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

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

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

$$F_{i,j}^t = \begin{cases} (x_{j,t} - x_{i,t}) \dfrac{q_{i,t}.q_{j,t}}{\|x_{j,t} - x_{i,t}\|^2} if, f(x_{i,t}) > f(x_{j,t}) \\ (x_{i,t} - x_{j,t}) \dfrac{q_{i,t}.q_{j,t}}{\|x_{j,t} - x_{i,t}\|^2} if, f(x_{i,t}) \le f(x_{j,t}) \end{cases} \quad ..5$$

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 $x_i = \{x_i(1), x_i(2), \ldots x_i(n)\}$ represent the ith randomly generated harmony vector.
$X_i(j) = l(j) + (u(j) - l(j))*$ rand(0,1) for j= 1,2,…….,n and i = 1, 2,……HMS …………6
Where: 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.

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

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:

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

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 becomea 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 informationand 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. Cuevasb, 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.