

A Review of Multilevel Thresholding Methods in Clinical Imaging

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1. Introduction

Standard medical practice makes extensive use of a variety of imaging modalities, including X-ray, computed tomography (CT), ultrasound (US), and magnetic resonance imaging (MRI). One common tool used by specialists for diagnosis is ultrasound imaging. Ultrasound pictures are so popular because they are inexpensive, portable, non-invasive, and radiation-free [1]. Segmentation aids in the detection and quantitative analysis of pictures, yielding valuable information about the disease's progression [1]. One of the most crucial steps in image processing applications is picture segmentation. The term refers to the steps used to categorize a group of nearby pixels that have common characteristics. It takes a picture and splits it up into smaller, more manageable pieces, and then uses those pieces to fill out the whole image [2]. In most cases, the gray-level histogram of the picture, namely its thresholding, forms the basis of this segmentation process. One may say that thresholding is the easiest. The Otsu technique, which maximizes the between-class variation of gray levels to choose the ideal thresholds, is one of two well-known classical approaches to bi-level thresholding. In order to get the best threshold values, Kapur's technique maximizes the histogram's entropy. It is assumed by Kittler and Illingworth that the gray levels of each item in a picture follow a normal distribution. In multilevel thresholding, the picture's histogram is used to separate the pixels of objects in the image using several thresholds.

2. Ultrasound Imaging Modality

One way to see what's going on within a person's body is via ultrasound imaging. It entails subjecting the area to ultrasonic pulses with a high frequency. They depict the anatomy and function of the organs, as well as the vascular system and the flow of blood. There are a number of anomalies in the kidneys. The cost of the operation is one of the criteria that determine the diagnosis of a certain ailment in a nation like India [3]. According to Well's research, considerations including resolution, contrast mechanism, speed, ease, acceptance, cost, and safety ultimately determine which imaging approach is ideal for solving a given clinical issue. For compared to other imaging modalities, ultrasound works better for seeing soft tissues because of its high spatial resolution for scanning the abdomen, excellent tissue contrast, real-time approach, user-friendliness, patient acceptance, and apparent safety in usage.

4. Images are separated.

In order to interpret images and recognize patterns, picture segmentation is crucial. This ensures that the analysis's end product is of excellent quality. Image areas or objects may be separated via segmentation [4]. The subdivision's degree of detail is determined by the issue being addressed. Put simply, segmentation should end once an application's objects or areas of interest are identified. How well computerized analysis processes work in the end is dependent on how accurate the segmentation is. That is why it is crucial to take all necessary precautions to increase the likelihood of precise segmentation.

Optimization of Bacterial Foraging (4.1)

In the realm of distributed optimization and control, the bacterial foraging optimization algorithm (BFOA) has gained widespread acceptance as an algorithm of present interest. The communal foraging behavior of *Escherichia coli* served as an inspiration for BFOA. Due to its effectiveness in resolving practical



optimization issues across several application areas, BFOA has already attracted the interest of academics. Bacterial foraging behaviors, or chemotaxis, have recently gained a lot of interest due to their abundance of possible engineering applications and computer models. A small number of models that attempt to simulate bacterial foraging behaviors have found use in addressing real-world issues. One of these methods is BFO, or Bacterial Foraging Optimization.

for numerical optimization. In order to statistically assess each threshold for its optimal performance, a global and generic objective function is necessary when multithresholding is needed in image processing applications. Using a consistent rate of bacterial elimination and dispersion, a constant swim and tumble of bacteria, and a fixed length of the chemo taxis, the BFO algorithm optimizes the specified threshold to its maximum [5,6]. From the provided threshold values, there is no natural optimization of the maxima possible with the constant swim, tumbling, elimination, and dispersion rates. With its heuristic nature, BFO is able to handle complicated, non-differentiable objective functions and solve non-gradient optimization problems. Chemotaxis, reproduction, and elimination dispersal activities are the three primary processes that search hyperspace. We characterize these stages as:

Bacterial chemotaxis is the process by which microbes voluntarily move to locations with abundant food sources. This method uses swimming S to mimic the motion of an *E. coli* cell.

and slipping through flagella. From a biological standpoint, there are two pathways that an *E. coli* bacteria may take [6]. Its whole life span is characterized by alternating swimming in one direction and tumbling in the other. Consider the i -th bacterium during the j -th chemotactic, k -th reproductive, and l -th elimination-dispersal steps, denoted as $\theta_i(j, k, l)$.

The expressions $\theta_i(j+1, k, l) > \theta_i(j, k, l) + \Delta(i) \Delta T(i) \Delta(i)$ and so on.

Where Δ denotes a directionally random vector with entries between -1 and 1.

Elimination and Dispersal: Gradual or sudden changes in the local environment where a bacterium population lives may occur due to various reasons e.g. a significant local rise of temperature may kill a group of bacteria that are currently in a region with a high concentration of nutrient gradients.

2.1 Electromagnetism like Optimization

The algorithm is designed to imitate the attraction–repulsion mechanism of the electromagnetism theory so it is called electromagnetism-like mechanism algorithm. A solution in electromagnetism like algorithm is the charged particle in search space and this charge is related to the objective function value. Electromagnetic force exists between two particles. With the force, the particle with more charge will attract the other and the other one will repel the former. The charge also determines the magnitude of attraction or repulsion the better the objective function value, the higher the magnitude of attraction or repulsion [7,8,11]. There are

Local search: The local search is mostly applied on each particle in order to improve the founded solutions of the group. The practical local search is the simplest linear searching. Search each particle of each dimension in accordance with a certain step and then stop the search once a better solution is found. It provides effective local information for the global search of the group, so this stage plays a very important role in the EM algorithm.

Calculate the resultant force: The calculation of the resultant force is the most significant step in the EM algorithm. The local and global information of the particles will be effectively combined together from this step. The superposition principle of the basic electromagnetic theory says that the electromagnetic force of one particle which is exerted by other particles is inversely proportional to the distance between particles and is directly proportional to the product of the amount of charge carried with them [11].

with probability PAR,
accordingly after the completion of the iteration of the EM algorithm.

2.2 Harmony Search Algorithm

Harmony search is a music-based metaheuristic optimization algorithm. It was inspired by the observation that the aim of music is to search for a perfect state of harmony. This harmony in music is analogous to find the optimality in an optimization process. The search process in optimization can be compared to a musician's improvisation process. In Harmony Search algorithm, each solution is called a harmony and is represented by an n-dimension real vector. An initial population of harmony vectors are randomly generated and stored within a harmony memory (HM)[12, 13]. A new candidate harmony is then generated from the elements in the harmony by using a memory consideration operation either by a random re-initialization or a pitch adjustment operation. Finally, the harmony memory is updated by comparing the new candidate harmony and the worst harmony vector in the harmony memory. The worst harmony vector is replaced by the new candidate vector when the latter delivers a better solution in the harmony memory. The above process is repeated until a certain termination criterion is met. The basic Harmony search algorithm consists of three main phases: initialization, improvisation, and updating.

Initialization: In this step the harmony memory vectors are initialized. Let $x_i = \{x_i(1), x_i(2), \dots, x_i(n)\}$ represent the i th randomly generated harmony vector.

$X_i(j) = l(j) + (u(j) - l(j)) * \text{rand}(0,1)$ for $j = 1, 2, \dots, n$ and $i = 1, 2, \dots, \text{HMS}$ 6

Where: $\text{rand}(0,1)$ is matrix of random numbers between 0 and 1, $u(j)$ and $l(j)$ is the upper bound and lower bound respectively. Then HM matrix is filled with HMS vectors accordingly.

Improvisation: In this phase, a new harmony vector X_{new} is built by applying the following three operators: memory consideration, random re-initialization, and pitch adjustment. Generating a new harmony is known as improvisation.

$\begin{cases} x_{\text{new}}(j), & \text{with probability } (1-\text{PAR}). \end{cases}$

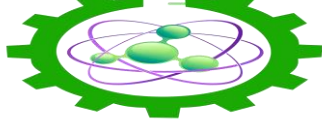
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Updating the harmony memory: After a new harmony vector X_{new} is generated, the harmony memory is updated by the survival of the fit competition between X_{new} and the worst harmony vector X_w in the HM. Therefore X_{new} will replace X_w and become a new member of the HM in case the fitness value of X_{new} is better than the fitness value of X_w .

3. Conclusion & Future Scope

Although there is a great amount of literature on the subject, segmentation is an active topic of study due to its importance in advanced image analysis and computer vision. Segmenting ultrasound pictures is still a tough process, despite the many image segmentation algorithms that have been developed in recent years.

The goal of future work on medical picture segmentation is to decrease the amount of human intervention while simultaneously increasing computational speed, accuracy, and precision of segmentation systems. Combining segmentation approaches based on discrete and continuous data and using previous knowledge may increase accuracy and precision. Evolutionary algorithms and other multi-scale processing methods show promise for improving computing efficiency. Search or optimization techniques that are efficient are necessary to resolve the optimization challenge. Multilevel thresholding difficulties have been solved using evolutionary strategies in an effort to eradicate such issues. In the field of artificial intelligence, evolutionary computation (EC) is a paradigm that attempts to reap the benefits of group phenomena in adaptable populations of problem solvers by mimicking the iterative process of natural selection, which includes growth, development, reproduction, and survival. Applications involving real-time processing will place a premium on computational efficiency. This method produces a multi-level segmentation algorithm that can accurately determine the digital image's threshold values within a fewer iterations and less processing complexity for the first suggestions. The peak signal-to-noise ratio (PSNR) evaluates the quality of the segmentation by taking into account the coincidences between the original and segmented pictures; it is used to examine the performance of the technique that is explained. When pitted against harmony search and the bacterial foraging optimization method, the electromagnetism-like optimization technique yielded the higher PSNR value. When comparing harmony search with bacterial foraging optimization, the latter comes out on top in terms of PSNR. However, when looking at computational time, electromagnetism-like optimization is the slowest and harmony search is the fastest.



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