





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.

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