

Survey of Some Multilevel Thresholding Techniques for Medical Imaging

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Abstract: Segmentation is a method of partitioning an image into useful object, image processing is a method of converting an image into digital form and performing some operations on it so to enhance and extract some useful information from it. It found various applications in the field of engineering, robotics, also analysis and computer vision techniques are increasing in prominence in medical science and in case of kidney stone disease the image segmentation of ultrasound images of stones are found to be effective in medical imaging. By using this technique, it is also possible to extract some features that will be very helpful for the diagnosis of the medical images to make comparative study on images for better decision making. For gray scale images, thresholding is widely considered to extract key features from input image. The main objective is to enhance the key feature of an image using the best possible bi-level as well as the multilevel threshold. This paper presents a latest review of different technologies used in medical image segmentation like bacterial foraging optimization, harmony search & Electromagnetism optimization etc.

Keywords: Image Processing; Bacterial Foraging Optimization; Harmony Search Optimization; Electromagnetism like Optimization; Image Segmentation; Multilevel Thresholding

1. Introduction

The X-ray, positron emission tomography (PET), computed tomography (CT), Ultrasound (US) and magnetic resonance imaging (MRI) are the widely available different medical imaging modalities which are broadly employed in regular clinical practice. Ultrasound imaging modality is one of popular method used by specialist to diagnose it. The reason behind the wide use of ultrasound images is because they are non-invasive, portable, radiation free, and affordable [1]. Segmentation help to detect and quantitatively analyze the images which provides useful information regarding the progress of the disease[1]. Image segmentation can be considered as one of the important step in image processing applications. It is the process of classifying the set of pixels with similar properties in the same region. It divides an image into several segments and those set of similar segments collectively cover the entire image [2]. Usually, this segmentation process is based on the image gray-level histogram, namely image histogram thresholding. The thresholding can be regarded as the simplest one. For bi-level thresholding there are two popular classical methods are Otsu method which chooses the optimal thresholds by maximizing the between class variance of gray levels. Kapur's method finds the optimal threshold values by maximizing the entropy of histogram. Kittler and Illingworth assume that the gray levels of each object are normally distributed in an image. Multilevel thresholding uses a number of thresholds in the histogram of the image to separate the pixels of the objects in the image.

2. Ultrasound Imaging Modality

The ultrasound imaging is a technique of viewing the internal organs of the body. It involves exposing that part of the body to high frequency sound waves. They show the organs structure and movement, as well as blood flowing through blood vessels. In the Kidney there are various abnormalities. In a country like India there are various factors which decide the diagnosis of a particular disease and one of the major factor is cost of procedure[3]. The

study made by Well suggests that the choice of the best imaging technique to solve any particular clinical problem is actually based on the factors such as resolution, contrast mechanism, speed, convenience, acceptability, cost and safety. The ultrasound imaging techniques performs better for imaging soft tissues in terms of the following factors: accurate spatial resolution for abdominal scanning, good tissue contrast, real-time methodology, convenient to use, highly acceptable to patients, and apparently safe in applications.

3. Image Segmentation

Image segmentation is very essential to image processing and pattern recognition. It leads to the high quality of the final result of analysis. Segmentation subdivides an image into its constituent regions or objects [4]. The level of detail to which the subdivision is carried depends on the problem being solved. That is, segmentation should stop when the objects or regions of interest in an application have been detected. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures. For this reason, considerable care should be taken to improve the probability of accurate segmentation.

3.1 Bacterial Foraging Optimization

Bacterial foraging optimization algorithm (BFOA) has been widely accepted as a global optimization algorithm of current interest for distributed optimization and control. BFOA is inspired by the social foraging behaviour of Escherichia coli. BFOA has already drawn the attention of researchers because of its efficiency in solving real-world optimization problems arising in several application domains. In recent years, bacterial foraging behaviours i.e., bacterial chemotaxis as a rich source of potential engineering applications and computational model have attracted more and more attentions. A few models have been developed to mimic bacterial foraging behaviours and been applied for solving practical problems. Among them, Bacterial Foraging Optimization (BFO) is a population-

based numerical optimization algorithm. If there is a need of the multithresholding in image processing application, a global and generic objective function is desired so that each threshold could be tested for its best performance statistically. The maxima of the selected threshold is optimized by using the BFO algorithm based on constant chemo taxis length, constant rate of elimination and dispersion of bacteria and constant swim and tumbling of bacteria[5,6]. The constant rate of swim, tumbling and rate of elimination and dispersion does not provide a natural optimization of the maxima of the threshold level from the given threshold levels. As a heuristic method, BFO is designed to tackle non-gradient optimization problems and to handle complex and non-differentiable objective functions. Searching the hyperspace is performed through three main operations, namely chemotaxis, reproduction and elimination dispersal activities. These steps are defined as:

Chemotaxis: Chemotaxis is the activity that bacteria gathering to nutrient-rich areas spontaneously. This process simulates the movement of an E.coli cell through swimming

$$J_{cc}(\theta, P(j, k, l)) = \sum_{i=1}^S J_{cc}(\theta, \theta^i(j, k, l)) = \sum_{i=1}^S [-d_{attractant} \exp(-w_{attractant} \sum_{m=1}^P (\theta_m - \theta_m^i)^2)] + \sum_{i=1}^S [h_{repellant} \exp(-w_{repellant} \sum_{m=1}^P (\theta_m - \theta_m^i)^2)] \dots\dots\dots 2$$

Where $J_{cc}(\theta, P(j, k, l))$ is the objective function value to be added to the actual objective function to be minimized to present a time varying objective function, S is the total number of bacteria, p is the number of variables to be optimized, which are present in each bacterium and $\theta = [\theta_1, \theta_2, \theta_3, \dots, \theta_p]^T$ is a point in the p-dimensional search domain. $d_{attractant}, h_{attractant}, w_{repellant}, h_{repellant}$ are different coefficients that should be chosen properly.

Reproduction: The least healthy bacteria eventually die while each of the healthier bacteria those yielding lower value of the objective function split into two bacteria, which are then placed in the same location. This keeps the swarm size constant.

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.

3.2 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

and tumbling via flagella. Biologically an E.coli bacterium can move in two different ways [6]. It can swim for a period of time in the same direction or it may tumble, and alternate between these two modes of operation for the entire lifetime. Suppose $\theta^i(j, k, l)$ represents i-th bacterium at j-th chemotactic, k-th reproductive and l-th elimination-dispersal step.

$$\theta^i(j + 1, k, l) = \theta^i(j, k, l) + C(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \dots\dots\dots 1$$

Where Δ indicates a vector in the random direction whose elements lie in [-1, 1].

Swarming: It has been observed for several motile species of bacteria including E.coli and S. typhimurium, where intricate and stable spatio-temporal patterns (swarms) are formed in semisolid nutrient medium. A cell-to-cell communication mechanism is established to simulate the biological behaviour of bacteria swarming.

four phases in EM algorithm: Initialization of the algorithm, calculation of the total force, movement along the direction of the force and neighborhood search to exploit the local minima

Initialize: Randomly select m points ($x_i = (x_i^1, x_i^2, \dots, x_i^n)$, $i = 1, 2, \dots, m$) from the feasible region as the initial particles. Distribute these initial particles randomly in the feasible field, then calculate the objective function value of every particle $f(x_i)$, and note the particle whose current objective function value is the most optimized as x_{best} .

$$x_t^B = \arg \max_{x_{i,t} \in S_t} \{f(x_{i,t})\} \dots\dots\dots 3$$

Where x_t^B is the element of S_t that produces the maximum value in terms of the objective function.

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].

From this perspective, EM provides information for next local search through calculating the resultant force.

$$q_{i,t} = \exp\left\{-n \frac{f(x_{i,t}) - f(x_t^B)}{\sum_{j=1}^N f(x_{i,t}) - f(x_t^B)}\right\} \dots\dots\dots 4$$

Force $F_{i,j}^t$ between two points $x_{i,t}$ and $x_{j,t}$ is calculated using:

$$F_{i,j}^t = \begin{cases} (x_{j,t} - x_{i,t}) \frac{q_{i,t} \cdot q_{j,t}}{\|x_{j,t} - x_{i,t}\|^2} \text{ if } f(x_{i,t}) > f(x_{j,t}) \\ (x_{i,t} - x_{j,t}) \frac{q_{i,t} \cdot q_{j,t}}{\|x_{j,t} - x_{i,t}\|^2} \text{ if } f(x_{i,t}) \leq f(x_{j,t}) \end{cases} \dots\dots\dots 5$$

Total force F_i^t corresponding to $x_{i,t}$ is calculated.

Move particles: After the force on particle is calculated it is moved in the resultant direction of the force with a random step size. And thus the position of each particle is updated accordingly after the completion of the iteration of the EM algorithm.

3.3 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 $i = 1, 2,\dots,HMS$ 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 newharmony 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.

$$X_{new}(j) = \begin{cases} x_i(j) \in \{x_1(j), x_2(j), \dots, x_{HMS}(j)\}, \\ \text{with probability HMCR}, \\ \{l(j) + u(j) - l(j)\} * \text{rand}(0,1), \\ \text{with probability } 1 - \text{HMCR}. \end{cases} \dots\dots\dots 7$$

Where: HMCR is harmony memory consideration rate.

Every component obtained by memory consideration is further examined to determine whether it should be pitch adjusted. For this operation, the pitch-adjusting rate (PAR) is defined as to assign the frequency of the adjustment and the bandwidth factor(BW) to control the local search around the selected elements of the HM. Hence, the pitch-adjusting decision is calculated as follows:

$$X_{new}(j) = \begin{cases} x_{new}(j) = x_{new}(j) \pm \text{rand}(0,1) * BW, \\ \text{with probability PAR}, \\ x_{new}(j), \text{ with probability } (1 - \text{PAR}). \end{cases} \dots\dots\dots 8$$

Updating the harmony memory: After a newharmony 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 .

4. Conclusion & Future Scope

Segmentation is an important step in advance image analysis and computer vision and therefore is an ongoing research area although a vast literature is available. Many image segmentation methods have been developed in the past few years for segmenting Ultrasound images, but still it remains a challenging task.

Future research in the segmentation of medical images will strive towards improving the accuracy, precision, and computational speed of segmentation methods, as well as reducing the amount of manual interaction. Accuracy and precision can be improved by incorporating prior information and by combining discrete and continuous-based segmentation methods. For increasing computational efficiency, and multi scale processing methods such as evolutionary techniques appear to be promising approaches. To solve the optimization problem efficient search or optimization algorithms are needed. To eliminate such problems evolutionary techniques have been applied in solving multilevel thresholding problems. Evolutionary computation (EC) is a paradigm in the artificial intelligence realm that aims at benefiting from collective phenomena in adaptive populations of problem solvers utilizing the iterative progress comprising growth, development, reproduction, selection, and survival as seen in a population computational efficiency will be particularly important in real-time processing applications. The approach generates a multilevel segmentation algorithm which can effectively identify the threshold values of a digital image within a

reduced number of iterations and decreasing the computational complexity of the original proposals. To measure the performance of the approach discussed, the peak signal-to-noise ratio (PSNR) is used which assesses the segmentation quality, considering the coincidences between the segmented and the original images. The electromagnetism-like optimization algorithm is found to have the better value of PSNR as compared to both bacterial foraging optimization algorithm and harmony search. And on the other hand bacterial foraging optimization is better as compared harmony search in terms of PSNR value. But when computational time is considered the harmony search is found to be faster as compared to both of these and electromagnetism-like optimization is found to be slowest.

References

- [1] P. R. Tamilselvi and P. Thangaraj, "An efficient segmentation of calculi from US renal calculi images using ANFIS system", *European Journal of Scientific Research*, vol. 55, No.2, pp. 323-333, 2011.
- [2] Tamilselvi and Thangaraj, "Computer aided diagnosis system for stone detection and early detection of kidney stones", *Journal of Computer Science*, vol. 7, No. 2, pp. 250-254, 2011.
- [3] P.R.Tamiselvi, "Detection of renal calculi using semi-automatic segmentation approach" *International Journal of Engineering Science and Innovative Technology (IJESIT)*, vol. 2, Issue 3, May 2013.
- [4] Jie-Yu He, Sui-Ping Deng and Jian-Ming Ouyang, "Morphology, particle size distribution, aggregation, and crystal phase of nano crystallites in the urine of healthy persons and lithogenic patients, " *IEEE Transactions on Nano Bioscience*, vol. 9, No. 2, pp. 156-163, June 2010.
- [5] S. Dasgupta and S. Das "Bacterial foraging optimization algorithm: theoretical foundations, analysis, and applications" *Studies in Computational intelligence volume 203*, pp.23-55, 2009.
- [6] M. Maitra, and A. Chatterjee, "A hybrid cooperative comprehensive learning based PSO algorithm for image segmentation using multilevel thresholding", *Expert Systems with Applications*, vol. 34, pp. 1341-1350, 2008.
- [7] D. Oliva, E. Cuevas, G. Pajares, D. Zaldivar and V. Osuna, "A multilevel thresholding algorithm using electro-magnetism optimization", *Neurocomputing*, 139, pp. 357-381, 2014.
- [8] L.dos, S. Coelho and P. Alotto, "Multiobjective electromagnetic optimization based on a non-dominated sorting genetic approach with a chaotic crossover operator", *IEEE transactions on magnetics*, vol. 44, no. 6, June 2008.
- [9] Jun-Lin Lin, Chien-Hao Wu, Hsin-Yi Chung, "Performance comparison of electromagnetism-like algorithms for global optimization", *Journal of Applied Mathematics*, 3, pp. 1265-1275, 2012.
- [10] C. T. Su and H. C. Lin, "Applying electromagnetism-like mechanism for feature selection," *Information Sciences*, vol. 181, No. 5, pp. 972-986, 2011.
- [11] C. Zhang, X. Li, L.Gao, and Q. Wu, "An improved electromagnetism like mechanism algorithm for constrained optimization", *Experts Systems with Applications*, 40 pp. 5621-5634, 2013.
- [12] K. Hammouche, M. Diaf and P. Siarry, "A comparative study of various meta-heuristic techniques applied to the multilevel thresholding problem." *Journal of Engineering Applications of Artificial Intelligence*, vol. 23, 5, pp. 676-688, 2010.
- [13] Miao MIAO, Jianguo JIANG, "Electromagnetism-like mechanism algorithm based on normalization and adaptive move operator", *Journal of Computational Information Systems* 8: 18 pp.7449-7455, 2012.
- [14] D. Oliva, E. Cuevas, G. Pajares, D. Zaldivar, and M. Perez-Cisneros, "Multilevel thresholding segmentation based on harmony search optimization", *Journal of Applied Mathematics* volume 2013.
- [15] E.Cuevas, N.Ortega-S´anchez, D.Zaldivar, and M.P´erez-Cisneros, "Circle detection by harmony search optimization," *Journal of Intelligent and Robotic Systems*, pp. 1-18, 2011.
- [16] O. M. Alia and R. Mandava, "The variants of the harmony search algorithm: an overview," *Artificial Intelligence Review*, vol. 36, no. 1, pp. 49-68, 2011.
- [17] X.-S. Yang, "Harmony Search as a metaheuristic algorithm", in: *music-inspired harmony search algorithm: theory and applications* (Editor Z. W. Geem), *Studies in Computational Intelligence*, Springer Berlin, vol. 191, pp. 1-14 (2009).
- [18] P. K. Sahoo, S. Soltani and A. K. C. Wong, "A survey of thresholding techniques", *Computer Vision, Graphics and Image Processing*, vol. 41, no. 2, pp. 233-260, 1988.
- [19] N. Otsu, "A threshold selection method from gray level histograms," *IEEE Transaction on Systems, Man and Cybernetics*, SMC-9(1), pp.62-66, 1979.
- [20] Kevin M Passino, "Biomimicry for optimization, control, automation" Springer-Verlag London, UK 2005.
- [21] Nobuyuki Otsu, "A threshold selection method from gray-level histograms," *IEEE transactions on systems, man and cybernetics*, vol. SMC-9, No.1, Jan 1979.
- [22] J. Kittler and J. Illingworth, "Minimum error thresholding," *Pattern Recognition*, vol. 19, no. 1, pp. 41-47, 1986.