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Image Segmentation Using Suprathreshold Stochastic Resonance

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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 proper segmentation steps involve 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 [6].

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 values of any color component lying in the interval of the two thresholds (the lower and the upper thresholds) is represented as

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

where y is the image pixel value, Δ_l is the lower threshold and Δ_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

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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 pixels 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.

$$I^a(x,y) = \bigcup_{i=1}^{N} I_i(x,y) \tag{2}$$

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

$$I^b(x,y) = \bigcap_{a=R,G,B} I^a(x,y) \tag{3}$$

- **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.

$$I^c(x,y) = \bigcup_{k=1}^{n} I^b_k(x,y) \tag{4}$$

- **Step-6** *Connected component analysis* is applied on $I^c(x,y)$ 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.

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$$Correlation\ Coefficient = \frac{E(xy) - E(x)E(y)}{\sqrt{(\sigma_x^2)}\sqrt{(\sigma_y^2)}} \quad (5)$$

Here x and y are actual input and output response signal, $E(x)$ and $E(y)$ are the expected values of x and y, σ_x^2 and σ_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 $P_{mismatch}$ between original template S_{ij} and an output segmented image Y_{ij} having $m \times n$ dimension has the form given below.

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

where

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

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.

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

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.

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

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 mismatched 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, horizonal 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 mismatched 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.

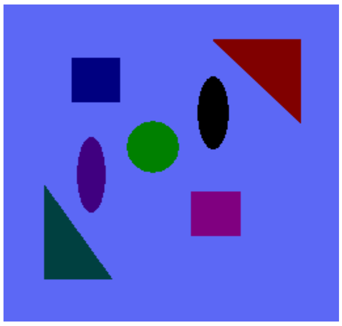
D. Quantitative Performance Analysis

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.

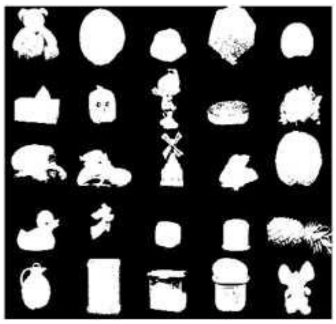


(a) Image-1 original image

(b) Segmented image

Fig. 1: Segmentation of Image-1.

(a) Image-2 original image



(b) Segmented image

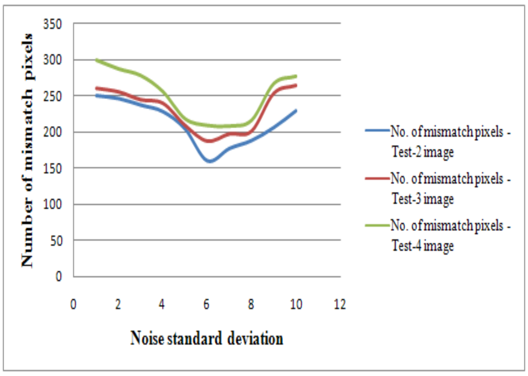
Fig. 2: Segmentation of Image-2.

TABLE I: Performance measures using 15 frames on Test-2, Test-3 and Test-4 images using Gaussian and Uniform noises.

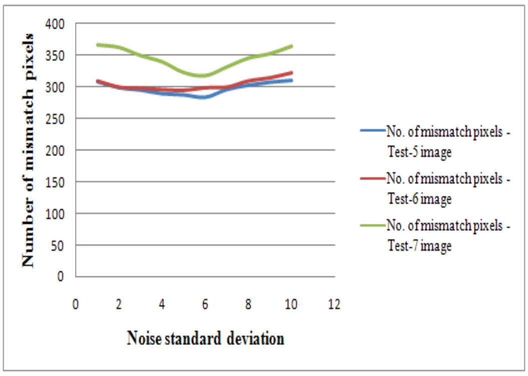
	Test-2			Test-3			Test-4		
Methods	Avg. no. mismatch pixels	Avg. Change in Object position	Avg. Corr. coeff.	Avg. no. mismatch pixels	Avg. Change in Object position	Avg. Corr. coeff.	Avg. no. mismatch pixels	Avg. Change in Object position	Avg. Corr. coeff.
SSR method (Gaussian)	**161**	**0.80**	**0.95**	**187**	**0.83**	**0.83**	**210**	**0.83**	**0.93**
SSR method (Uniform)	**150**	**0.79**	**0.944**	**157**	**0.797**	**0.937**	**163**	**0.804**	**0.935**
SR-extend (Gaussian)	230	0.87	0.88	241	0.93	0.88	263	0.98	0.87
SR-extend (Uniform)	201	0.89	0.90	224	0.91	0.893	248	0.95	0.88
IRM	245	1.80	0.84	260	1.97	0.83	288	2.21	0.83
Watershed	349	5.30	0.80	396	6.63	0.78	419	8.22	0.78
MCW	330	4.31	0.86	337	4.80	0.84	374	5.30	0.82

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

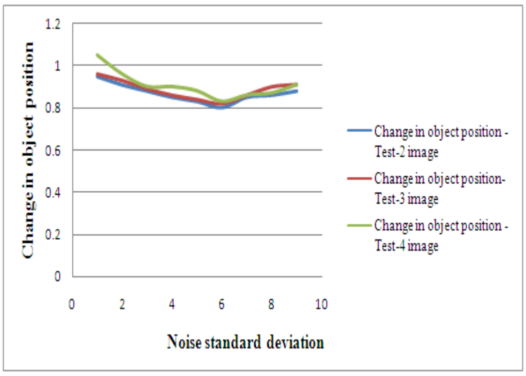
	Test-5 image			Test-6 image			Test-7 image		
Methods	Avg. no. mismatch pixels	Avg. Change in Object position	Avg. Corr. coeff.	Avg. no. mismatch pixels	Avg. Change in Object position	Avg. Corr. coeff.	Avg. no. mismatch pixels	Avg. Change in Object position	Avg. Corr. coeff.
SSR method (Gaussian)	**283**	**18**	**0.883**	**295**	**23**	**0.880**	**318**	**26**	**0.872**
SSR method (Uniform)	**280**	**16**	**0.877**	**297**	**23**	**0.874**	**321**	**26**	**0.870**
SR-extend (Gaussian)	567	41	0.80	723	53	0.76	854	61	0.72
SR-extend (Uniform)	551	34	0.79	625	39	0.77	803	47	0.69
IRM	1181	84	0.71	1343	112	0.63	1389	127	0.62
Watershed	945	57	0.750	1010	72	0.75	1190	77	0.72
MCW	632	45	0.82	646	47	0.81	652	48	0.80



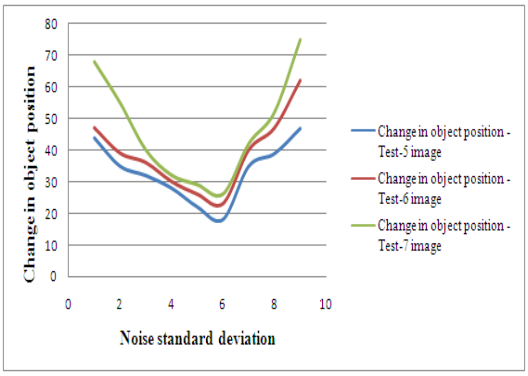
(a) Number of mismatch pixels



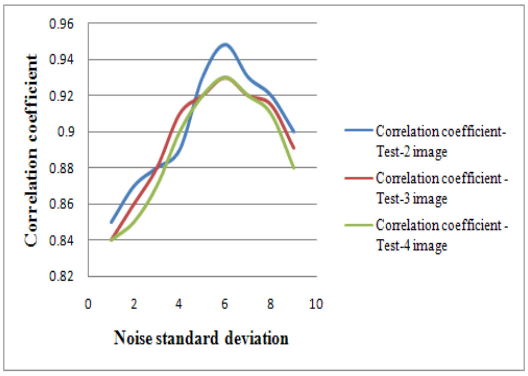
(b) Number of mismatch pixels



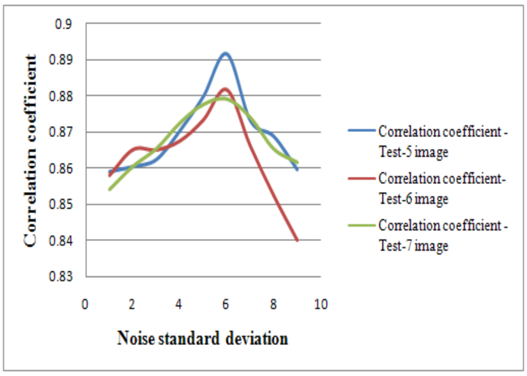
(c) Change in object position



(d) Change in object position

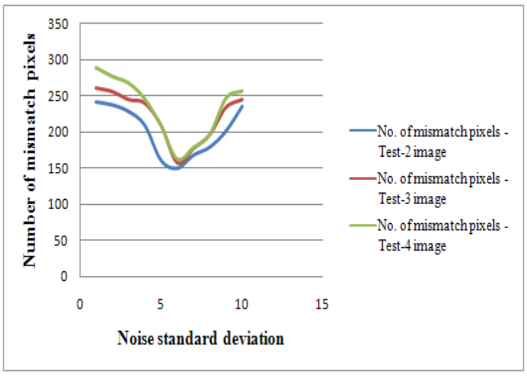


(e) Correlation coefficient

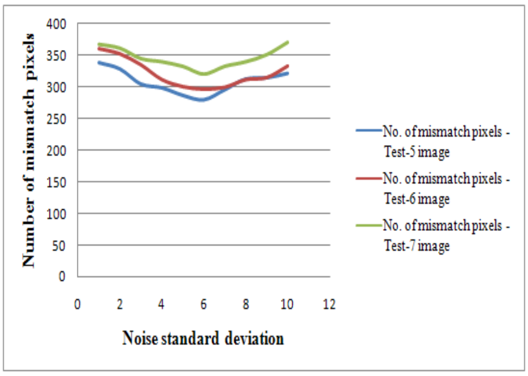


(f) Correlation coefficient

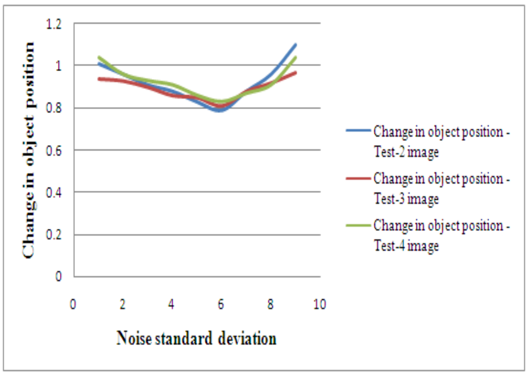
Fig. 3: Performance measures using Gaussian noise in all test images (Number of frames, 15).



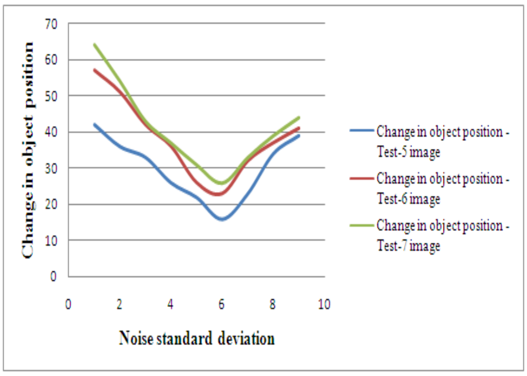
(a) Number of mismatch pixels



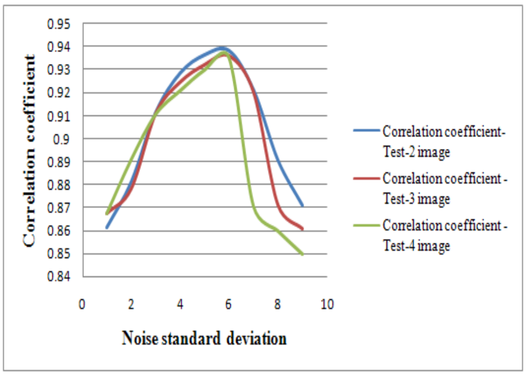
(b) Number of mismatch pixels



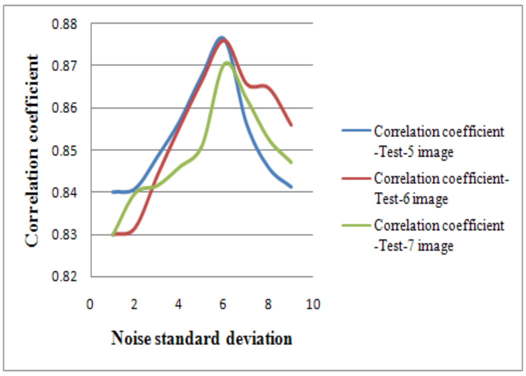
(c) Change in object position



(d) Change in object position

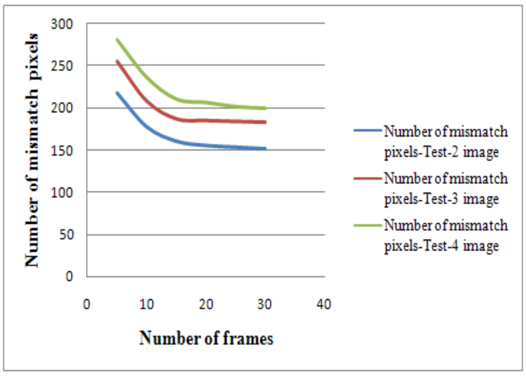


(e) Correlation coefficient

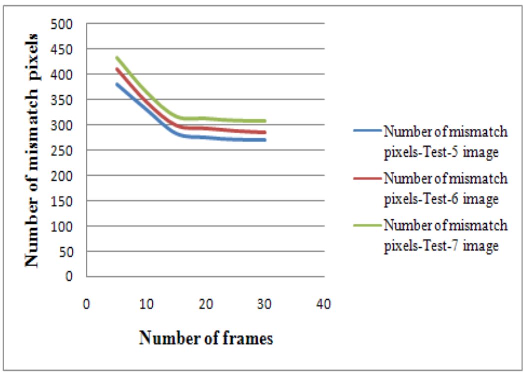


(f) Correlation coefficient

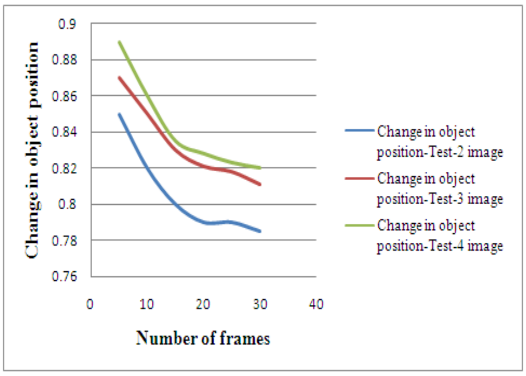
Fig. 4: Performance measures using Uniform noise in all test images (Number of frames, 15).



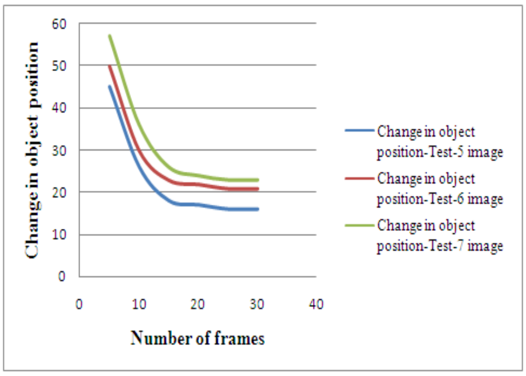
(a) Mismatch pixels vs. frame numbers.



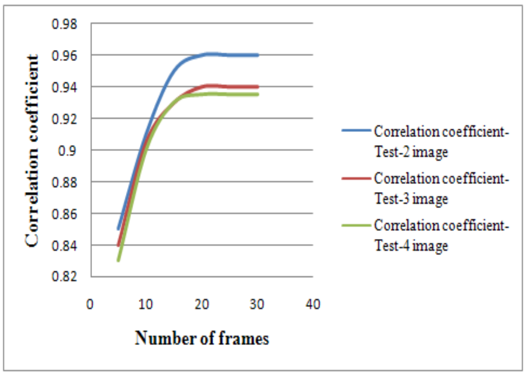
(b) Mismatch pixels vs. frame numbers.



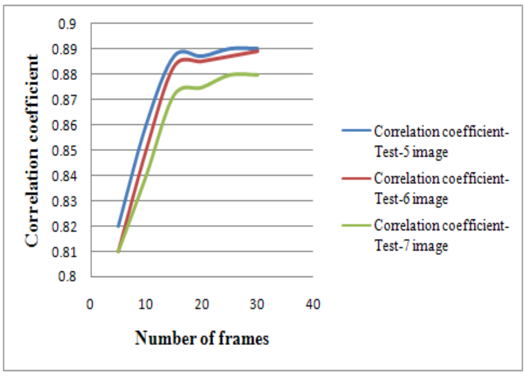
(c) Object position vs. frame numbers.



(d) Object position vs. frame numbers.



(e) Correlation coefficient vs. frame numbers.



(f) Correlation coefficient vs. frame numbers.

Fig. 5: Variation of performance measures with frame numbers in all test images using Gaussian noise (Noise standard deviation, 1-18).

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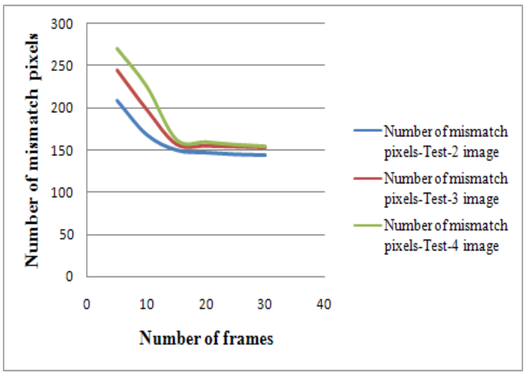
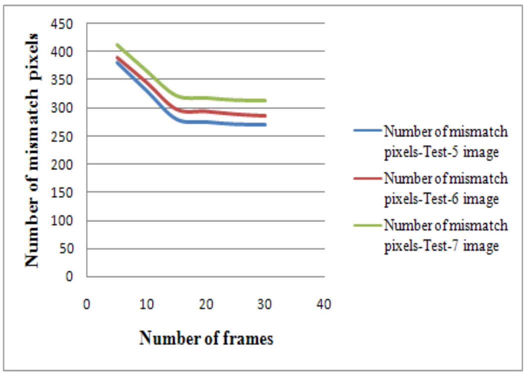
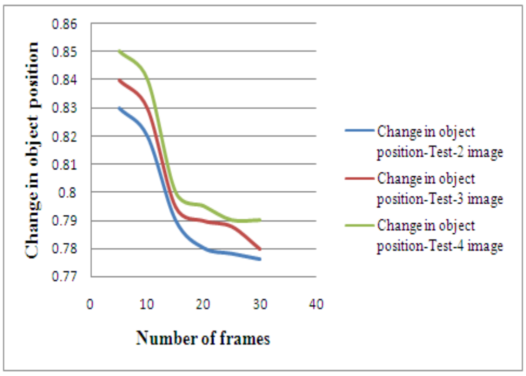


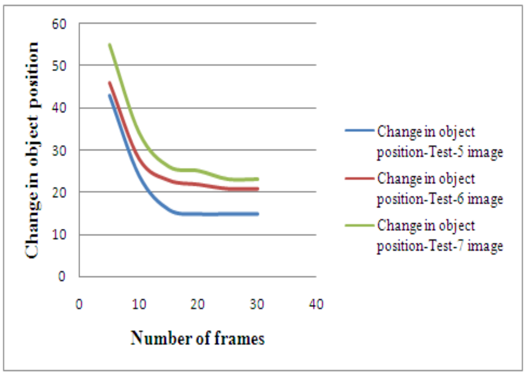
(a) Mismatch pixels vs. frame numbers.



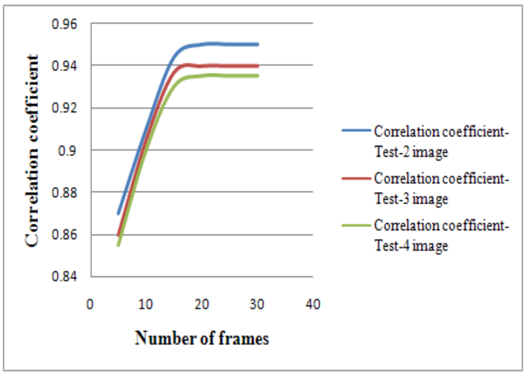
(b) Mismatch pixels vs. frame numbers.



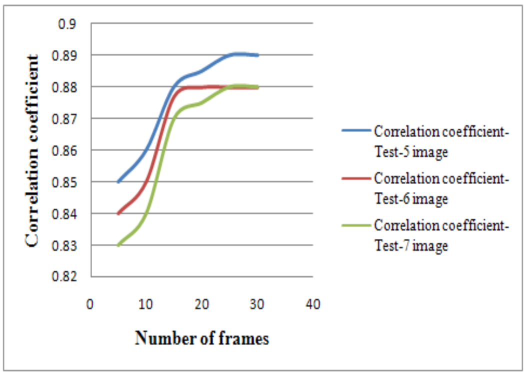
(c) Object position vs. frame numbers.



(d) Object position vs. frame numbers.



(e) Correlation coefficient vs. frame numbers.



(f) Correlation coefficient vs. frame numbers.

Fig. 6: Variation of performance measures with frame numbers in all test images using Uniform noise (Noise standard deviation, 1-18).

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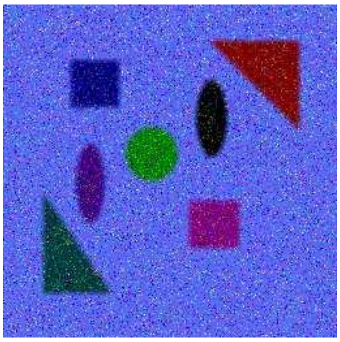
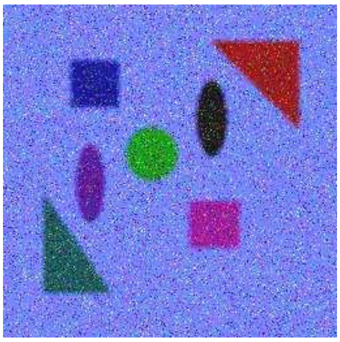
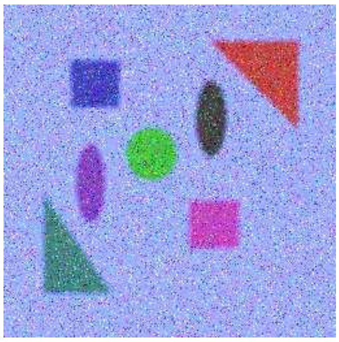


(a) Test-2 image (gain=0.10)

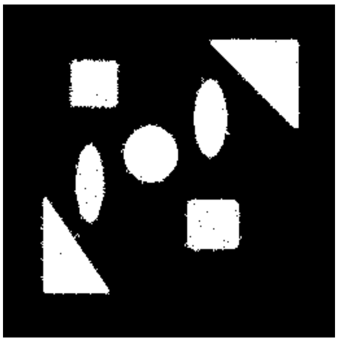


(b) Test-3 image (gain=0.30)

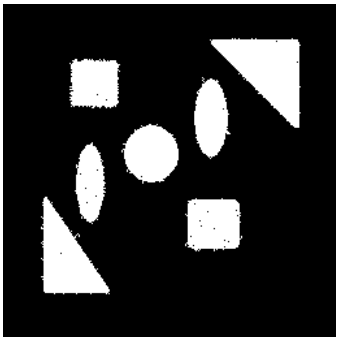


(c) Test-4 image (gain=0.60)

(d) SSR on Test-2 image



(e) SSR on Test-3 image



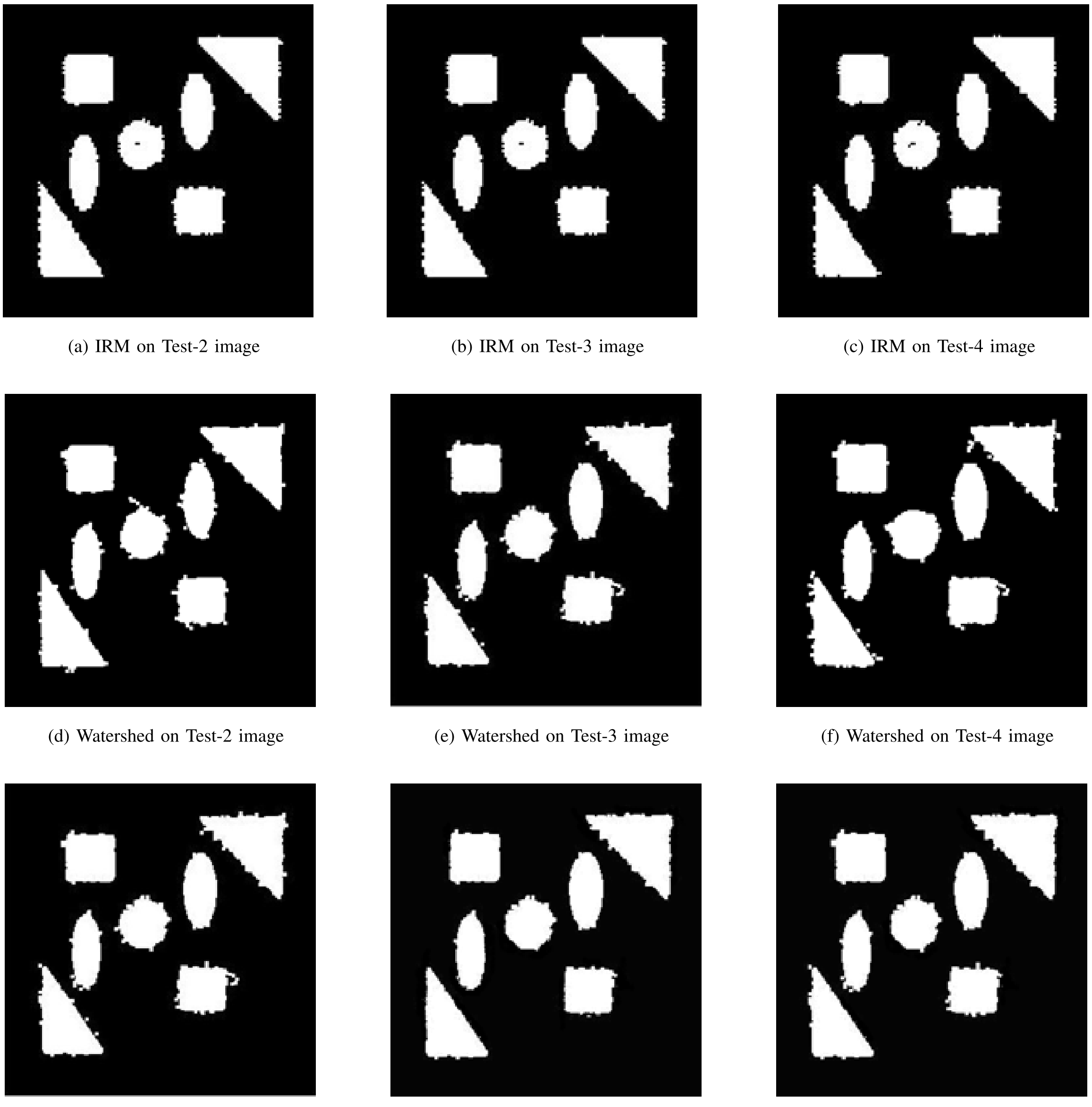
(f) SSR on Test-4 image

(g) SR-extended on Test-2 image

(h) SR-extended on Test-3 image

(i) SR-extended on Test-4 image

Fig. 7: Segmented output of Test-2, Test-3 and Test-4 images by proposed SSR method and SR-extended method.

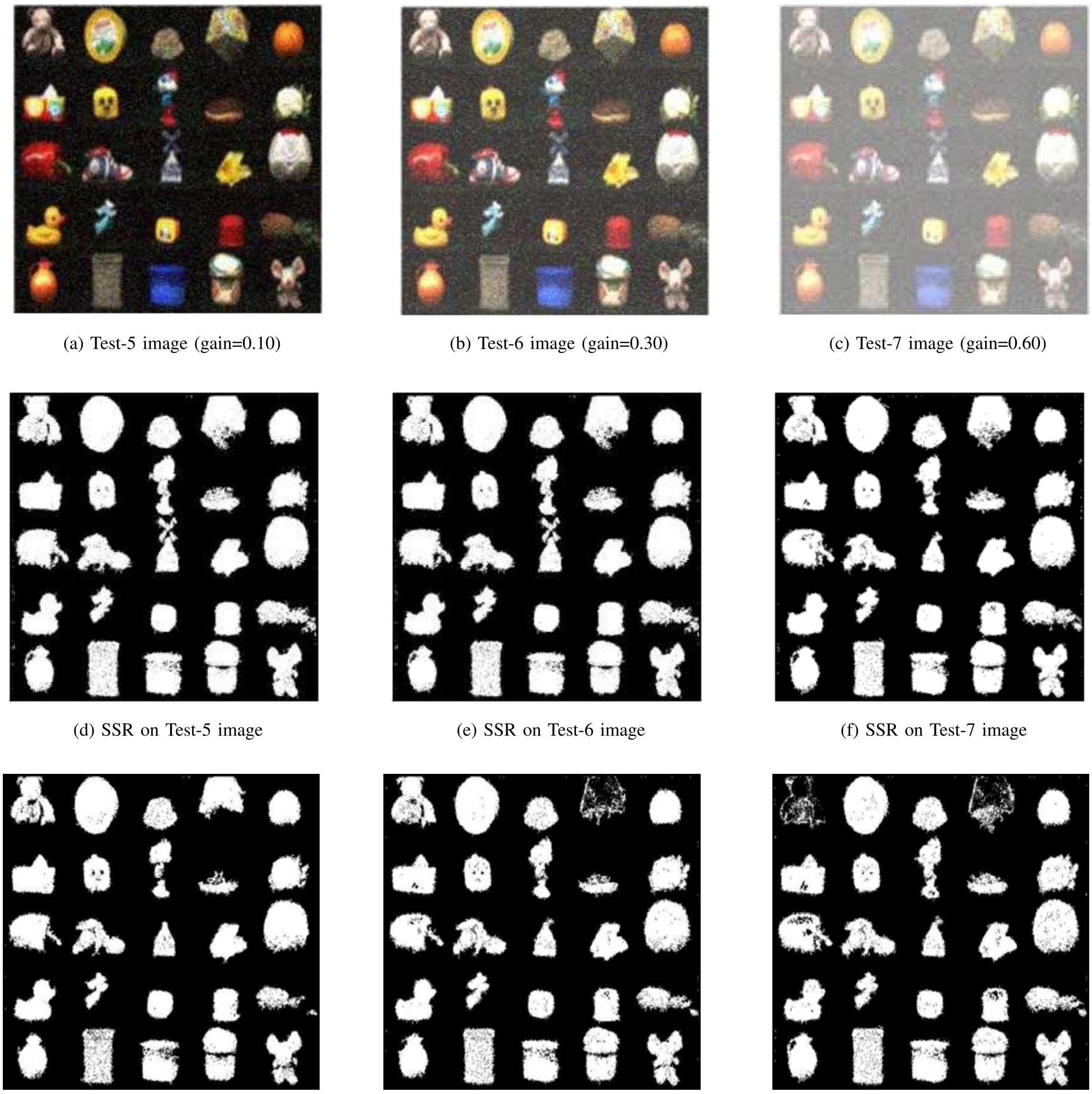


(a) IRM on Test-2 image (b) IRM on Test-3 image (c) IRM on Test-4 image

(d) Watershed on Test-2 image (e) Watershed on Test-3 image (f) Watershed on Test-4 image

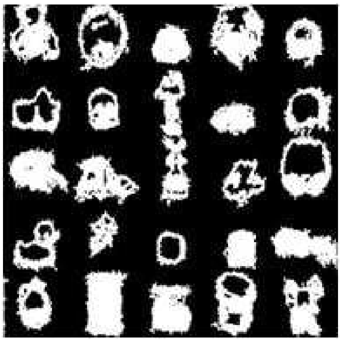
(g) MCW on Test-2 image (h) MCW on Test-3 image (i) MCW on Test-4 image

Fig. 8: Segmented output of Test-2, Test-3, Test-4 images using Integrated region matching (IRM), Watershed and Marker controlled watershed (MCW) method.

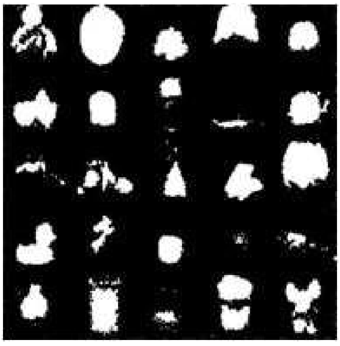


(a) Test-5 image (gain=0.10)
(b) Test-6 image (gain=0.30)
(c) Test-7 image (gain=0.60)
(d) SSR on Test-5 image
(e) SSR on Test-6 image
(f) SSR on Test-7 image
(g) SR-extended on Test-5 image
(h) SR-extended on Test-6 image
(i) SR-extended on Test-7 image

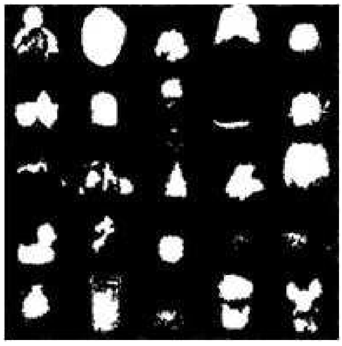
Fig. 9: Segmented output of Test-5, Test-6, Test-7 images by proposed SSR method and SR-extended method.



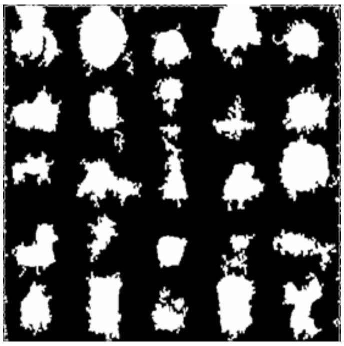
(a) IRM on Test-5 image



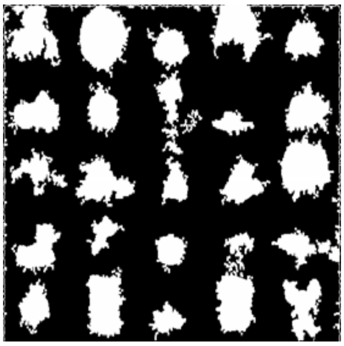
(b) IRM on Test-6 image



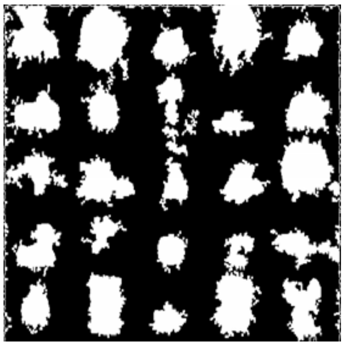
(c) IRM on Test-7 image



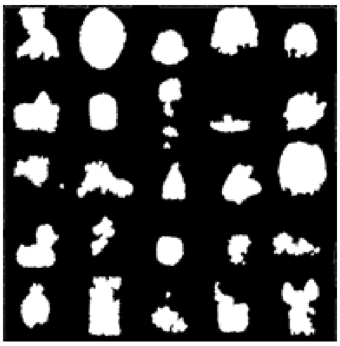
(d) Watershed on Test-5 image



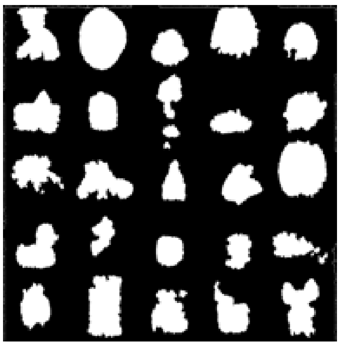
(e) Watershed on Test-6 image



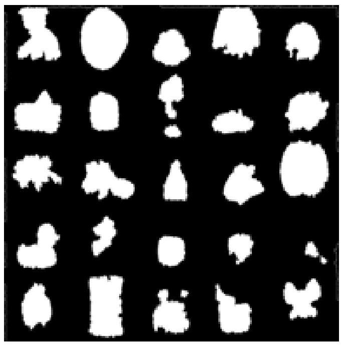
(f) Watershed on Test-7 image



(g) MCW on Test-5 image



(h) MCW on Test-6 image



(i) MCW on Test-7 image

Fig. 10: Segmented output of Test-5, Test-6, Test-7 images by Integrated region matching (IRM), Watershed and Marker controlled watershed (MCW) method.

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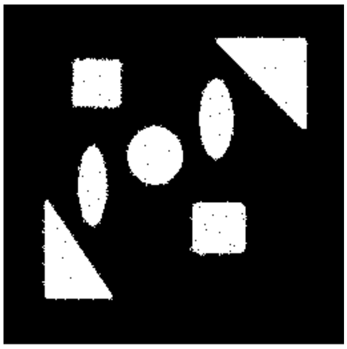
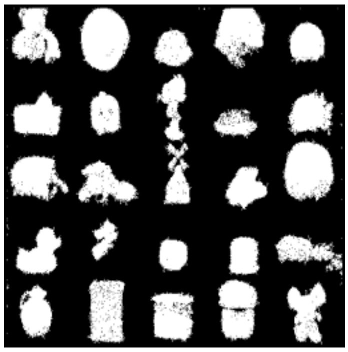
(a) SSR on Test-2 image

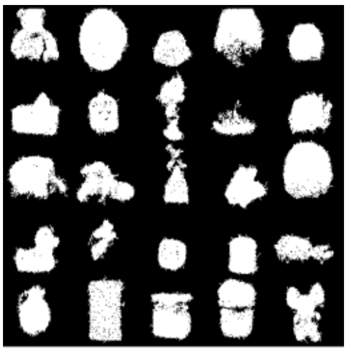


(b) SSR on Test-3 image

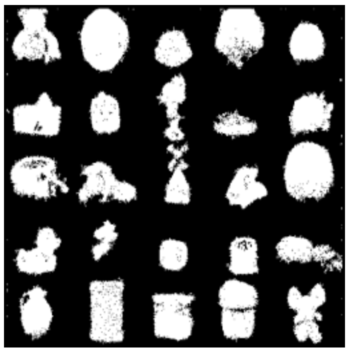
(c) SSR on Test-4 image



(d) SSR on Test-5 image



(e) SSR on Test-6 image



(f) SSR on Test-7 image

Fig. 11: Segmented output of proposed method in all Test images using uniform noise.

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