IMAGE SEGMENTATION USING PARTICLE SWARM OPTIMIZATION AND HARMONY SEARCH ALGORITHM

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(2014-2016)

CERTIFICATE

This is to certify that **Mansi Seth (2k14/ISY/07)** has carried out the major project titled "**Image Segmentation using Particle Swarm Optimization and Harmony Search Algorithm**" in partial fulfilment of the requirements for the award of Master of Technology degree in Information Systems by **Delhi Technological University**.

The major project is bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2013-2015. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree or diploma.

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It humbly extend my words of gratitude to other faculty members of this department for providing their valuable help and time whenever it was required.

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ABSTRACT

Segmentation holds a very important place in the field of Image Processing. It is a technique used to divide an image into segments which correlate with the real world. The regions having common characteristics are grouped together and are thus differentiated from other regions of the image making the image more clear and distinguishable. It also helps to differentiate the foreground and background of the image thus helping to analyze the image better. Segmentation can be performed by variety of evolutionary algorithms. In the present work Particle Swarm Optimization and Harmony Search Algorithm have been applied. PSO is an evolutionary computational technique which imitates the social behavior of bird flock. It is use to optimize variety of computational problems. Harmony Search algorithm is a population based algorithm which imitates the music improvisation process. It consists of Harmony memory which is initialized with initial population which are further updated and improvised until a termination criteria is met. The combination of the above two algorithms increases the convergence rate and accuracy of the result of the segmentation with low computational overhead. Finally the Berkley data set is used to to display the result of the algorithm.

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Chapter 1

INTRODUCTION

Segmentation holds a very important place in the field of Image Processing[1]. It is a technique used to divide an image into segments which correlate with the real world. The regions having common characteristics are grouped together and are thus differentiated from other regions of the image making the image more clear and distinguishable[2]. It also helps to differentiate the foreground and background of the image thus helping to analyze the image better.

Nowadays, segmentation has a important place in variety of domains such as medical imaging, the face recognition, the machine vision,the expert system,the automatic traffic control system, and also the satellite images, etc[3][4]. Image segmentation is one of the great focus owing to its various practical applications. It can be performed by variety of evolutionary algorithms[4]. The advantage of using evolutionary algorithm is that they are able to optimize computational problems efficiently and quickly[5].

1.1 BACKGROUND

Different image segmentation methods have been proposed and also been applied to numerous applications in real world [6]. Here, our concern is thresholding where we divide the image depending upon the pixel intensities known as the thresholds[7]-[9]. This procedure helps in dividing the image into various levels of segments depending upon the thresholds. This approach gives more clear image as the image is clearly divided into foreground and background.

The main task is to find the thresholds optimally. There are meta-heuristic approaches introduced to deal with NP-hard problems and the problems for which the data is uncertain and not readily available. These optimization techniques include Particle swarm optimization, Genetic Algorithms (GA) , Ant Colony Optimization[11]-[14]. Also the harmony search algorithm which is a population based algorithm which imitates the music improvisation process[17]. It consists of Harmony memory which is initialized with initial population which are further updated and improvised until a termination criteria is met.HSA has the advantage of solving the problems with low computational overhead.

1.2 MOTIVATION

Accurate image segmentation is very difficult problems in computer vision[3]. Before high-level reasoning could be applied to an image, it must be divided into its major structural components. Taking an example, in radiation treatment planning, radiologists needs to calculate the best path to apply radiation to a tumor while trying to avoid crucial structures such as the eye and the kidney. To accomplish this task, image segmentation has to be performed.

Segmentation partitions an image into distinct regions having each pixels with similar properties. To be meaningful and useful for image analysis and interpretation, the divided sections should strongly relate to features of interest. Meaningful segmentation is the very first step from the low-level image processing transformation of a grayscale or color image into one other images of high-level image description in terms of features, and scenes. The success of image analysis relies on reliability of segmentation. And an meaningful partitioning of an image in general is a very challenging problem.

1.3 GOAL OF MASTER THESIS

Our aim is to study about the segmentation and also about the various methods through which segmentation can be performed. We will also study about various evolutionary algorithms which nowadays provide a new approach for image segmentation. Our focus is on particle swarm optimization and harmony search algorithm [29]. The advantages of both the algorithm will be combined to efficiently solve a segmentation problem. Also how the new approach is better than the basic algorithm will be evaluated.

1.4 RELATED PREVIOUS WORK

Tremendous research work has been done in the field of Image Segmentation over the years[4]. Research papers have been published to focus on particle swarm optimization to solve the problem of Image Segmentation[10]-[12].

Until now the Image Segmentation is done via thresholding and clustering but now many evolutionary techniques of optimization for image segmentation have been introduced. These evolutionary techniques give us a new approach of Image Segmentation. The evolutionary methods are Ant Colony Optimization algorithm, Genetic algorithm, Particle Swarm Optimization algorithm and Differential Evolution algorithm.

1.5 THESIS ORGANIZATION

Chapter two describes in detail work done previously in the field of image segmentation and also analyze various segmentation techniques. This chapter also covers details about PSO and HSA. Chapter three will cover the proposed work. It will contain the algorithm used for image segmentation. And how it is better than the basic PSO algorithm is also shown .Chapter four consists of the results of our approach used. The result will be validated against the ground truth using dice and jaccard coefficients which are used as a quantitative measure. Berkley dataset images are used to validate the result.

Chapter five concludes thesis and then the further ideas for future work is presented.

Chapter 2

LITERATURE SURVEY

2.1 IMAGE SEGMENTATION

Segmentation is a technique used to divide an image into segments which correlate with the real world. The regions having common characteristics are grouped together and are thus differentiated from other regions of the image making the image more clear and distinguishable. It also helps to differentiate the foreground and background of the image thus helping to analyze the image better.

2.2 DIFFERENT IMAGE SEGMENTATION TECHNIQUES

Image segmentation though can be done by variety of approaches. Broadly we can classify the approaches into two classes:

1. Similarity

2. Discontinuity

In similarity based segmentation, the image is segmented based on similar characteristics. The pixels having common properties are placed in one cluster. Thus it tries to maintain large inter cluster difference and small intra cluster difference. Approaches used in this technique are clustering, region growing etc

Discontinuity approach tries to find the abrupt change in intensity. it is useful in edge detection.

2.2.1 Edge detection based segmentation:

In edge based segmentation, the result of segmentation is in form of edges/boundaries between different regions. Edges are formed where there is sharp and significant change in the pixel intensity. [1] A variety of edge operators can be used for edge detection. Some of the popular ones are Prewitt, Sobel, Canny, LoG (Laplacian-of-Gaussian), etc. This technique works well on images having good contrast between different regions. Some of its drawbacks include inadequate detection of areas with low contrast boundaries, inadequate detection of thin areas, etc.

2.2.2 Thresholding based segmentation

This is a very simple technique which is used to segment the image into various levels of segments. The approach is as follows: according to the level up to which the image has to be segmented, pixel intensities are found out which are known as thresholds and then the image is divides based on these thresholds. This helps to divide the image into various levels thus increasing the clarity of the image. The thresholding can be local or global. The thresholding approach is very effective in images which have lighter and darker foreground and backgrounds. This can be done manually or algorithms are also present for thresholding.

2.2.3 Region based segmentation

It is further classified into:

Region growing: The process [4] starts with selecting a pixel(seed) or group of pixels. Subsequently, based on some predefined criteria neighbouring pixels that exhibit similar property are added to the region. This process is continued until no more pixels can be appended to the growing region. This process helps in getting the connected region that have certain structure of interest.

Region splitting and merging: This process [2] starts with few initial segmentation and then sub-dividing the regions that do not satisfy the predefined criteria. This is region splitting. This splitting of regions is further accompanied with region merging to add up the advantages of both the approaches.

2.2.4 Clustering based segmentation

Clustering is basically unsupervised learning scheme in which we need to find out the number of clusters to group the pixels of an image into those clusters. Based upon some similarity criteria, similar pixels are appended to a particular cluster.[4] The basic goal is to maximize the intra cluster similarity and to minimize the inter cluster similarity. Clustering is of two types- one is hard clustering and another is soft clustering. Clustering based approaches yields better results and are very efficient.

2.3 APPLICATIONS OF IMAGE SEGMENTATION

Image segmentation has applications in various domains. Some of them are listed below:

1. **Content based Image Retrieval**: it is used to extract images from a large database. Rather than using keywords or tokens in queries, it uses features that can be inferred from images like color, texture, shape etc, thus segmentation helps in finding such features ehich in turn helps to retrieve the images from a huge database.

2. **Machine Vision**: it provides imaging based automatic inspection. The primary uses are automatic inspection and industrial robotic guidance

3. **Medical imaging**: it helps in analyzing the internal structure of the human body by allowing it to represent the internal parts in more clear way.It helps in variety of things like
   - Measure tissue volumes
   - Surgery planning
   - Virtual surgery simulation
   - Study of anatomical structure
   - Locates tumors

4. **Object detection** :It is related to that part of image processing where objects have to be identified from a image or a video thus helping in:

   - Pedestrian detection
   - Face detection

2.4 PARTICLE SWARM OPTIMIZATION

Kennedy and Eberhart introduced the concept of function-optimization by means of a particle swarm. Suppose the global optimum of an *n*-dimensional function is to be located. The function may be mathematically represented as:

$$f(x1, x2, x3, . . . , xn) = f(X)$$

Where x is the search-variable vector, which actually represents the set of independent variables of the given function[8]. The task is to find out such a x, that the function value $f(x)$ is either a minimum or a maximum denoted by f* in the search range. If the components of x assume real values then the task is to locate a particular point in the n-dimensional hyperspace.

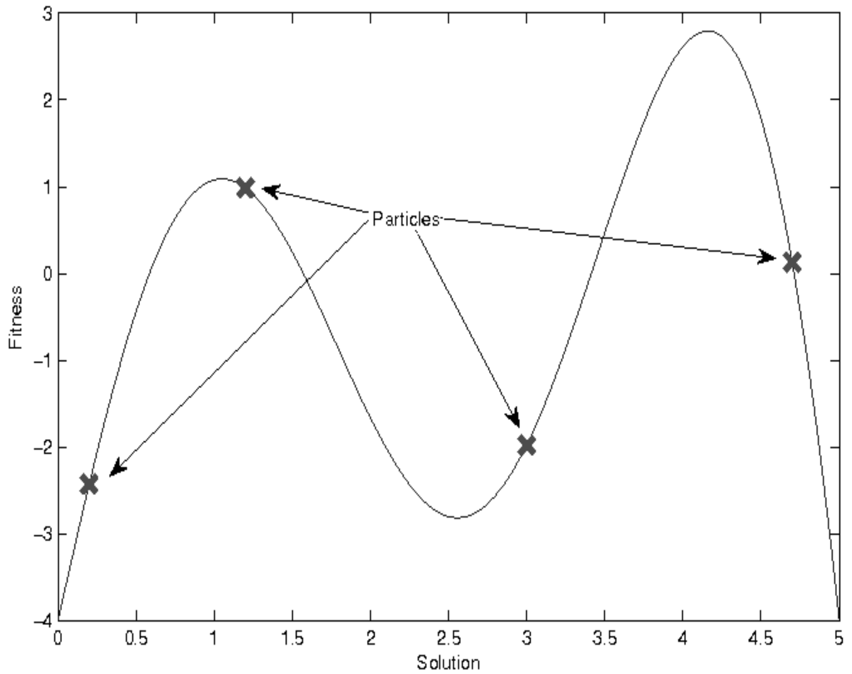


Figure 2.1: Initial state of four particles in PSO

Figure 2.2 shows the initial state of a four-particle PSO algorithm seeking the global maximum in a one-dimensional search space. The search space is composed of all the possible solutions along the x-axis; the curve denotes the objective function.

The PSO algorithm works by simultaneously maintaining several candidate solutions in the search space. During each iteration of the algorithm, each candidate solution is evaluated by the objective function being optimized, determining the fitness of that solution. Each candidate solution can be thought of as a particle "flying" through the fitness landscape finding the maximum or minimum of the objective function.[10]

Initially, PSO is initialized with some solutions which are generated randomly. The process goes as follows: in each iteration the solutions are updated such that the best solutions replace the worst solutions. In each iteration two variables are updated. These are:

- Pbest
- Gbest

Pbest is the personal best. Each particles pbest is maintained which is the best value of that particle till now whereas gbest is the best value amongst all the values of all the particles hence known as global best. These two variables helps in maintaining the personal best and global best values of the particles.

Table I: Generation of the Population

	T1	T2	T3	T4	T5
particle 1	P3	P2	P1	P2	P2
particle 2	P1	P2	P3	P1	P1
particle 3	P1	P3	P2	P1	P2
particle 4	P2	P1	P2	P3	P1
particle 5	P2	P2	P1	P3	P1

Local best value or we can say lbest value is one when a particle becomes a part of topological neighbor. Therefore the best value among all the neighbours becomes the local best. Eventually the two best values helps in updating the position and velocity of each particle using two equations which are as follows.

v[k+1] = v[k] + c1 * rand() * (pbest[] - present[]) + c2 * rand() * (gbest[] - present[]) (a)
present[] = present[] + v[] (b)

where,

v ----- particle velocity

present ------particles current solution

rand------random number

c1,c2----- learning factors , in general value is 2

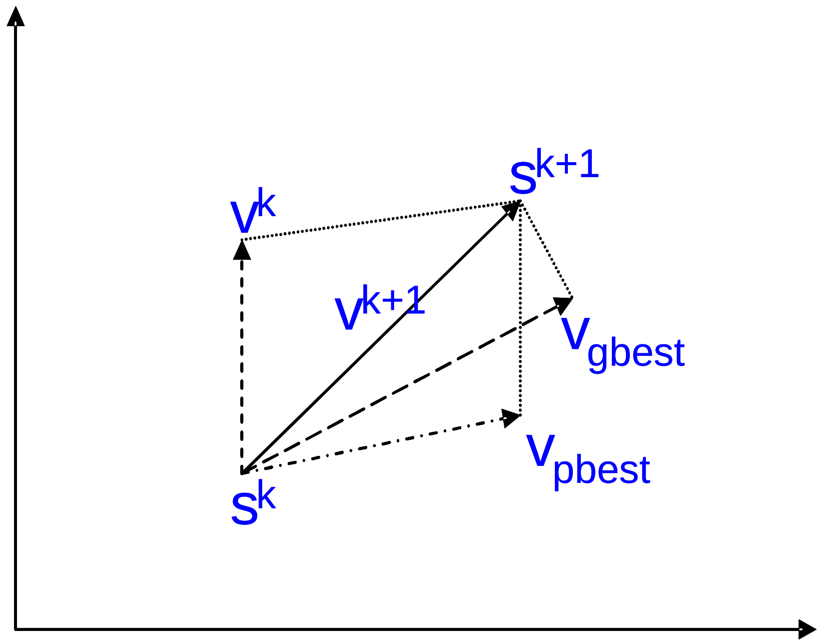


Figure 2.2 :Concept of Modification of a searching point by PSO

s^k : current searching point.
s^{k+1}: modified searching point.
v^k: current velocity.
v^{k+1}: modified velocity.
v_{pbest} : velocity based on pbest.
v_{gbest} : velocity based on gbest

2.4.1 Pseudo Code

The pseudo code of the procedure shown in figure 2.3 is as follows

for each particle i = 1 : N_p **do**
  Initialize all the particles (randomly within their range) and corresponding random velocities
  Calculate the fitness value
end for
for iterations j = 1 : N_i **do**
  for each particle i = 1 : N_p **do**
    Calculate new fitness value
    //Set $pbest$ as personal best solution of i^{th} particle achieved so far
    if $(J((\mathrm{I}_e)_i) > J(\mathrm{pbest}_i))$ **then**
      $pbest_i = (N_p)_i$
      $//(N_p)_i$ is the i^{th} particle
    end if
    //Set $gbest$ as global best solution achieved so far among all generations
    if $(J((\mathrm{I}_e)_i) > J(\mathrm{gbest}))$ **then**

$gbest = (N_p)_i$

end if

end for

for each particle i = 1 : N_p **do**

Update the velocity

Update the position

end for

The algorithm keeps on iterating untill aterminating criteria is met. In each iteration the Vmax value keeps on imcreasing. If the algorithm keeps iterating then the value of Vmax has to be limited.

2.4.2 PSO Flowchart

The following figure 2.3 shows the steps for the implementation of the Particle swarm optimisation algorithm:

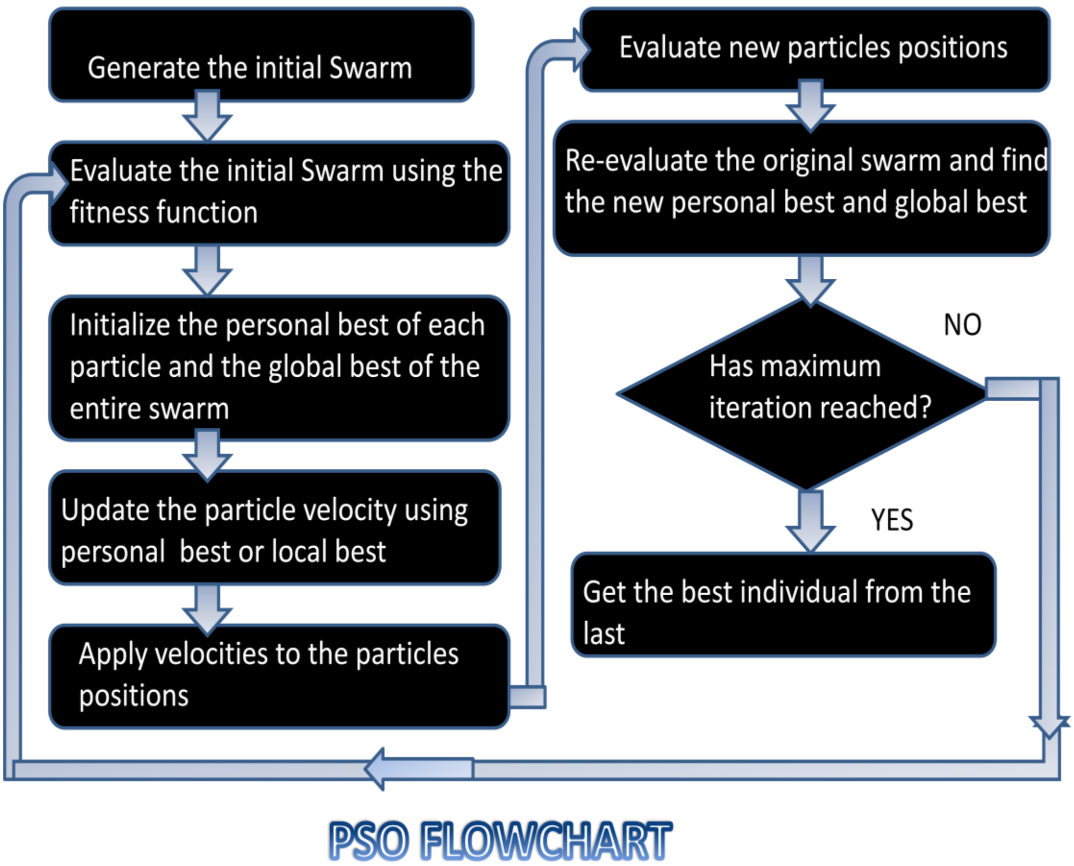


Figure 2.3 Flowchart for the Particle Swarm Optimization algorithm

2.5 HARMONY SEARCH ALGORITHM

Harmony search algorithm is an evolutionary optimization problem which imitates the improvisation process of the musicians while they search for better state of harmony[17]. It generates a new solution from the set of existing solutions. The solution resembles the harmony in music while the local and global searches correspond to the music improvisations. As compared to other historical algorithms it requires fewer mathematical requirements. Also the convergence rate for this is higher as compared to other evolutionary algorithms [18][19].

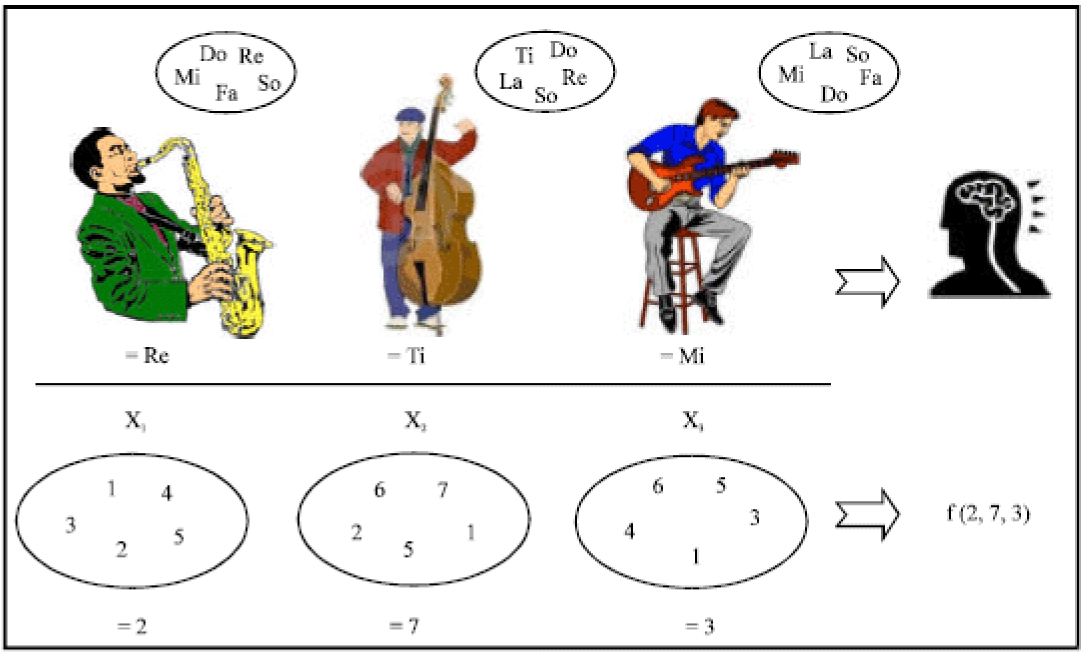


Figure 2.4: Harmony Search Algorithm[33]

Harmony search has several advantages over other techniques :

1. It does not require initial value setting for the initial decision variables.
2. It uses stochastic random search.
3. It does not need information for decision.
4. It has few parameters.
5. It can be easily combined with other computational algorithms.

In HSA, each solution is known as "harmony" and is represented by an *d*imension real vector. An initial population of harmony vectors are generated randomly and stored within a memory known as harmony memory (HM). A new candidate harmony (solution) is thus generated from the existing elements in the HM by using a memory consideration operation by a random reinitialization or a pitch adjustment operation[20]. Finally, the HM is updated by comparing the New Harmony and the worst harmony vector in the HM. The worst harmony vector is deleted and replaced by the new candidate vector when the newer one delivers a better solution in the HM. The above process keeps on repeating until a certain termination criterion is met. The basic algorithm consists of three phases:

- HM initialization,
- improvisation of new harmony vectors,
- Updating the HM[22].

Initially the optimization function f(x) can be defined as

$$\text{minimize} \quad f(\mathbf{x}), \quad \mathbf{x} = (x(1), x(2), \ldots, x(n)) \in \mathbf{R}^n,$$

$$\text{subject to: } x(j) \in [l(j), u(j)] \quad j = 1, 2, \ldots, n,$$

Where f(x) is the objective function, n is the number of designed .l(j) and u(j) are the upper bounds and lower bounds for j respectively.

The parameters required for the algorithm are

1. Harmony memory size
2. Harmony memory consideration rate (HMCR)
3. Pitch adjusting rate (PAR)
4. Bandwidth (BW)
5. Number of iterations (NI)

The performance of the algorithm greatly depends on the values assigned to these parameters initially. harmony search due to its properties is quite flexible as compared to the other evolutionary algorithms.

2.5.1 Pseudo Code

STEP 1: initialize the parameters

Input data:parameters of the HSA(HMCR,BW,PAR,NI)

STEP 2: initialize the harmony memory

Construct the vector of harmony memory

Recognixe the worst vector in harmony memory. Xworst

STEP 3: improvise a new harmony

for (j=1 to n)do
if(r_1 < HMCR) then
x_{new} (j)=x_a(j) where a ∈ (1,2,3,…..HMS)
if(r_2 < PAR) then
x_{new} (j)= x_{new} (j) + r_3
end if
if x_{new} (j) < l(j)
x_{new} (j)=l(j)
end if
if x_{new} (j) > u(j)
x_{new} (j)=u(j)
end if
else
x_{new} (j)=l(j)+r(u(j)-l(j))
End if
End for

STEP 4: update the harmony memory

Incluse the best solution generated

Exclude the worst solution

STEP 5:check the termination criteria

While(not termination criteria is speified by NI)

Repeat STEP 3 and STEP 4

2.5.2 HSA Flowchart

The following figure shows the steps for the implementation of the Harmony Search algorithm:

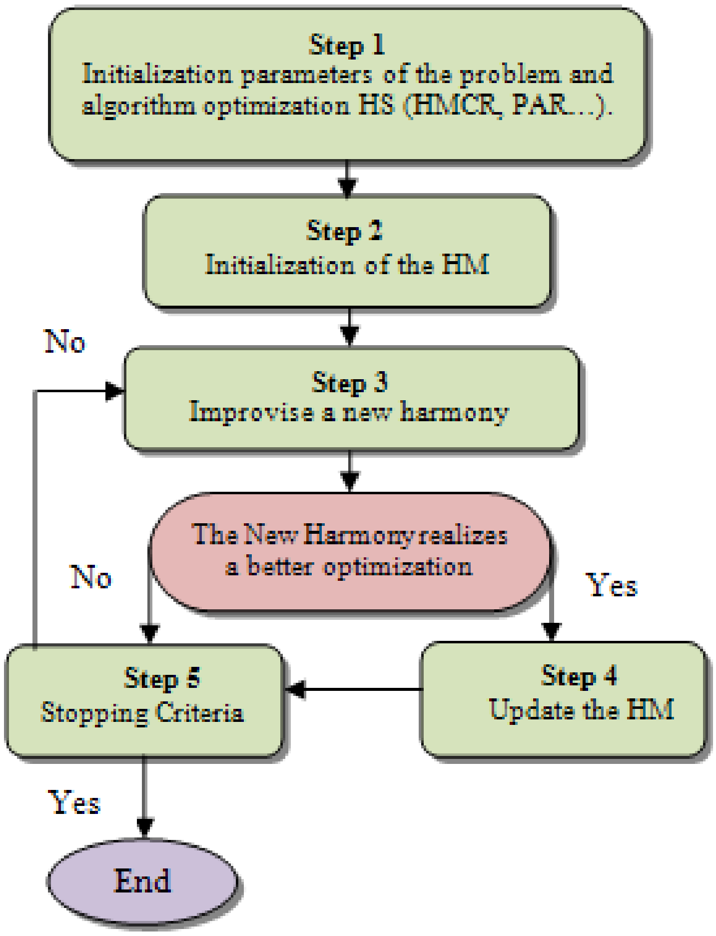


figure 2.5: HSA flowchart

Chapter 3

PROPOSED APPROACH

In this work, harmony search and particle swarm optimization are combined to take the advantages of both the algorithms[29]. Harmony search is a population based algorithm which can be successfully applied to numerous evolutionary algorithms. Here we are combining it with particle swarm optimization to increase the efficiency and convergence problem.

Modification of the HS is basically done in two aspects

1. By changing the parameter setting of the basic algorithm.
2. By combining it with other evolutionary algorithms.

Combining it with meta heuristic algorithm helps to converge to global best quickly without getting trapped into local optimum[30].The combination is done such that the advantages of both the algorithms can be withdrawn. Like here we are combining the advantages of both the pso and the hsa. The advantage of HAS is that it converges to the solution quickly with low computational overhead. PSO increases the efficiency and accuracy of the output thus giving clearer image after segmentation.

The performance of the harmony search increases as PSO makes full use of the direction information of the best harmony to supervise the search. In the algorithm PSO and HSA are hybridized to optimize the function. PSO algorithm is used as an initialization scheme in order to enhance the quality of the solutions of the Harmony memory. The characteristics of both the algorithms are extracted to increase the performance.

The basic algorithm for segmenting the image using the two algorithms is described step by step as follows:

3.1 PSEUDOCODE

STEP 1: Read the input image I.

STEP 2: obtain histogram of the image.

STEP 3: calculate the probability distributions from the histogram.

STEP 4: Initialization of the parameters.

1. Parameters of HS: HMS,HMCR,PAR_{min} ,PAR_{max} ,BW,NI
2. Parameters of PSO:W_{max} ,W_{min} ,c1,c2,T,V_{max} ,p

STEP 5: HM initialization

Harmony memory is filled with solution vectors as generated by particle swarm optimization.

$v_{id}^{(t+1)}$=$w^{(t)}v_{id}^{(t)}$+$c_1R_1(pbest_{id}^{(t)}$ - $C_{id}^{(t)})$ + $c_2R_2(gbest_{id}^{(t)}$ - $C_{id}^{(t)})$

$C_{id}^{(t+1)}$ = ($C_{id}^{(t)}$ + $v_{id}^{(t+1)}$)

STEP 6: Improvise a new harmony.

The harmony memory is improvised as follows.

```
for (j=1 to n)do
    if(r_1 < HMCR) then
        x_new (j)=x_a(j)  where a ∈ (1,2,3,…..HMS)
        if(r_2 < PAR) then
         x_new (j)= x_new (j) + r_3
         end if
          if x_new (j) < l(j)
          x_new (j)=l(j)
          end if
          if x_new (j) > u(j)
          x_new (j)=u(j)
          end if
     else
            x_new (j)=l(j)+r(u(j)-l(j))
      End if
  End for
```

STEP 7 : update Harmony memory

x_{new} (j)= x_{new} (j)+rand(1,D)xx_{new} (j)

Judge the ranfe of x_{new} (j)’

If f(x_{new} (j)) <= x_{new} (j)' then
x_{new} (j)' = x_{new} (j)
End if
If f(x_{new} (j))' <+ f(x_{worst} (j)) then
x_{worst} (j) = f(x_{new} (j)'
End if

STEP 8: check for the termination criteria or repeat the steps.

STEP 9: select the harmony that has the best objective function value

STEP 10 : Apply the thresholds to the image I.

Chapter 4

EXPERIMENTAL RESULTS

The following configuration of the system has been used while performing the experiments:

- Processor: Intel Core i3
- Clock Speed: 2.40 GHz
- Main Memory: 4 GB
- Hard Disk Capacity: 512 GB
- Software Used: MATLAB R2010a

Berkley database has been used as a standard set of reference. The basic PSO algorithm is applied to it. And also the pso and harmony algorithm is applied to the same dataset.
Then the segmented image is checked against the original image. For evaluation, Quantitative measures are taken. Here Dice coefficient and Jaccard coefficient are used as quantitative measure.

The two coefficients are described below.

1. Jaccard's Coefficient:

It is also one of the quantitave measure used to check the similarity of the image segmentation from the ground truth. It can give both the similarity as well as dissimilarity between the given two images.

$J(P,Q)=(P \cap Q)/(P \cup Q)$

The value of the Jaccard similarity is present between 0 and 1. 0 implies no match/overlap and 1 implies complete match/overlap.

2. Dice Coefficient

It is a statistic which is used to compare the similarity between two images. It is also called as "similarity coefficient ".

D(P,Q)=2(|P && Q|)/(|P|+|Q|)

Where P and Q are two sets and |.| represents the size of each set.

The value of the dice coefficient comes between 0 and 1. 0 implies no match/overlap and 1 implies complete match/overlap. In field of segmentation P is representing the segmented image and Q is representing the ground truth. The middle value gives the degree of similarity between the two images.

Relationship between the Dice coefficient and the Jaccard similarity is

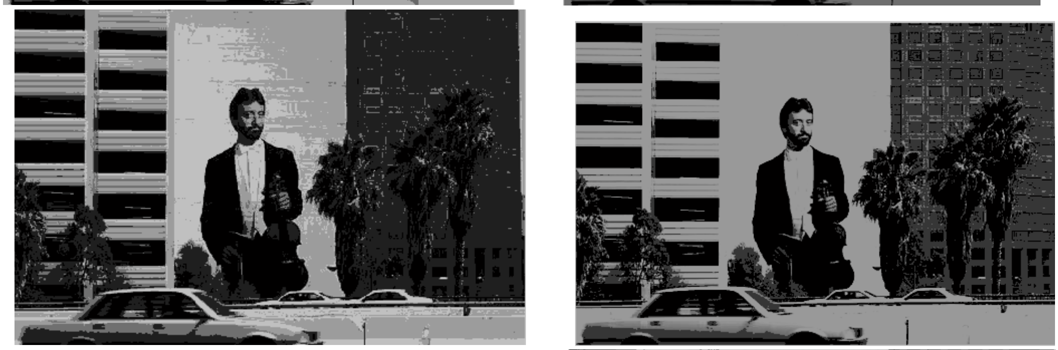
defined as follows: D=2*J/(1+J)

The more the value of dice coefficient is close to 1, the better is the segmentation accuracy. It is studied that dice coefficient's value >0.7 implies good segmentation.

Below images shows the result of the segmentation applied on the images of the Berkley dataset. Different levels of segmentation are shown for each of the algorithms defined. The images are 3 level segmented, 4 level segmented and 5 level segmented each by the proposed algorithm and PSO.

(a)

(b)



(c)

(d)

Figure 4.1 (a)original image, (b)3 level segmentation, (c)4 level segmentation, (c)5 level segmentation of HAS-PSO and PSO respectively.

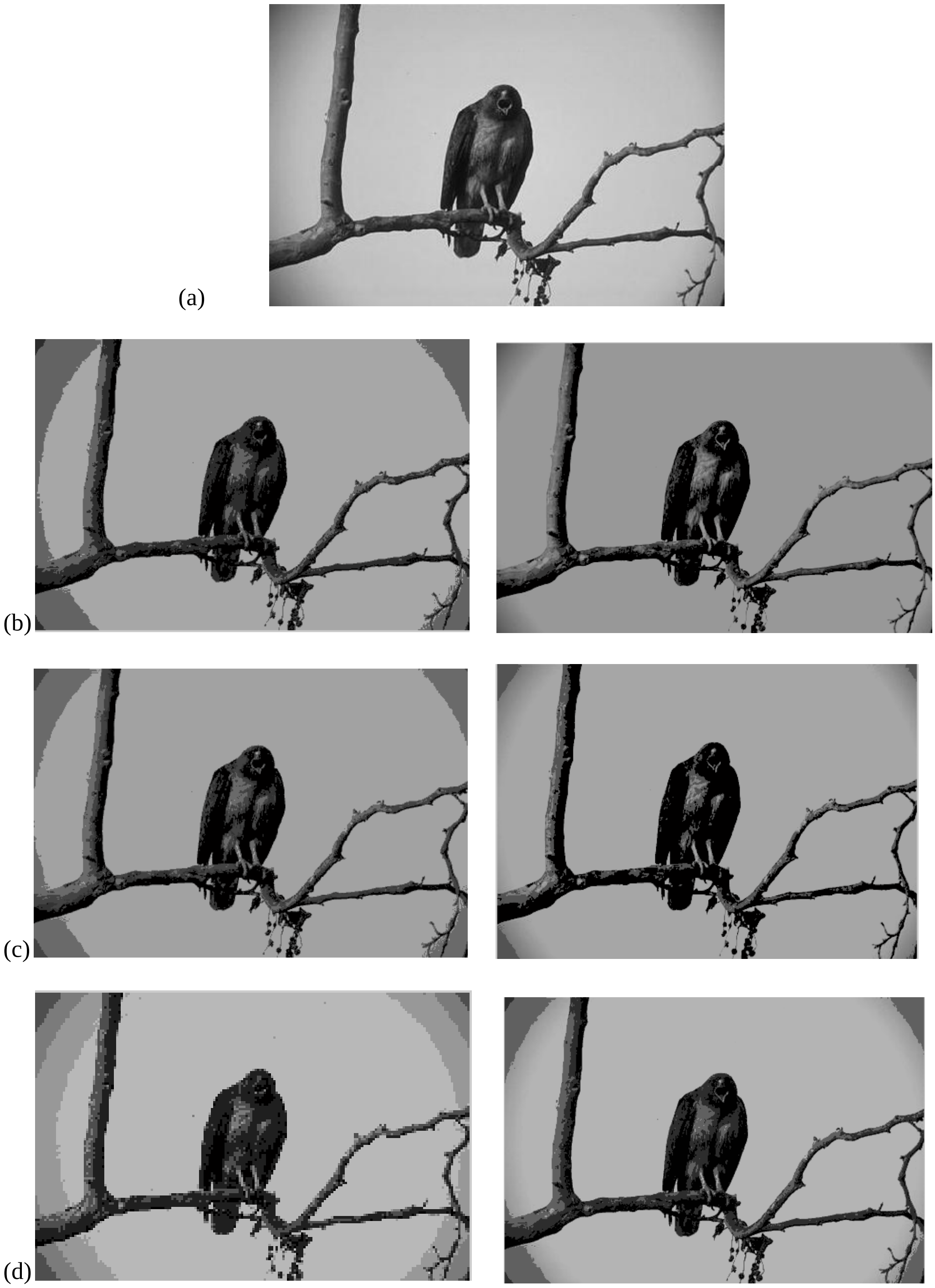
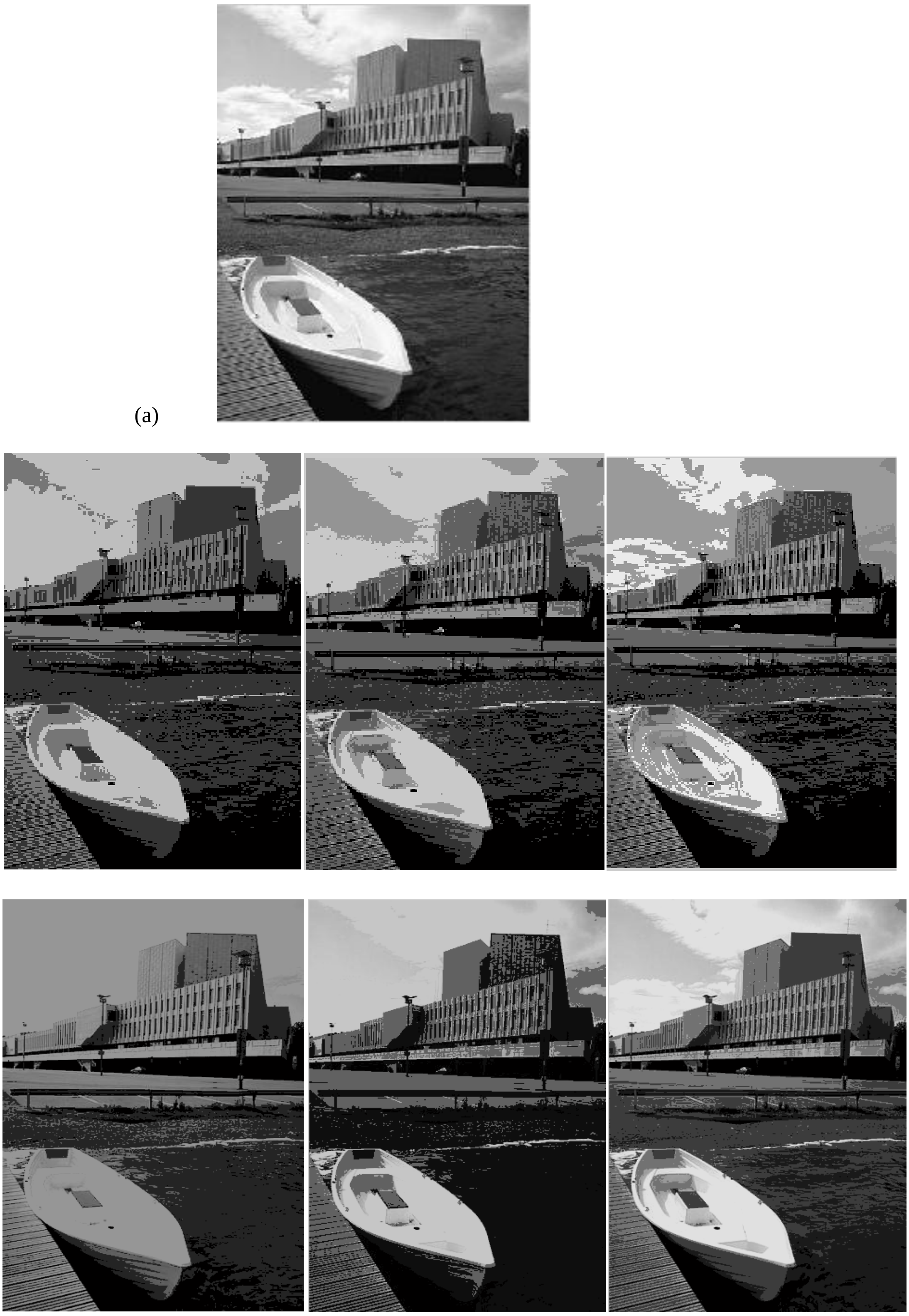


Figure 4 .2 (a)original image, (b)3 level segmentation, (c)4 level segmentation, (c)5 level segmentation of HAS-PSO and PSO respectively.



(a)

(b)

(c)

Figure 4.3 (a)original image, (b)3 level segmentation,4 level segmentation, 5 level segmentation of HAS-PSO, (c) 3 level segmentation,4 level segmentation, 5 level segmentation of PSO.

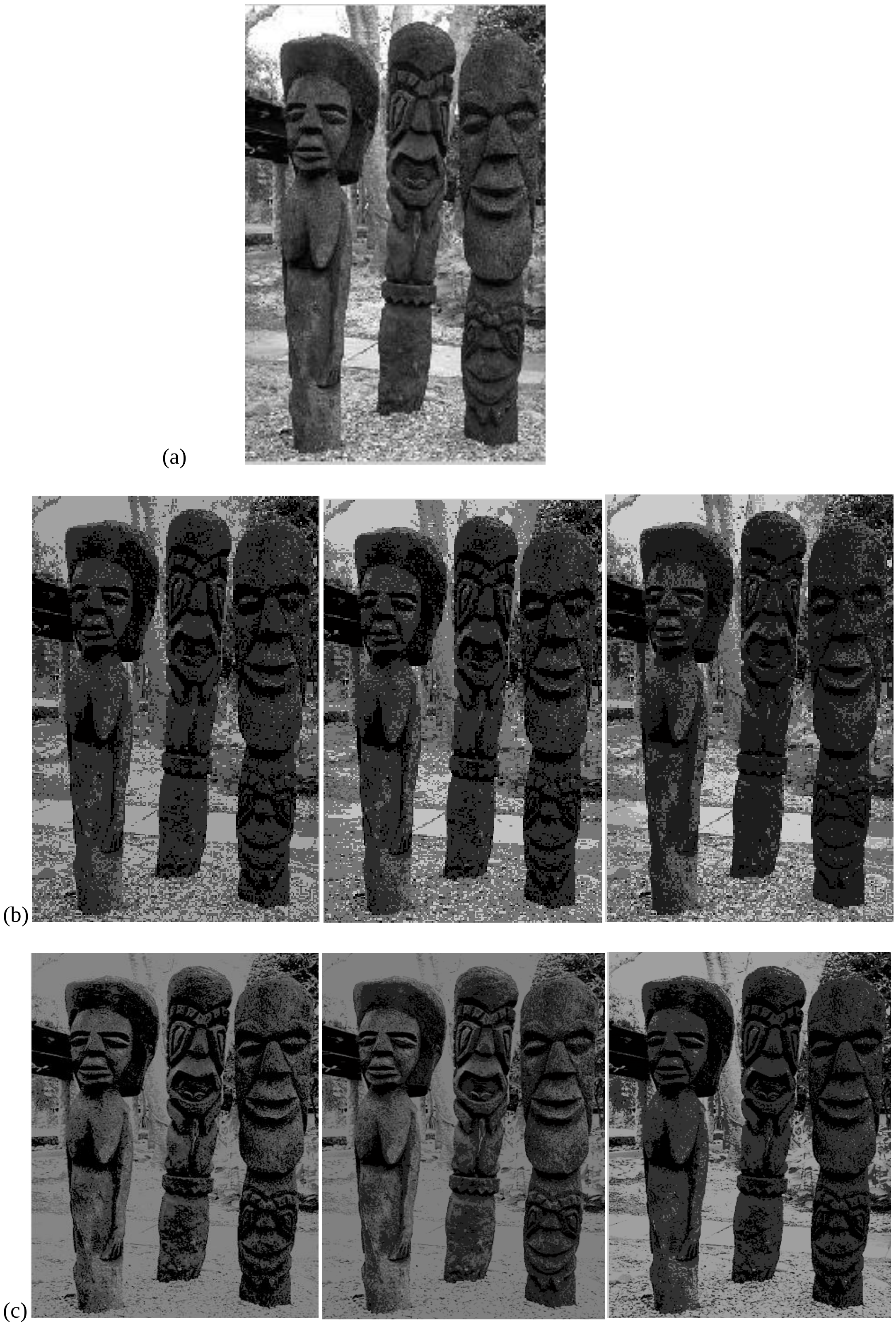


Figure 4.4 (a)original image, (b)3 level segmentation,4 level segmentation, 5 level segmentation of HAS-PSO, (c) 3 level segmentation,4 level segmentation, 5 level segmentation of PSO

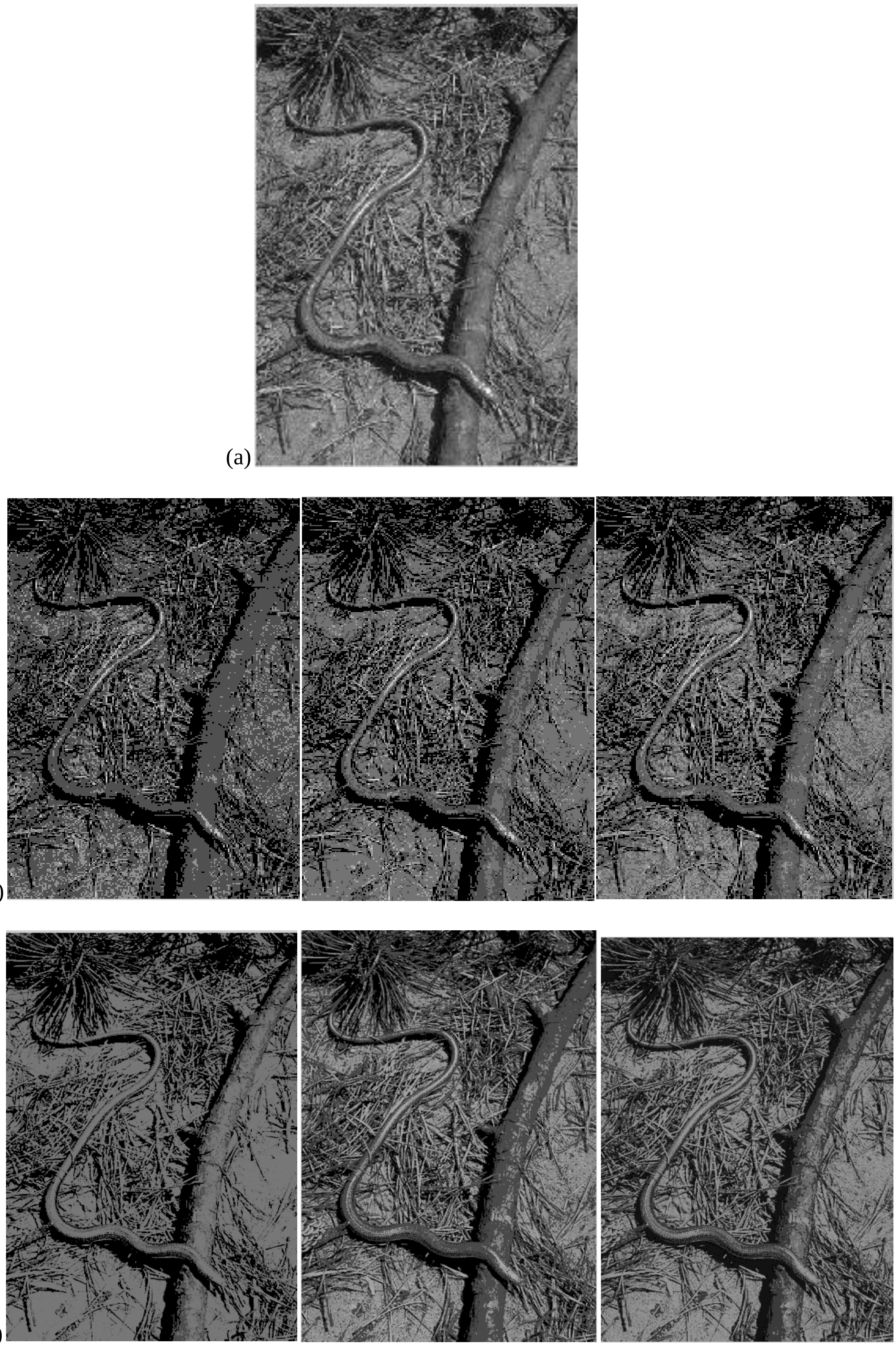


Figure 4.5 (a)original image, (b)3 level segmentation,4 level segmentation, 5 level segmentation of HAS-PSO, (c) 3 level segmentation,4 level segmentation, 5 level segmentation of PSO.

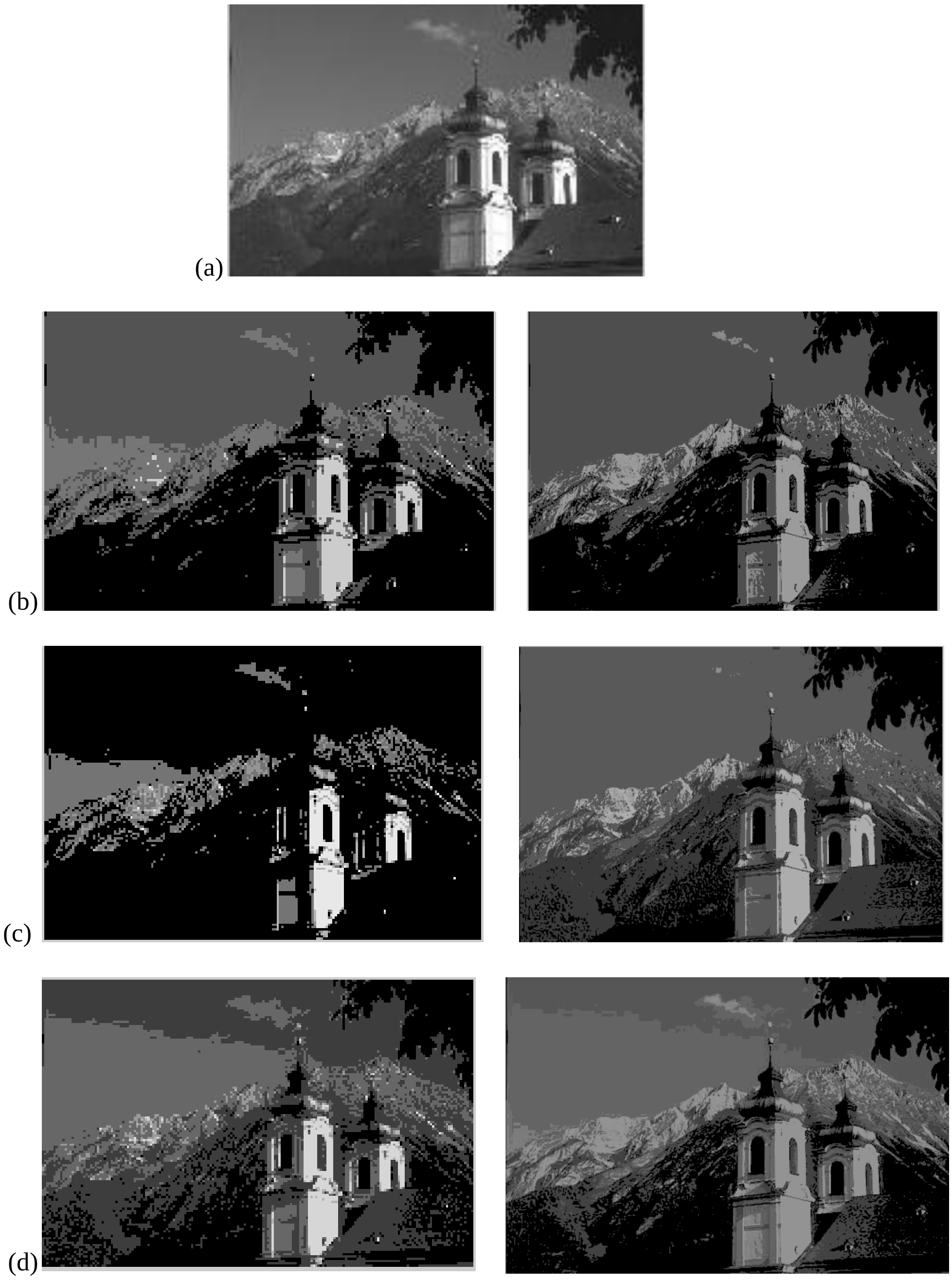
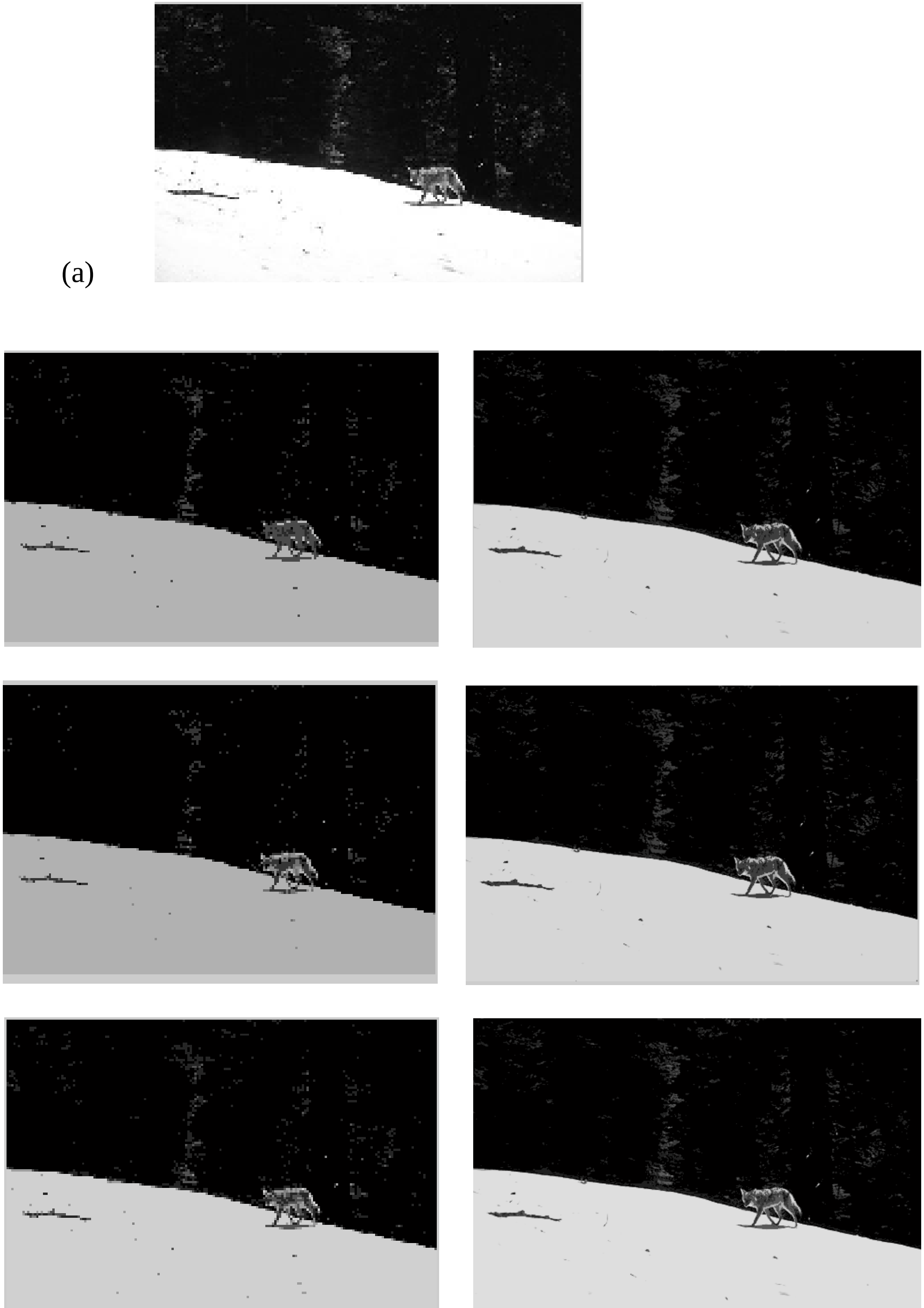


Figure 4.6 (a)original image, (b)3 level segmentation, (c)4 level segmentation, (c)5 level segmentation of HAS-PSO and PSO respectively.



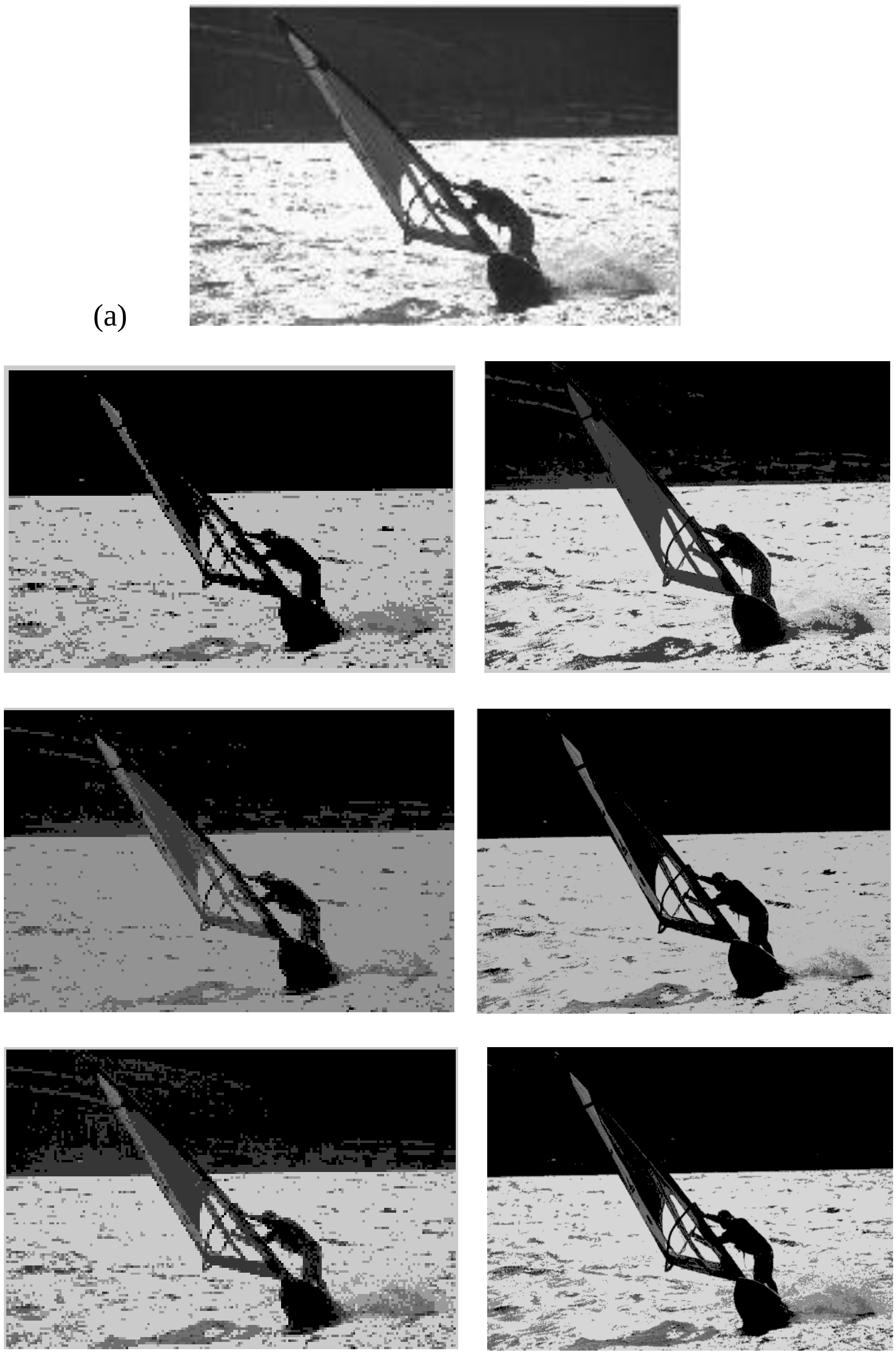
(a)

(b)

(c)

(d)

Figure 4.7 (a)original image, (b)3 level segmentation, (c)4 level segmentation, (c)5 level segmentation of HAS-PSO and PSO respectively.



(a)

(b)
\

(c)

(d)

Figure 4.8 (a)original image, (b)3 level segmentation, (c)4 level segmentation, (c)5 level segmentation of HAS-PSO and PSO respectively.

The above images show that there is clear segmentation. The images are segmented for 3 level segmentation, 4 level segmentation and 5 level segmentation and it can be seen that the clarity increases with increase in number of segments.

Dice and jaccard coefficient have been computed for each level of the segmentation for all the images and the values validate the result. It can be seen that segmentation done by the proposed algorithm is better than the basic PSO algorithm.

Below tables shows the dice and jaccard coefficients computed for the above images. It can be analyzed from the table that coefficient values are greater for the proposed algorithm than the PSO algorithm.

TABLE II

Dice Coefficient

	PSO-HSA				PSO		
	Dice Coefficient				Dice Coefficient		
Image #	**3 seg**	**4 seg**	**5 seg**	**Image #**	**3 seg**	**4 seg**	**5 seg**
I1	0.8512	0.8492	0.8963	I1	0.8492	0.8450	0.8941
I2	0.9391	0.9568	0.9699	I2	0.7372	0.9568	0.9699
I3	0.8743	0.8892	0.8962	I3	0.7456	0.8256	0.8657
I4	0.8923	0.9247	0.9554	I4	0.8443	0.8971	0.9045
I5	0.8612	0.8986	0.9012	I5	0.8012	0.8142	0.8552
I6	0.8796	0.9543	0.9653	I6	0.7562	0.9213	0.9378
I7	0.8975	0.9089	0.9375	I7	0.8087	0.8567	0.8657
I8	0.9095	0.9123	0.9345	I8	0.7575	0.8447	0.8557

Dice Coefficient is volume overlap metric that measures the segmentation results quantitatively given the segmentation volumes pairs. The algorithm is run over images of the Berkley dataset. The average of several runs was calculated using Dice Coefficient.

It is observed that the significant improvement can be seen in the result obtained from our approach (PSO-HSA) as compared to standard PSO .The classification of images is more promising in case of PSO-HSA as there are more number of correctly classified pixels.

TABLE III
jaccard coefficient.

	PSO-HSA				PSO		
	Jaccard Similarity				Jaccard Similarity		
Image #	**3 seg**	**4 seg**	**5 seg**	**Image #**	**3 seg**	**4 seg**	**5 seg**
I1	0.7385	0.7565	0.8092	I1	0.7379	0.7453	0.8086
I2	0.8851	0.9172	0.9496	I2	0.5838	0.8236	0.8956
I3	0.7546	0.7634	0.7945	I3	0.7265	0.7454	0.7536
I4	0.8287	0.8479	0.8594	I4	0.7095	0.8295	0.8456
I5	0.7462	0.7532	0.7562	I5	0.7016	0.7256	0.7524
I6	0.7526	0.7596	0.7742	I6	0.7025	0.7123	0.7426
I7	0.7652	0.7953	0.8214	I7	0.7526	0.7912	0.8014
I8	0.7145	0.8046	0.8156	I8	0.7032	0.7956	0.8045

Similar to Dice Coefficient is the Jaccard's similarity measure. However, Dice Coefficient is more famous than jaccard ratio as it may sometimes result in a mismatch when there is a strong volumetric overlap. We have presented below the estimated results using Jaccard's ratio as well to have a better outlook of classification system.

$J=D/(2-D)$

J- Jaccard's ratio

D- Dice coefficient

After considering the entropy function as objective function, it has been analyzed that the coefficient value for the hybrid algorithm is greater than the value generated by basic evolutionary algorithms. Hence the hybrid algorithm provides better results for each of the image and also for each of the segments of the individual image. The algorithm converges quickly after certain number of iterations depending upon the threshold value. As the number of segments increases, the image becomes more and more clear. It can be seen that PSO helps to provide globally optimal solution and helps HSA to converge faster by guiding the search after using the direction information of the harmony memory. HSA reduces the computational overhead and provides improved result.

Chapter 5

CONCLUSION

In the present work, image segmentation is done using Harmony Search Algorithm and Particle Swarm Optimization. Step by step procedure for image segmentation is presented. The basic algorithms of both the approaches are described. The combination of two helps to find more accurate result with low computational overhead. Also trapping in local optima is avoided and probability of reaching the global optima is increased. Our work also ensures better classification in case of presence of such noise as well. Berkley dataset images have been used as a ground truth and algorithm has been implemented on these images. The results of work also has been evaluated and validated against the ground truth. Dice coefficient and Jaccard coefficients are being used for the evaluation purpose. Both the real time database and the simulated database with different level of noise is used to test accuracy. Significant improvement in correct segmentation of images can be observed as compared to standard Particle swarm optimization algorithm. In future, the thesis work can be extended to further enhance the accuracy and efficiency of the algorithm.

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