time, the only way to solve Np-Hard problems is by using heuristic or metaheuristic techniques. The literature contains many optimisation issues and, consequently, many optimisation algorithms, but not every optimisation issue can be solved by a single algorithm. The look for an effective algorithm continues to get significant scientific attention. Researchers have recently become interested in metaheuristic algorithms in the field of optimization. Metaheuristic algorithms, which outperform traditional algorithms in many ways, are frequently inspired by nature.

Author created the evolutionary and metaheuristic optimization technique known as Cuckoo Search in 2009.[1] The cuckoo bird is the source of inspiration for the theory underlying this optimization search technique. Known as obligatory blood parasitism, mature cuckoos deposit their eggs in the nests of other species or hosts in order to reproduce.[1] Cuckoos are beautiful sounding birds with an aggressive reproductive system. Cuckoo Search is a metaheuristic method that was developed by Yang et al.[1] in 2009 to solve optimization challenges. The algorithm is founded on the Levy flight behaviour of different birds and fruit flies, as well as the behaviour of several cuckoo species as obligate brood parasites. In 2010, author provided a thorough examination of Cuckoo Hashing and highlighted some disadvantages as well as advantages.[3] A modified cuckoo search algorithm was developed in 2011,[4] who discovered that it outperformed the original cuckoo search algorithm. Numerous design issues in engineering are frequently multiobjective when subjected to difficult nonlinear constraints. A multiobjective cuckoo search was introduced by Vaishya et al.[5] in 2011 to address the multi-objective problem of design optimization. To solve binary optimisation challenges,[6] offer a private variant of cuckoo search in 2012. A Cuckoo Search Algorithm-based optimisation model that can discover better structural designs for vehicle components, provide efficient and optimal fuel economy, and lower vehicle design costs was introduced in 2012.[7] In 2013, Valian et al.[8] suggested an enhanced and expanded cuckoo search methodology for the optimization of dependability problems. Cuckoo search was introduced by Yildiz[9] and effectively utilised in milling operations for the machining parameter choosing optimally. In order to address the Traveling Salesman Problem, suggested an expanded version of the fundamental cuckoo optimization search algorithm in 2014.[10] These days, image segmentation is widely utilised to choose the important objects. To use entropy to optimise the criterion, a segmentation is used to retrieve the appropriate threshold value. Using the cuckoo search algorithm and wind-driven optimization,[11] suggested a method for multilevel thresholding of satellite image segmentation. Because of the energy crisis and environmental issues, finding alternatives to conventional energy sources is crucial today. One alternative that has recently drawn the attention of many researchers is solar energy. Extreme Learning Machine and the Cuckoo Search algorithm were used to create a hybrid model for predicting solar radiation.[12] Machine learning algorithms are frequently utilised in the medical industry for diagnosis detection and prediction. However, to improve the accuracy and precision of the machine model. The use of improved cuckoo search algorithms and extreme learning machines was suggested by Mohapatra et al.[13] One of the major requirements in distribution networks is the increase in power stability and the reduction of power loss. According to Thanh et al.[14] approach for properly reconfiguring the network and allocating dispersed generation in distributed networks, this problem can be optimised. For the optimal sizing of renewable energy systems such as wind batteries, photovoltaic batteries, and photovoltaic wind battery systems that are appropriate in remote places,[15] suggested a method employing the Cuckoo Search Algorithm. The power system's most crucial component is the forecasting of the effective and accurate electric load. Singular spectrum analysis, support vector machines, and Cuckoo search algorithms were used to create a successful and trustworthy technique for electric load forecasting by Simhan et al.[16] Social media platforms like Twitter, Facebook, and Google Plus, among others, have altered how people communicate online. Due to the fact that social media has developed into a significant platform for sharing and expressing human sentiment, data mining-based effective and optimal sentiment evaluations are required.[17] suggested a method of sentimental analysis on the Twitter data set using a meta-heuristic hybrid approach utilising cuckoo search and K-means Algorithms. To improve the predictability of the necessary effort in software development,[19] proposed a concept based on artificial neural networks and the cuckoo search algorithm.[21] suggested a method based on a flexible mix of Cuckoo Search and artificial neural networks to identify damage in bridges and beam-like structures. Cuckoo search was employed in the suggested strategy to enhance bias and weight training parameters for artificial neural networks. An adaptable Cauchy mutation-based cuckoo optimization search technique was put out by Zhang et al.[22] By positioning the Static VAR Compensator in the most advantageous and effective area,[25] were able to reduce power losses. Chen et al.[26] suggested an enhanced cuckoo search algorithm that is dimension by dimension based. Task scheduling needs to be efficient and effective to provide cloud computing services that are faster and of higher quality. To overcome the difficulties of work scheduling in cloud computing, Prem et al.[27] suggested an optimised technique based on a hybrid approach by fusing Particle Swarm Optimization and Cuckoo Search Algorithm. The user cost and performance cost were decreased by the suggested strategy. The complexity problems in Recurrent Neural Networks are solved by the neural network known as the Echo State Network. An echo state network was proposed by Bala et al.[28] and employed the cuckoo optimal search method for the proper parameter and topology. It was found that the cuckoo search algorithm outperformed the binary particle, particle swarm optimization, and classical echo state network. Utilizing a turbofan engine, the proposed technique was evaluated for degradation prediction. Multi-objective optimization problems are those that must be solved in both production and real life at the same time and involve numerous conflicting points. Cuckoo search with multiple objectives algorithm-based optimization solution for the type of problems was suggested by Cai et al.[29]

**Theoretical Aspect of Techniques**

**Variety of Thresholding Methods Used for the Segmentation of MRI Images**

These methods are frequently utilised in the process of segmenting a picture. The threshold establishes the luminance value for the picture and classifies the pixels into a number of distinct categories. Image segmentation can generally be broken down into one of two categories of thresholding methods. Two-level thresholding and multilayer thresholding are the names of the first and second strategies, respectively.[18,31]

**Bi-level thresholding**:

This image has pixels with values that can vary from 0 to M-1, where M is the highest pixel value. This picture is a grayscale image. The foreground, background, and object of the image are then made distinguishable from one another by using the two-level thresholding technique to determine a suitable intensity value of that image. Equation 1 is the mathematical expression that can be used to create it.

$$TH_0 = \{I(x,y) \in J : 0 \leq I(x,y) \leq th_1 - 1\}$$
$$TH_1 = \{I(x,y) \in J : t\,h_1 \leq I(x,y) \leq th_{max} - 1\} \quad \text{.... (1)}$$

J stands for the initial MRI pictures, and intensity levels are denoted by the symbol I (x, y).

**Multilevel thresholding**:

In the event that two-level thresholding is not adequate for differentiating the foreground from the object of interest. In circumstances like these, the application of multilayer thresholding is useful. The object of interest in the image can be more clearly seen using this technique because it can encounter multiple grey level threshold values. Equation 2 displays the various mathematical formulas that can be used.

$$TH_0 = \{I(x,y) \in J : 0 \leq I(x,y) \leq th_1 - 1\}$$
$$TH_1 = \{I(x,y) \in J : t\,h_1 \leq I(x,y) \leq th_2 - 1\}$$
$$TH_i = \{I(x,y) \in J : t\,h_i \leq I(x,y) \leq th_{i+1} - 1\}$$
$$TH_q = \left\{I(x,y) \in J : t\,h_q \leq I(x,y) \leq th_{max} - 1\right\} \quad \text{..... (2)}$$

J stands for the initial MRI pictures, and intensity levels are denoted by the symbol I (x, y). q gives the total number of different thresholding levels, while the original image's maximum intensity number is indicated by the symbol $th_{max}$. can take the values 1, 2, or q.

**Otsu's method**:

Assume that t represents an image's threshold. The two classes below can be applied to the corresponding grey-level histogram: $Q_a$= (0, 1,..., t) and $Q_b$= (t+1,..., L-1) and their respective cumulative probabilities can be shown as follows:

$$P_a = \sum_{i=0}^{t} p_i\,, P_b = \sum_{i=t+1}^{L-1} p_i \qquad \text{..... (3)}$$

The following formulas provide the mean values of $Q_a$ and $Q_b$'s grey levels:

$$\omega_a = \frac{1}{P_a}\sum_{i=0}^{t} ip_i\,, \omega_b = \frac{1}{P_b}\sum_{i=t+1}^{L-1} ip_i \qquad \text{..... (4)}$$

The image's mean grey-level value, using the same idea, is:

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$$\omega_G = \sum_{i=0}^{L-1} i p_i \qquad ..... (5)$$

As a result, the variances of $Q_a$ and $Q_b$ and the overall histogram can be expressed as follows, respectively:

$$\sigma_a^2 = \sum_{i=0}^{t} (i - \omega_a) \frac{p_i}{p_a}$$
$$\sigma_b^2 = \sum_{i=t+1}^{L-1} (i - \omega_b) \frac{p_i}{p_b}$$
$$\sigma_G^2 = \sum_{i=0}^{L-1} (i - \omega_G)\, p_i \qquad ..... (6)$$

According to Equation 6, the terms "within-class variance" and "between-class variance" are as follows:[19]

$$\sigma_W^2 = \omega_a \sigma_a^2 + \omega_b \sigma_b^2$$
$$\sigma_B^2 = P_a(\omega_a - \omega_G)^2 + P_b(\omega_b - \omega_G)^2 \qquad ..... (7)$$

and the relationship shown below is true:

$$\sigma_B^2 + \sigma_W^2 = \sigma_G^2 \qquad ..... (8)$$

It is clear that the following relationships apply regardless of the threshold value chosen, t:

$$P_a \omega_a + P_b \omega_b = \omega_G$$
$$P_a + P_b = 1 \qquad ..... (9)$$

The Otsu algorithm's main goal is to decrease between-class variance by choosing a suitable threshold value, t*, i.e.;

$$t^* = Argmax\{\sigma_B^2(t)\} \qquad ..... (10)$$

Between-class variance can be represented as follows using equation[21]

$$\sigma_B^2 = P_a P_b (\omega_b - \omega_a)^2 \qquad ..... (11)$$

The two components $(\omega_b - \omega_a)^2$ and $P_aP_b$ are shown to dominate the between-class variation in equation 11. The concept of picture segmentation coincides with maximisation of the factor $(\omega_b - \omega_a)^2$, which means that an appropriate threshold $t_1$ sets the grey level difference between $Q_a$ and $Q_b$ to its maximum value. Pa = Pb = ½, that states that how many pixels are present in the backdrop and regardless of origin, must be satisfied in order to maximise the $P_aP_b$ factor. For a given image, if , $t_1$=$t_2$ then the compromise between the ideal thresholds $t_1$ and $t_2$ is represented by threshold t*. As a result, the Ostu algorithm consistently has a propensity to equally divide each pixel in an image, highlighting its shortcomings in the extraction of minute objects from the backdrop.

**Kapur's entropy method:**

Based on the clustering hypothesis, a conventional global thresholding technique is the Otsu algorithm. Despite the fact that both algorithms start from the histogram of the image, the entropy-based technique has a very different concept from Otsu's. With regard to entropy-based image thresholding, Shannon entropy is frequently used. Tran-ngoc et al.[21] made the initial suggestion, and Zhang et al.[20] improved it in 1985. The centre and background's a priori entropy is used to create an objective function in order to determine the ideal threshold in accordance with the Maximum Entropy Principle. The distribution of an image's grey-level histogram can be used to compute Shannon entropy.

$$S_k = -\sum_{i=0}^{L-1} p_i \, ln p_i \qquad ...... (12)$$

Following the histogram's division into associated entropies by the threshold t are components (a and b):

$$S(a) = -\sum_{i=0}^{t} \frac{p_i}{P_t} ln \frac{p_i}{P_t} = lnP_t + \frac{S_t}{P_t}$$
$$S(b) = -\sum_{i=t+1}^{L-1} \frac{p_i}{1-P_t} ln \frac{p_i}{1-P_t} = ln(1-P_t) + \frac{S_k - S_t}{1-P_t}$$
$$P_t = \sum_{i=0}^{t} p_i , S_t = -\sum_{i=0}^{t} p_i \, ln \frac{p_i}{P_t} \qquad ..... (13)$$

S(a) and S(b) added together form the objective function φ(t):

$$\varphi(t) = S(a) + S(b) \qquad ...... (14)$$

these factors are used to calculate the Kapur algorithm's ideal threshold:

$$t^*=Argmax\{\varphi(t)\} \qquad ...... (15)$$

L is the overall number of different intensity levels in the image in greyscale and pi is a pixel's brightness value, which can vary from 0 to 255, will be that value.

**Tsallis entropy method:**

In image processing, Shannon entropy exhibits the property of extensivity and is additive. In thermodynamics, entropy was first used to describe physical systems with a wide variety of microstates. Furthermore, it is assumed that the system's microstates are independent of one another for entropy's extensibility. Tsallis proposes a non-extensive entropy(22) to describe these systems. It is denoted as:

$$S_T = \frac{1-\sum_{i=1}^{L} p_i^q}{q-1} ..... (16)$$

The real integer q in equation 16 represents the system's nonextensivity. Shannon entropy replaces Tsallis entropy in the q → 1 limit, restoring the system's extensibility. The information theory was additionally clarified by the non-extensive generalisation of entropy. The foreground and background have the following cumulative probabilities in the Tsallis entropy algorithm:(23)

$$P_a = \sum_{i=0}^{t} p_i , P_b = \sum_{i=t+1}^{L-1} p_i \qquad ..... (17)$$

The entropy of each component can be defined as(23) using equation(27).

$$S_T^a(t) = \frac{1 - \sum_{i=1}^{t} \left(\frac{p_i}{P_a}\right)^q}{q-1}$$
$$S_T^b(t) = \frac{1-\sum_{i=t+1}^{L} \left(\frac{p_i}{P_b}\right)^q}{q-1} \qquad ..... (18)$$

Given that nonextensivity makes a and b components of the complete image. The following is how the image's overall entropy is expressed:

$$S_q^{a+b}(t) = S_q^a(t) + S_q^b(t) + (1-q) S_q^a(t) S_q^b(t) \qquad ..... (19)$$

The pseudo-additivity of Tsallis entropy is depicted in equation 19's third portion on the right. The ideal threshold t* is produced by maximising , and it is denoted by:

$$t^* = Argmax\{S_q^{a+b}(t)\} \quad ..... (20)$$

The answer to equation 20 is determined by the non-extensive measure q, which identifies how strongly the

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internal correlation in the image is correlated. There may be long-range correlations between the grey level values of any two randomly chosen pixels in the image. More particular, even though they are not contiguous to one another, the pixels of objects in an image with many objects will have comparable gray-level values. Such long-range association can be measured by non-extensive entropy.[23,24] This concept served as the inspiration for a novel technique that will be covered below. The precise value of the parameter q for a given image must be ascertained because it is an extra index that may be used to tweak the ideal threshold.

**Brief explanations of evolutionary algorithms:**
**Cuckoo search algorithm**:

An organic algorithm, the cuckoo search algorithm was created by Valian et al.[8] The CS imitates the cuckoo's egg-laying procedure. Cuckoos typically leave their fertilised eggs in host nests in the hopes that they will be raised by substitute parents come spring. The host may recognise that the eggs in their nests are not their own occasionally. In these situations, either the entire nest is cast out or the foreign eggs are removed from the nests. The following three guiding concepts serve as the foundation for the CS optimisation algorithm:

1. It's interesting to note that each cuckoo bird only deposits only single egg at once, which haphazardly inserts in the nest of a host bird.
2. The finest beds that lay superior eggs are passed down to the successive families.
3. A number of a fixed amount of host nests available. With chance $p_α$, the host bird finds foreign eggs with a probability that ranges from 0 to 1. Keep in mind that the finest nests are chosen for the subsequent calculations.

For the sake of simplicity, principle 3 can be described as follows: with probability $p_α$, new nests will replace the existing n nests. The CS method can be distilled into the following three ideas based on these three principles: A Lévy light is carried out while creating fresh solution for cuckoo i.[8]

$$x_i^{t+1} = x_i^t + \alpha_0(x_i^t - x_{best}) \oplus Levy(\lambda) \quad ..... (21)$$

$α_0$ is the step size, $α_0 > 0$, and represents the current optimal solution, Element-wise multiplication. Levy flights are selected using a Levy distribution, which is given by:

$$Levy(\lambda) \sim u = t^{-\lambda}, \ (1 < \lambda \leq 3) \quad ..... (22)$$

**Lévy flight modelling:**

There are two steps in the implementation of random numbers with Levy flight. The first stage is choosing the random flying direction, and the second stage considers creating the steps that will follow the selected Levy distribution. A uniform distribution is used to choose the random direction. The following is a definition of the Levy step size:

$$Levy(\beta) = \frac{u}{|v|^{\frac{1}{\beta}}} \qquad \text{where, } \lambda - 1 = \beta \qquad ..... (23)$$

Normal distributions are used to derive u and v. This suggests,

$$u \sim N(0, \sigma_u^2), v \sim N(0, \sigma_v^2), \sigma_u = \left\{ \frac{\Gamma(1+\beta)\, sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\beta 2^{\frac{\beta-1}{2}}} \right\}^{\frac{1}{2}}, \sigma_v = 1 \qquad ..... (24)$$

Where Γ correspond standard gamma function.

**Challenges of Cuckoo Search Algorithm:**

From the literature survey, show that CS is superior compare to other metaheuristic algorithms. Levy step size and $x_{best}$ are the main challenges of the cuckoo search algorithm. $x_{best}$ is found using optimization. Different methods are used to maximize the function, like; using Ostu's method, using Kapur entropy method, using Tsallis entropy method, etc.

**Proposed Cuckoo search (CS) algorithm**:

We typically work with images that have more than two classes of segments when solving segmentation problems in the real world. As per the literature survey CS using Kapur's entropy gives higher PSNR values than using Otsu technique. Because Tsallis entropy is non-extensive, when two identical systems come together, their total entropy does not equal the sum of the entropies of their individual components. Utilizing Kapur's entropy technique, compare to CS. Higher numbers for PSNR and other parameters are provided by Tsallis entropy. The broad connections in a picture can be described using the non-extensive entropy technique. Its use is limited by the fact that, similar to other entropy-based algorithms, it is still very vulnerable to signal disruption. For small target extraction, the Otsu method is more reliable but less precise. The benefits of the two can thus be combined to create a new algorithm with a broader range of applications. We proposed new method, combined Otsu and Tsallis entropy as an objective function to find the $x_{best}$. For characterising the extended connections in a picture, the non-extensive entropy technique is appropriate. The Otsu algorithm is accurate for small target extraction but not steady. The advantages of the two could be combined to produce a novel algorithm with more varied uses. Noting that information redundancy now governs the non-extensive parameter q in Tsallis entropy and cannot be set arbitrarily.(32) Based on equation 10 and equation 20, The following is an example of a novel objective function:

$$\mu(t) = S_q^{a+b} - (\sigma_W^2)^{1-q} \qquad \text{.... (25)}$$

In order to keep Tsallis entropy concave, q > 0 must be fulfilled (22). In contrast, q < 1 is referred to as superextensivity, which raises the system's overall entropy in compared to the extensive case (q = 1).(25) Practically speaking, practically all kinds of images display the superextensivity feature.(26) Consequently, 0 < q < 1 can be the appropriate range for the non-extensive parameter. We can see that each of the two strategies are designed to maximise the objective functions from equations 10 and 20. Maximizing the objective function is the goal of equations 25,

t^*=Argmax{μ(t)} ….. (26)

With the range of q stated above, equation 25 yields the ideal threshold. According to figure 1, each peak's profile is the normalised q-Gaussian distribution function for a fabricated picture with a bimodal histogram distribution.(27) Equations 10 and 20 show that the grey area in the valley between the two summits, which precisely matches the result of equation 26, is the best threshold for the Otsu algorithm and the Tsallis entropy algorithm. There is no proof that the result of equation 10 and equation 20 coincide for other natural photographs with an arbitrary histogram distribution, however equation 36 shows an exchange between them and equation 37 may produce an appropriate proposal. It should be noted that $S_q^{a+b}$ and $\sigma_w^2$ have extremely different magnitudes in the histogram of Figure 2. Both of them, as depicted in figure 3, are functions of the limit t. For any conceivable threshold t, the Otsu method, however, entirely suppresses the outputs of the Tsallis entropy algorithm. Consequently, combining $S_q^{a+b}$ and $\sigma_w^2$ directly is not suitable.

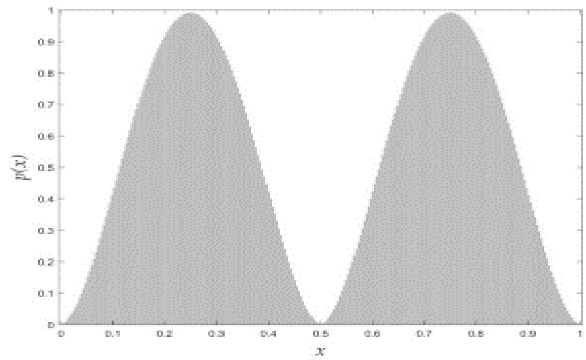


**Figure 1.** Distribution of the normalised histogram

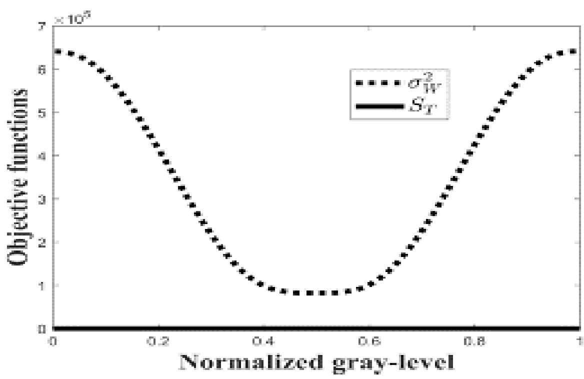


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**Figure 2.** The Ostu and Tsallis algorithms' objective functions

The magnitude of $\sigma_w^2$. can be revised using the q-exponential function (28) to minimise the effects of the magnitude difference. The following is the definition of Tsallis entropy for a continuous probability distribution function:

$$S_T = \frac{1-\int_0^1 p(x)^q dx}{(q-1)} \qquad \text{..... (27)}$$

The normalised grey-level value's probability distribution is represented by the letter p(x). The q-Gaussian function can be used to represent the proper probability distribution for a system with non-extensive q-entropy (27),

$$p(x) = \frac{1}{Z_q}\left[1-(1-q)\frac{x^2}{\sigma^2}\right]^{\frac{1}{1-q}} \qquad \text{..... (28)}$$

Zq is the partition function required to maintain the criterion for probability normalisation and $\sigma^2$ is the variance of x,

$$Z_q = \int_0^1 \left[1-(1-q)\frac{x^2}{\sigma^2}\right]^{\frac{1}{1-q}} dx = \frac{\sigma\sqrt{\pi}\,\Gamma\left(1+\frac{1}{1-q}\right)}{2\sqrt{1-q}\,\Gamma\left(\frac{3}{2}+\frac{1}{1-q}\right)} \qquad \text{..... (29)}$$

presuming that k is a number and that Γ(k) reduces to factorial(k - 1)!. Equation 27 becomes: when p(x) is added.

$$S_T = \frac{1-\int_0^1 \frac{1}{x_q^q}\left[1-(1-q)\frac{x^2}{\sigma^2}\right]^{\frac{q}{1-q}} dx}{q-1} = \frac{\xi(\sigma^2)^{\frac{1-q}{2}}}{q-1} \qquad \text{..... (30)}$$

where:

$$\xi = \left[\frac{\pi}{4(1-q)}\right]^{\frac{1-q}{2}} \left[\frac{\Gamma\left(\frac{3}{2}+\frac{1}{1-q}\right)}{\Gamma\left(1+\frac{1}{1-q}\right)}\right]^q \frac{\Gamma\left(\frac{1}{1-q}\right)}{\Gamma\left(\frac{3-q}{2(1-q)}\right)} \qquad \text{..... (31)}$$

For a specific number of q, where is the integration constant. Given that Tsallis entropy is non-extensive and $p_a$ and $p_b$ are two equivalent q-Gaussian distribution functions, the following expression of total entropy is possible:

$$S_T(a+b)= S_T(a)+ S_T(b)+(1-q)S_T(a)\, S_T(b)$$

$$S_T(a+b) = \frac{1-\xi_a(\sigma_a^2)^{\frac{1-q}{2}}}{q-1} + \frac{1-\xi_b(\sigma_b^2)^{\frac{1-q}{2}}}{q-1} + (1-q)\frac{1-\xi_a(\sigma_a^2)^{\frac{1-q}{2}}}{q-1}\,\frac{1-\xi_b(\sigma_b^2)^{\frac{1-q}{2}}}{q-1} \qquad \text{..... (32)}$$

Equation 32 is produced by putting = = as follows:

$$S_T(a+b) = \frac{1-\xi_a\xi_b(\sigma_W^2)^{1-q}-1}{1-q} \qquad \text{..... (33)}$$

The logic of equation 25 is demonstrated as a result of the magnitude of $(\sigma_W^2)^{(1-q)}$ being similar with $S_T(a+b)$ at the appropriate range of q.

## RESULT ANALYSIS

In Table 1, The cuckoo search algorithm uses the ostu's, kapur, tsallis, and suggested objective functions, as well as its novel objective function. In the novel multi-thresholding cuckoo algorithm combined ostu and Tsallis entropy used as an objective function. Using the different threshold values 2, 3, 4, 5 compares the objective function values for all four method. In this is number of threshold increases then objective function value is increases. Compare to the other methods suggested approach gives the best segmentation output.

**Table 1.** Examining the effects of the Cuckoo Search Algorithm on a variety of Objective Functions

| IMAGE | Threshold | Suggested approach using Cuckoo search algorithm | Cuckoo search algorithm whose objective function is the Tsallis entropy | Cuckoo search algorithm whose objective function is the Kapur entropy | Cuckoo search algorithm whose objective function is the Otsu |
|---|---|---|---|---|---|
| **1** | 2 | 9,7263 | 9 | 9,2155 | 9,2136 |
| | 3 | 14,2517 | 13,1 | 11,6876 | 11,329 |
| | 4 | 17,1335 | 16,9 | 13,931 | 13,5003 |
| | 5 | 21,2455 | 20 | 16,1127 | 15,7427 |
| **2** | 2 | 9,7263 | 9 | 9,2155 | 9,2136 |
| | 3 | 14,2517 | 13,1 | 11,6876 | 11,329 |
| | 4 | 17,1335 | 16,9 | 13,931 | 13,5003 |
| | 5 | 21,2455 | 20 | 16,1127 | 15,7427 |
| **3** | 2 | 10,0572 | 9,1 | 9,2585 | 9,2568 |
| | 3 | 14,0417 | 13,3 | 11,5653 | 11,3036 |
| | 4 | 17,8741 | 16,7 | 13,8132 | 13,5556 |
| | 5 | 20,1028 | 19,8 | 15,9036 | 15,6613 |
| **4** | 2 | 10,4342 | 9,2 | 9,2447 | 9,2433 |
| | 3 | 14,6088 | 13,3 | 11,5184 | 11,2299 |
| | 4 | 17,6493 | 16,7 | 13,7491 | 13,3646 |
| | 5 | 21,9156 | 19,8 | 15,6564 | 15,3383 |
| **5** | 2 | 9,8971 | 9,4 | 9,3314 | 9,3073 |
| | 3 | 15,1313 | 13,4 | 11,6618 | 11,3313 |
| | 4 | 17,1881 | 16,8 | 13,7808 | 13,496 |
| | 5 | 21,9445 | 19,9 | 15,6838 | 15,3237 |
| **6** | 2 | 9,3038 | 8,5 | 8,5283 | 8,5127 |
| | 3 | 14,0653 | 12,3 | 10,9216 | 10,6913 |
| | 4 | 17,9429 | 15,6 | 12,9409 | 12,592 |
| | 5 | 19,2354 | 18,6 | 14,8327 | 14,5403 |
| **7** | 2 | 8,7536 | 7,9 | 8,1476 | 8,1308 |
| | 3 | 12,2409 | 11,7 | 10,4429 | 10,0312 |
| | 4 | 16,0353 | 15,1 | 12,6845 | 12,3148 |
| | 5 | 19,0512 | 18,6 | 14,5872 | 14,2802 |
| **8** | 2 | 9,8497 | 9,1234 | 9,3389 | 9,337 |
| | 3 | 14,3751 | 13,2234 | 11,811 | 11,4524 |
| | 4 | 17,2569 | 17,0234 | 14,0544 | 13,6237 |
| | 5 | 21,3689 | 20,1234 | 16,2361 | 15,8661 |
| **9** | 2 | 9,4892 | 8,8234 | 9,3878 | 9,3851 |
| | 3 | 15,0391 | 13,4234 | 11,7314 | 11,4601 |
| | 4 | 17,2355 | 16,9234 | 13,9873 | 13,6182 |
| | 5 | 20,3243 | 19,9234 | 16,0342 | 15,7813 |
| **10** | 2 | 10,1806 | 9,2234 | 9,3819 | 9,3802 |
| | 3 | 14,1651 | 13,4234 | 11,6887 | 11,427 |
| | 4 | 17,9975 | 16,8234 | 13,9366 | 13,679 |
| | 5 | 20,2262 | 19,9234 | 16,027 | 15,7847 |

https://doi.org/10.56294/saludcyt2023408

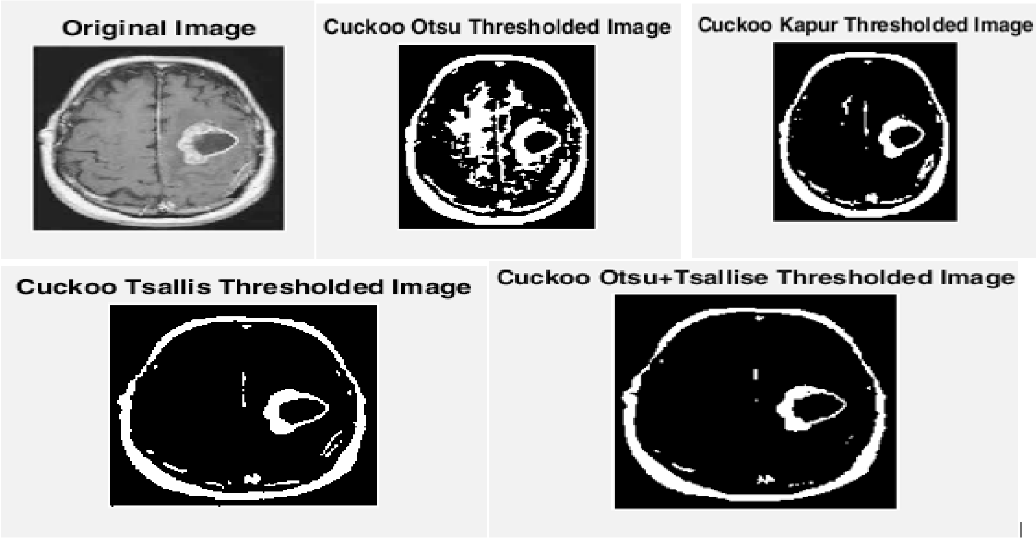


**Figure 3.** Segmentation output of the Cuckoo search algorithm, which uses a number of different objective functions.

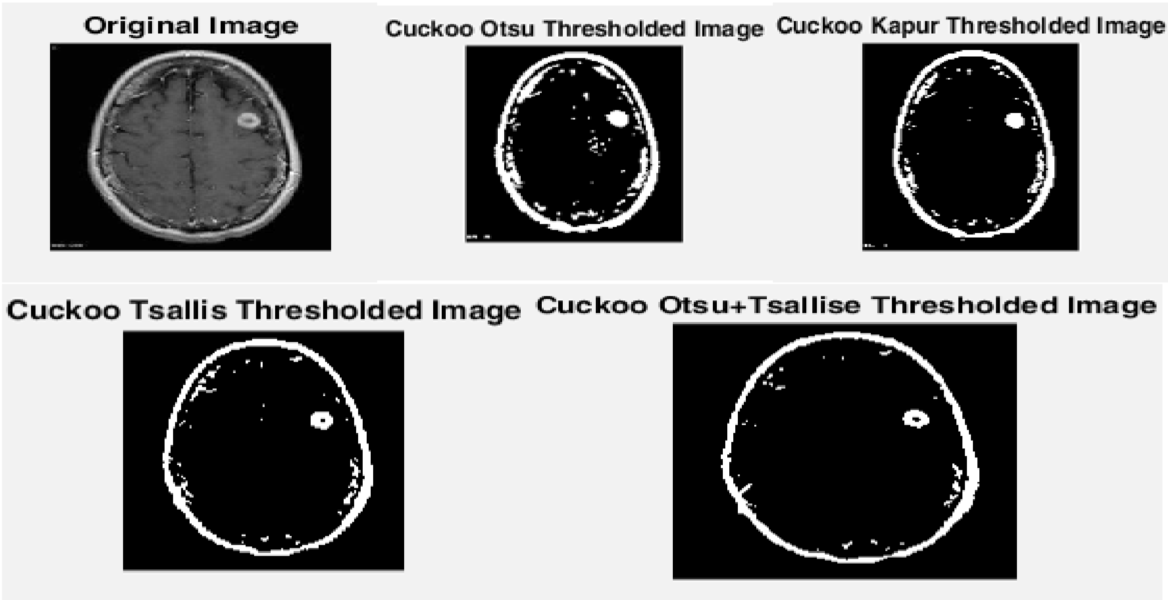


**Figure 4.** Segmentation output of the Cuckoo search algorithm, which uses a number of different objective functions.

Figure 3 and 4 sees the segmentation output, which includes the Cuckoo Ostu Threshold, Cuckoo Kapur Threshold, Cuckoo Tsallis Threshold and Cuckoo Otsu & Tsallis Threshold is vividly represented. The suggested approach Cuckoo search algorithm gives best output.

## CONCLUSION

Various thresholding, entropy, and evolutionary techniques, such as Two-level thresholding, Multilevel thresholding, Otsu's method, Kapur's entropy method, Tsallis entropy method & Cuckoo search algorithm, Lévy flight modelling are detailed in segmentation. It is observed that the Cuckoo Otsu & Tsallis Threshold combination delivers outstanding outcome in segmentation. Using different threshold levels, compare cuckoo ostu, cuckoo kapur, cuckoo tsallis and proposed method. If the number of threshold level increases then objective function value is increases. So, from the table 1 suggested approach gives the best output compare to the others. The suggested approach reflects the effective way to identify the nature of brain tumors along with adequate MRI scan.

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