ABSTRACT:
Many techniques have been in use for image segmentation some of which use histograms, some of them used spatial while some used fuzzy but none of them worked well under noisy environment. Otsu method is one the thresholding technique which converts the gray scale images into binary image. Thereafter 2d Otsu was adopted which was proven to be more effective than simple Otsu method. 2D Otsu was implemented using histogram to reduce the computation complexity. Further to improve computational efficiency many evolutionary algorithms were proposed of which particle swarm optimization with its simplicity and computationally efficient as it required very few parameters compared to other algorithms like Differential Evolution in which mutation crossover are also taken into consideration. But the particle swarm optimization (PSO) did not do well for problems which were discrete and lead to found in a loop of local optima when dealt with problems in multi-modal. Thus a new technique was adopted named quantum particle swarm optimization (QPSO) which worked on discrete problems very well. Many hybridized QPSO have been proposed like Cooperative QPSO, Cooperative Gaussian QPSO etc. and has been applied for image segmentation. Cultural QPSO has also been proposed which used Cultural algorithms but has not been applied in the field of image segmentation. Thus to obtain a simple and highly reliable and efficient results during image segmentation this algorithm has been applied. It also results in good convergence rate which when compared with PSO, QPSO, CQPSO, CGQPSO. All the findings and results have been done on matrix laboratory (MATLAB). The images that are segmented using QPSO are simple images like temple, ant, leaf. The results that are obtained are satisfactory and are stable with low population and iterations thus the application of the proposed work can be done in the area of medical where deep and enhanced knowledge of images of internal human body organs like brain, lungs are required.

Keywords: Image Segmentation, PSO, QPSO, Thresholding, Cultural QPSO.

[1] INTRODUCTION

Image segmentation can be defined as extracting or withdrawing the information from an image. On the other hand image segmentation may also be defined as to partition an image to set of pixels (changing the representation of image) which is more knowledgeable with ease of analysis. To better understand the images and to gather as much information from images different techniques have been developed like
clustering methods, thresholding, compression based methods, histogram based methods etc which has been applied in real world.

Different thresholding techniques have been deployed so far but to obtain optimal thresholding quickly with higher efficiency none of them worked well. Thus 2d Otsu technique here has been used as it is the only technique which provides with optimal threshold results.

[2] PSO AND QPSO

Particle Swarm Optimization (PSO) is one amongst several optimization population based algorithms given by Kennedy and Eberhart [1] which is used on nonlinear functions. PSO has close bond with artificial life, and has adopted the strategy followed by flock of birds, fish schooling, swarm theories. [Figure-1] shows the flowchart of PSO.

![Figure 1: Flowchart of PSO](image)

In Quantum based Particle Swarm Optimization each and every particle is defined by quantum bit $Q(k)$. The QPSO results in global convergence which is not given by PSO. Random observations are made instead of sigmoidal functions which were done in simple PSO for discrete [2].

The pseudo code for QPSO is given below:

Start

$k = 0$

initialize $Q(k)$ and $P(k)$
evaluate $P(k)$
store the best solution among $P(k)$
while (termination condition not met)
do

evaluate $P(k)$
store the best solution among $P(k)$

begin
$k = k + 1$

now using PSO Q($k$)
change
$q_{lb}(k) = \alpha p_{lb} + \beta(1 - p_{lb})$
$q_{gb}(k) = \alpha p_{gb} + \beta(1 - p_{gb})$
$q(k + 1) = c_{1q}(k) + c_{2} q_{lb}(k) + c_{3} q_{gb}(k)$

$P(k)$ is obtained after observing $Q(k)$.

If rand $> q_{i}^{j}(k)$
$p_{i}^{j}(k) = 1$
Else $p_{i}^{j}(k) = 0$

Evaluate $P(k)$
Storing best among $P(k)$
End
End

[Figure-2] shows the flowchart of QPSO.
[3] CULTURAL QPSO

The cultural QPSO has been adopted for image segmentation since it improves the convergence performance. Cultural algorithm has two central mechanisms: Population Space and Belief Space. To evaluate Population Space performance function $per(\cdot)$ is used and then the Belief Space is updated by the individuals through acceptance function $acp(\cdot)$ and in next iteration, old individuals with the updated individuals forms a new generation of population.

The pseudo code for CQPSO:

Initialize input: P(k) and B(k)
(Where P(k) is the population size at time t and B(k) belief space at time k)
While until termination criteria met
Do:

For each particle
    Update each particle using QPSO algorithm
    For k=0
        Evaluate P(k)
        {fitnessk()}
    Generating P(k), Influence(B(k))
        Using normative and situational knowledge
        Particle=N.ratio // ratio is the number of particles to be mutated in population
        // normal distributed random variable
        Update B(k)
        {AcP(P(k))}
    For each dimensional particle
        selecting either $P_{th}$ or $P_{gb}$ //based on cost
        k=k+1;
    end
end

then applying 2d Otsu threshold functions over it to obtain good convergence performance from the segmented image.
[4] EXPERIMENTAL RESULTS

<table>
<thead>
<tr>
<th>Function</th>
<th>Range</th>
<th>PSO</th>
<th>QPSO</th>
<th>Cooperative QPSO</th>
<th>Cultural QPSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Akley</td>
<td>[-30,30]</td>
<td>3.99</td>
<td>8.306</td>
<td>2.5126e+00</td>
<td>1.0051e-02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>68e-013</td>
<td>7e+0</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Grieewang</td>
<td>[-600,600]</td>
<td>1.92</td>
<td>13.23</td>
<td>8.6211e+00</td>
<td>2.3730e-01</td>
</tr>
<tr>
<td></td>
<td></td>
<td>95e-007</td>
<td>70e+0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Rastrigin</td>
<td>[-5,12,5,12]</td>
<td>6.01</td>
<td>0.004</td>
<td>3.5527e-015</td>
<td>3.3293e-01</td>
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<tr>
<td></td>
<td></td>
<td>19e-014</td>
<td>0e+0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Schwefel</td>
<td>[-500,500]</td>
<td>13.1</td>
<td>5.657</td>
<td>5.3637e+00</td>
<td>1.1341e-01</td>
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<tr>
<td></td>
<td></td>
<td>220</td>
<td>5e+0</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>e+0</td>
<td>6</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Function global best mean values (class variance)

For experimental results the dimension set to 30
No. of particles = 20
No of iterations=200

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No of iterations=200

<table>
<thead>
<tr>
<th>Input Image</th>
<th>Std CQPSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leaf</td>
<td>1.742e-13</td>
</tr>
<tr>
<td>Temple</td>
<td>2.4509e-12</td>
</tr>
</tbody>
</table>

Table 2 Evaluation Results Using Standard Deviation

Figure 3: Akley function comparing algorithms
Quantum Based PSO Technique For Image Segmentation

Figure 4: Griewangk function comparing algorithms

Figure 5: Rastrigin function comparing algorithms

Figure 6: Schwefel function comparing algorithms
CONCLUSION

Otsu’s method is a well-known method for image segmentation. However, a drawback of Otsu’s method is its high computational time and high computational complexity. In the present study a method is proposed by integrating 2d Otsu method and cultural quantum PSO. It was observed that the proposed method reduces the computational time and computational complexity. Using this method, stability is improved of the segmented image. In this paper, we proposed a Cultural QPSO-based algorithm for image segmentation that have better convergence rate than other population-base algorithm. The proposed algorithm reaches optimum threshold faster through experimental results in lower size population and a few iterations.

However computation time is an important factor in practical applications. Hence the proposed method which is computationally more efficient than others and thus can perform better in still and moving images to achieve the target results.
REFERENCES
