Image Segmentation Using Suprathreshold Stochastic Resonance

Rajib Kumar Jha, Student Member, IEEE, P. K. Biswas, Member, IEEE, and B. N. Chatterji

Abstract—None of the method is available in image processing which can properly segment noisy, blurred image having different brightness levels. Therefore, a novel method called suprathreshold stochastic resonance (SSR) is presented for image segmentation. The input image is taken as noisy, blurred images having different brightness levels. The proposed segmentation algorithm is based on logical OR and AND operation with SSR. The proposed segmentation algorithm is tested on multi-object multi-colored images. Two types of noise distributions Gaussian and uniform are used in SSR for image segmentation. The segmentation accuracy in terms of correlation coefficient, number of mismatch pixels, and change in object position are very appreciable. The effectiveness of the proposed method is compared with the different existing methods qualitatively and quantitatively and it was found satisfactory.

Keywords—Image segmentation, suprathreshold stochastic resonance, stochastic resonance.

I. INTRODUCTION

IMAGE processing and pattern recognition covers various techniques which are applicable to a wide range of real life applications. Image segmentation [1], [2], [3] is one of the most challenging tasks of that. Segmentation is a very important step in many applications such as object classification, scene interpretation, feature extraction which depend solely on the quality of the segmented output [4].

One of the most widely used techniques for image segmentation is color thresholding that can successfully segment objects under controlled lighting conditions [5], [6], [7]. These algorithms use two thresholds for each individual R, G and B components. However, in many applications such thresholds can not be used in many images, because the lighting conditions of the images may be different due to the surrounding environment. This can significantly deteriorate the performance of the color thresholding algorithm for segmentation, if the threshold do not match with the image histogram. Thresholds can be adapted to image’s lighting conditions but the algorithm becomes complex [5].

Suprathreshold stochastic resonance based image segmentation on the other hand has two main advantages over the existing color threshold based segmentation. Firstly, it segments the noisy, blurred color images having different brightness values very accurately. Furthermore, as an additional advantage, suprathreshold stochastic resonance based segmentation gives better results as compared to SR-extended [9]. Integrated region matching [8], Watershed [10] and Marker controlled watershed [11] method even for different lighting conditions. This motivated us to use suprathreshold stochastic resonance phenomenon for segmentation of noisy images.

Rest of the paper is organized as follows. Section II discusses the existing color object segmentation techniques. Section III discusses the proposed approach of color image segmentation algorithm using SSR method. Section IV elaborates the quantitative measures of segmented images using three parameters. Simulation results is discussed in Section V using Gaussian noise and uniform noise distributions. The final Section VI concludes the paper.

II. COLOR IMAGE SEGMENTATION

This section describes the RGB thresholding technique for color image segmentation. Region extraction algorithm extract the correct segmented pixels.

A. RGB Color Image Thresholding

RGB color segmentation provides possible regions of objects [1], [5]. It needs six threshold values, two for each R, G, and B color components. A pixel value of any color component lying in the interval of the two thresholds (the lower and the upper thresholds) is represented as

\[
I'(y) = \begin{cases} 
1 & \text{if } \Delta_l \leq y \leq \Delta_u \\
0 & \text{otherwise}
\end{cases}
\]

where \( y \) is the image pixel value, \( \Delta_l \) is the lower threshold and \( \Delta_u \) is the upper threshold, and \( I'(y) \) is the output image after thresholding.

The above algorithm repeats this operation for full image and for all color components. Output of these operations are three binary images corresponding to three color components. A bit-wise logical AND operation between the pixels of the three binary images gives a binary RGB thresholded image.

B. SR Extended Segmentation

Adaptive stochastic resonance for color object segmentation is reported by Janpaiboon et al. [9] in 2006. This method uses \( N \) stages of noisy RGB color thresholding. Each stage simply adds independent white Gaussian noise to a noisy input image before performing the color thresholding. Threshold
value is selected manually using histogram plot of individual component of color image. Binary output images of all stages are combined with an OR operation to obtain a binary output image. Then region extraction and object identification algorithm is used to connect the possible pixels of this target object while deleting other irrelevant pixels and form a final segmented object.

C. Region Extraction and Object Identification

This algorithm is used to identify an object from the regions of connected pixels in a binary image. From the RGB thresholded image connected pixel regions are found using connected pixel component analysis [1], [5] and get the segmented image. The algorithm scans similar pixels (8-connected pixels) around a seed pixel value as possible object pixels (white pixels). It labels these white pixels along with a seed pixel as a connected region. To grow the connected region, all new similar white pixels are defined to belong to the seed pixel. This process repeats until the connected region ceases to grow. Afterwards, a new connected region emerges by growing a new non-labeled seed pixel. Finally, connected regions are identified with their labels.

III. SUPRATHRESHOLD STOCHASTIC RESONANCE BASED IMAGE SEGMENTATION

This section describes the proposed SSR based image segmentation. Two types of noise distributions are used for segmentation of images: Gaussian and uniform noise distributions. The input image is taken as multi-object, multi-colored image having different color background. The algorithm steps are given below.

- **Step-1** $N$ number of different noisy frames with Gaussian noise (uniform noise) of mean zero and standard deviation one are generated. The generated Gaussian noise (uniform noise) frames are added to the R, G and B component of the color input noisy image. Thus $N$ different frames of R components, G components and B components are obtained. These frames of R components, G components and B components are thresholded. Threshold value is obtained for R component, G component and B component using Chao et al. [12] bi-level thresholding approach. Noise addition for segmentation of input noisy image is tested using number of noisy frames. This is because, as the number of noisy frames increases the segmentation performance improves. However, we have to select the optimum number of noisy frames to reduce computation time.

- **Step-2** All the $N$ thresholded frames of individual R, G, and B components are logically ORed to obtain one R frame, one G frame, and one B frame respectively. In our simulation, experimental value of $N=15$ is used. This operation provides the maximum connected regions of the object in the input noisy, blurred image corresponding to noise standard deviation one. These three frames are three binary images $I^a(x, y)$ corresponding to R, G and B components. The mathematical representation of this operation is given in eq. 2.

$$I^a(x, y) = \bigcup_{i=1}^{N} I_i(x, y)$$

**Step-3** Logical bit-wise ANDing of all R, G, and B frames together provides common segmented regions $I^a(x, y)$ as given in eq. 3.

$$I^a(x, y) = \bigcap_{a=R,G,B} I^a(x, y)$$

**Step-4** Step-1 to Step-3 are repeated with noise of different standard deviations (2 to $n$) giving altogether $n$ binary images.

**Step-5** Finally, ORing all the $n$ frames provides the final segmented output. The logical OR operation between $n$ frames for different noise standard deviation provides the maximum common as well as the maximum connected regions which were left in using the lower noise standard deviations. It has been observed experimentally that use of $n=18$ provides optimum results.

$$I^a(x, y) = \bigcup_{k=1}^{n} I^a_k(x, y)$$

**Step-6** Connected component analysis is applied on $I^a(x, y)$ image to obtain SSR segmented image.

**Step-7** Correlation coefficient, number of mismatched pixels and change in object position (discussed in Section IV) are used for quantitative performance analysis of segmentation technique. High correlation coefficient and low number of extra pixels as well as change in object position provides correct segmented image. These parameters are calculated for full image.

IV. PERFORMANCE MEASURES

Performance of our proposed segmentation algorithm is compared with that of SR-extended, integrating region matching, watershed and marker controlled watershed algorithms. Three performance measures namely correlation coefficients, number of mismatched pixels and change in object position between input template and output segmented image are used for comparison purpose.

A. Correlation Coefficient

For real life signals, correlation coefficient is a measure of how well the output response is similar to the input. The correlation coefficient is a number having a value between 0 and 1. If there is no relationship between the output response signal and the actual template signal, the correlation coefficient becomes 0 or very low. As the strength of the correlation coefficient increases the relationship between the output data and actual data increases. A perfect similarity gives a correlation coefficient equal to 1. Thus higher the correlation coefficient better is the matching between original template and output image. The general mathematical expression for correlation coefficient is given below.
\[
\text{Correlation Coefficient} = \frac{E(xy) - E(x)E(y)}{\sqrt{\sigma_x^2 \sigma_y^2}}
\]  
(5)

Here \(x\) and \(y\) are actual input and output response signal, \(E(x)\) and \(E(y)\) are the expected values of \(x\) and \(y\), \(\sigma_x^2\) and \(\sigma_y^2\) are respective variances.

B. Number of Mismatched Pixels

Number of mismatch pixels between two binary images can be calculated by the logical bit-wise XOR operation. The number of extra pixels can be obtained by counting the results of 1 of the bit-wise XOR. The number of mismatch pixels count \(P_{\text{mismatch}}\) between original template \(S_{ij}\) and an output segmented image \(Y_{ij}\) having \(m \times n\) dimension has the form given below.

\[
P_{\text{mismatch}} = \sum_{i=1}^{m} \sum_{j=1}^{n} S_{ij} \oplus Y_{ij}
\]
(6)

where

\[
S_{ij} \oplus Y_{ij} = \begin{cases} 
0 & \text{if } S_{ij} = Y_{ij} \\
1 & \text{if } S_{ij} \neq Y_{ij}
\end{cases}
\]
(7)

C. Change in Object Position

In many image processing applications [5, 7], the object position in an image is needed. During segmentation usually there is an error in the estimation of an object position due to noise. To determine the change in object position relative to whole image, centroid of an image is calculated using eq. 8, where \((x_i, y_i)\) is the coordinate of objects point, \(N\) is the number of pixels in the objects point and \(C_x, C_y\) are the coordinates of the centroid of the objects.

\[
\begin{bmatrix} C_x \\ C_y \end{bmatrix} = \frac{1}{N} \sum_{i=1}^{N} \begin{bmatrix} x_i \\ y_i \end{bmatrix}
\]
(8)

The change in object position relative to whole image \(P_c\) is obtained using eq. 9 and its value should be as low as possible.

\[
P_c = \sqrt{[(C_{xin} - C_{xout})^2 + (C_{yin} - C_{yout})^2]}
\]
(9)

V. SIMULATION RESULTS

The algorithm has been tested on synthetic as well as real life images using Gaussian and uniform noise distributions. The proposed SSR segmentation method is implemented on Linux platform using C language. Two images namely Image-1 (Figure 1a) and Image-2 (Figure 2a) each of size 512 × 512 have been used for experiments. Image-1 is synthetically generated using Paint software where as Image-2 is obtained from [13]. These images are edited using Matlab 7.4 to generate six images (Test-2 to Test-7) with different noise levels, different intensity values and different blurring. Blurring is introduced using low pass filtering operation with box filter of size 5 × 5. Salt and pepper noise of density 0.30 is added to all. Test-2 and Test-5 have gain 0.10, Test-3 and Test-6 have gain of 0.30 where as Test-4 and Test-7 have gain of 0.60. These images are given in Figures 7a to 7c and Figures 9a to 9c. Image-1 (Figure 1a) and Image-2 (Figure 2a) are segmented using Chao et al. [12] method and are shown in Figure 1b and Figure 2b respectively. These segmented images are used as reference while evaluating the performance of our proposed technique. The segmentation performance of the SSR based algorithm using Gaussian and uniform noise is discussed below.

A. Optimum Range of Noise Intensity

The first experiment was targeted to ascertain the optimum range of noise intensity (Step-4 in Section III) to be used in SSR for best output. The experimental result in terms of performance measures (Number of mismatch pixels, Change in object position, Correlation coefficient) considering different number of frames were obtained. The result with 15 frames (N=15 in step-1 of Section III) on all the test images is plotted in Figure 3 and Figure 4 for Gaussian and uniform noise respectively. In all the plots, horizontal axis indicates range of noise standard deviation (i.e. scale 2 and 6 for example indicates range of noise standard deviation 1 to 6 and 1 to 18 respectively). From all these plots it is observed that number of mismatch pixels and change in object position is minimum and at the same time correlation coefficient is maximum when range of noise standard deviation is 1 to 18. These performance measures are computed with respect to the reference segmented outputs in Figure 1b and Figure 2b.

Because of above observation for all experiments noise standard deviation range 1 to 18 was considered.

B. Effect of Number of Frames

The next experiment was to find optimum number of frames (N in Step-1 of Section III). The variation of quantitative performance measures with number of frames are plotted in Figure 5 and Figure 6. It is observed that at approximately 15 frames the performance measures become stable.

Hence subsequent results are presented for N=15 and range of noise standard deviation 1 to 18.

C. Visual Output

SSR based segmentation algorithm using both Gaussian and uniform noise was applied on test images Test-2 to Test-7. Segmented output using Gaussian noise are shown in Figure 7 to Figure 10. Figure 7d to Figure 7f show the segmentation result on test images Test-2 to Test-4 using the proposed SSR based segmentation using Gaussian noise. This result is compared with the segmentation outputs using SR-extended method [9] using Gaussian noise (Figure 7g to Figure 7i), Integrated region matching [8] (Figure 8a to Figure 8c), Watershed algorithm [10] (Figure 8d to Figure 8f) and Marker controlled watershed [11] (Figure 8g to Figure 8i). Similar segmentation results on test images Test-5 to Test-7 are given in Figure 9 and Figure 11. From all these visual outputs it is quite evident that SSR based segmentation technique...
outperforms all other segmentation algorithms in presence of noise and intensity variation. Segmentation results of SSR based technique using uniform noise are shown in Figure 11. This also show the superiority of SSR based segmentation technique.

D. Quantitative Performance Analysis

Segmented images Figure 1b and Figure 2b using Chao et al. [12] were taken as reference for quantitative performance analysis of different segmentation algorithms. Quantitative performance analysis in terms of number of mismatched pixels, change in object position and correlation coefficient on test images Test-2 to Test-4 and Test-5 to Test-7 are given in Tables I and Tables II respectively. From these tables it is quite clear that number of mismatched pixels and change in object position using our proposed SSR based segmentation technique (using Gaussian as well as uniform noise) is less than that with all other algorithm. Correlation coefficient (with reference segmented images in Figure 1b and Figure 2b) using our proposed technique is higher than that using all other techniques. This establishes the robustness of proposed SSR based segmentation method in presence of noise and varying intensity.

Variation of performance measures with intensity of Gaussian and uniform noise are shown in Figure 3 and Figure 4 respectively.

VI. Conclusions

Suprathreshold Stochastic Resonance for image segmentation is presented in this paper. Two types of noises, Gaussian and uniform, have been used in SSR phenomenon. The proposed segmentation technique has been applied on noisy images under different intensity levels for segmentation purpose. The segmentation outputs have been compared with outputs of existing techniques such as SR-extended, Integrated region matching, Watershed and Marker controlled watershed. Quantitative performance measures, such as, number of mismatched pixels, change in object position and correlation coefficient with respect to reference segmented image have been used for comparison purpose. It has been observed that number of mismatched pixels and change in object position is much less at the same time the correlation coefficient is much higher with our proposed method than with other existing methods. The same improvement in segmentation is observed for all images with different levels of noise and under different intensity conditions. Visually also, the outputs with our proposed technique are better than that with other techniques. This establishes the robustness of our technique against noise and intensity variation.
TABLE I: Performance measures using 15 frames on Test-2, Test-3 and Test-4 images using Gaussian and Uniform noises.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Test-2</th>
<th>Test-3</th>
<th>Test-4</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSR method (Gaussian)</td>
<td>161 0.80 0.95</td>
<td>187 0.83 0.83</td>
<td>210 0.83 0.93</td>
</tr>
<tr>
<td>SSR method (Uniform)</td>
<td>150 0.79 0.944</td>
<td>157 0.797 0.937</td>
<td>163 0.804 0.935</td>
</tr>
<tr>
<td>SR-extend (Gaussian)</td>
<td>230 0.87 0.88</td>
<td>241 0.93 0.88</td>
<td>263 0.98 0.87</td>
</tr>
<tr>
<td>SR-extend (Uniform)</td>
<td>201 0.89 0.90</td>
<td>224 0.91 0.893</td>
<td>248 0.95 0.88</td>
</tr>
<tr>
<td>IRM</td>
<td>245 1.80 0.84</td>
<td>260 1.97 0.83</td>
<td>288 2.21 0.83</td>
</tr>
<tr>
<td>Watershed</td>
<td>349 5.30 0.80</td>
<td>396 6.63 0.78</td>
<td>419 8.22 0.78</td>
</tr>
<tr>
<td>MCW</td>
<td>330 4.31 0.86</td>
<td>337 4.80 0.84</td>
<td>374 5.30 0.82</td>
</tr>
</tbody>
</table>

TABLE II: Performance measures using 15 frames on Test-5, Test-6 and Test-7 images using Gaussian and Uniform noises.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Test-5 image</th>
<th>Test-6 image</th>
<th>Test-7 image</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSR method (Gaussian)</td>
<td>283 18 0.883</td>
<td>295 23 0.880</td>
<td>318 26 0.872</td>
</tr>
<tr>
<td>SSR method (Uniform)</td>
<td>280 16 0.877</td>
<td>297 23 0.874</td>
<td>321 26 0.870</td>
</tr>
<tr>
<td>SR-extend (Gaussian)</td>
<td>567 41 0.80</td>
<td>723 53 0.76</td>
<td>854 61 0.72</td>
</tr>
<tr>
<td>SR-extend (Uniform)</td>
<td>551 34 0.79</td>
<td>625 39 0.77</td>
<td>803 47 0.69</td>
</tr>
<tr>
<td>IRM</td>
<td>1181 84 0.71</td>
<td>1343 112 0.63</td>
<td>1389 127 0.62</td>
</tr>
<tr>
<td>Watershed</td>
<td>945 57 0.750</td>
<td>1010 72 0.75</td>
<td>1190 77 0.72</td>
</tr>
<tr>
<td>MCW</td>
<td>632 45 0.82</td>
<td>646 47 0.81</td>
<td>652 48 0.80</td>
</tr>
</tbody>
</table>
Fig. 3: Performance measures using Gaussian noise in all test images (Number of frames, 15).
Fig. 4: Performance measures using Uniform noise in all test images (Number of frames, 15).
Fig. 5: Variation of performance measures with frame numbers in all test images using Gaussian noise (Noise standard deviation, 1-18).
Fig. 6: Variation of performance measures with frame numbers in all test images using Uniform noise (Noise standard deviation, 1-18).
Fig. 7: Segmented output of Test-2, Test-3 and Test-4 images by proposed SSR method and SR-extended method.
Fig. 8: Segmented output of Test-2, Test-3, Test-4 images using Integrated region matching (IRM), Watershed and Marker controlled watershed (MCW) method.
Fig. 9: Segmented output of Test-5, Test-6, Test-7 images by proposed SSR method and SR-extended method.
Fig. 10: Segmented output of Test-5, Test-6, Test-7 images by Integrated region matching (IRM), Watershed and Marker controlled watershed (MCW) method.
Fig. 11: Segmented output of proposed method in all Test images using uniform noise.
REFERENCES


Rajib Kumar Jha: Rajib Kumar Jha (M03) received the B.Tech. (Hons) degrees in electronics and communication engineering from Institute of engineering and Technology (IIT), CSJM University, Kanpur, UP, in 2001. He obtained his M.Tech. and Ph.D degree from Indian Institute of Technology, Kharagpur, India, in 2003 and 2010 respectively. From July 2006 onwards, he is working as a Assistant Professor in Indian Institute of Information Technology, Design and Manufacturing, Jabalpur. He has published about 13 papers in international journals and conferences. His research interests include image processing, pattern recognition and Use of Suprathreshold stochastic Resonance and Stochastic Resonance for Image applications. Dr. Jha has received the prestigious National Award for Best M.Tech thesis, year 2003 from Indian Society for Technical education, New Delhi, India. He is a Student member of IEEE.

P. K. Biswas: P. K. Biswas (M'05) received the B.Tech. (Hons), M.Tech., and Ph.D. degrees from the Indian Institute of Technology, Kharagpur, India, in 1985, 1989, and 1991, respectively. From 1985 to 1987, he was with Bharat Electronics Ltd., Ghaziabad, as a Deputy Engineer. Since 1991, he has been working as a Faculty member in the Department of Electronics and Electrical Communication Engineering, Indian Institute of Technology, where he is presently holding the position of Professor. He has visited the University of Kaiserslautern, Germany, under an Alexander von Humboldt Research Fellowship from March 2002 to February 2003. He has published more than 60 research publications in international and national journals and conferences and has filed seven international patents. His areas of interest are image processing, pattern recognition, computer vision, video compression, parallel and distributed processing, and computer networks.

B. N. Chatterji: B. N. Chatterji received the B.Tech. (Hons) and the Ph.D. degrees from the Indian Institute of Technology, Kharagpur, India, in 1965 and 1970, respectively. In 1972/1973, he was a Postdoctoral Fellow at the University of Erlangen, Germany. From 1965 to 1966, he was with the Central Electronics Engineering Research Institute, Pilani, India, as a Senior Research Fellow. Since 1967, he has been working as a Faculty member in the Department of Electronics and Electrical Communication Engineering, Indian Institute of Technology, where he is presently holding the position of Professor. He has served the Institute under various administrative capacities as Head of Department, Dean (Academic), etc. He has chaired several international and national symposiums and conferences organized at Kharagpur apart from organizing 15 short-term courses for industries and engineering college teachers. He has published more than 200 papers in reputed international and national journals apart from authoring three scientific books. His research interests are low-level vision, image analysis, pattern recognition, and motion analysis. Dr. Chatterji received the prestigious Shri Hari Om Ashram Prerit Dr. Vikram Sarabhai Award in 1983 for his achievements in the field of electronics and telecommunication. He also received the prestigious National Crime Records Bureau's prize for his research papers in fingerprint-related techniques and technologies for three consecutive years 1990, 1991, and 1992. He is a Fellow of IETE and the Institution of Engineers.