International Journal of Control Theory and Applications

ISSN : 0974-5572

Volume 10 • Number 32 • 2017

Object Recognition in Underwater Sonar Images Using Support Vector Machine

R. Kumudham[a] and V. Rajendran[b]

[a]*Assistant Professor, Department of ECE, School of Engineering, Vels University, Chennai. Email: kumudham.sree@gmail.com*
[b]*Head of Department, Department of ECE, School of Engineering, Vels University, Chennai*

Abstract: Object recognition in Underwater is a daunting task nowadays. Underwater images especially Sonar images suffer from speckle noise, shadowing and spatially varying clutters. When we utilize those images much of the fine details in the image are lost, so the images must be post-processed to retain information and enhance the quality. Filters are used as a preprocessing tool to suppress noise, preserves edges and corners, and to enhance the image. So we used wavelet filter for smoothing the image by removing speckle noise. Using centralized sparse representation we have converted the low resolution image into high resolution image. Gray level co-occurrence matrix features are extracted from the clustered patches created. Then the object in the sparse represented image is identified using support vector machine.

Keywords: Underwater image, SONAR image, Side Scan Sonar Image, Wavelet Denoising, Thresholding, GLCM, Sparse, Support Vector Machine, Object recognition, Classification, Gray level occurrence matrix.

1. INTRODUCTION

Underwater has abundant resource of wealth hidden inside. Due to poor visibility conditions, 95 percent of the underwater resource is still not well explored.. The imaging technique is one of the methods adopted to reveal the hidden treasure to the world. Underwater imaging plays a vital role in oil exploration, mine's detection navigation, seabed mapping, fishing, ocean drilling, and etc. Underwater object recognition is becoming a daunting task and is also inviting competition among the researchers nowadays. For the purpose of underwater object recognition optical imaging technique is used. When we look back through optical imaging technique, we find that the image obtained suffers from poor visibility condition due to absorption of certain wavelengths and attenuation of light (Sowmyashree M.S. et. al., 2014).

Figure 1 shown above pictures the absorption of certain wavelengths of light. Much of the finer details in the image are lost due to absorption and attenuation of light wave. Moreover the passion of knowing what lies in underwater is still increasing, so side scan sonar equipment is used to capture the sea bed which holds the hidden treasure.

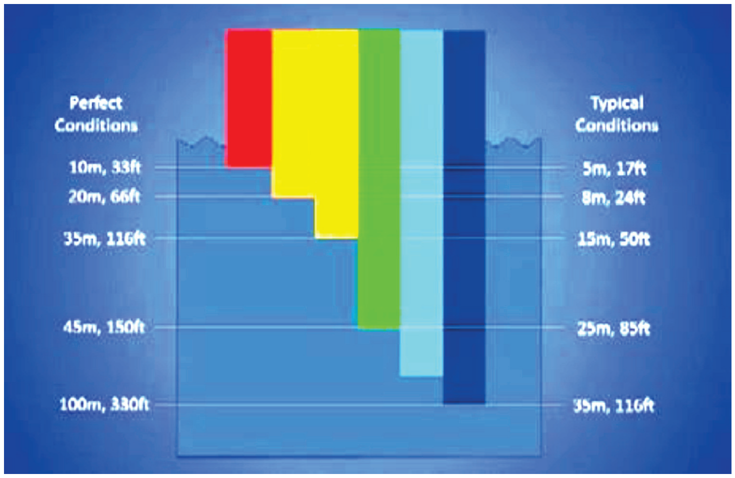


Figure 1: Light absorption in underwater

Side scan sonar equipment captures large area and works based on acoustic or "echo sounding "principle and at the frequency range of 500 kHz. The acoustic signal used suffers from less attenuation when compared to light. But the backscattering of acoustic signals produce speckle noise, shadows and spatially varying clutters. Therefore it becomes a challenging task to post process the acquired sonar images, which are prone to speckle noises, ambient noises, etc. Inaddition to this sonar images are sentient to grazing angle, which makes the target object to appear differently with respect to the surrounding scene (Naveen Kumar et. al. 2012). The post processing includes denoising, image partition, feature extraction and classification which are the significant processes in image analysis. To remove speckle noise from the sonar images without affecting the quality and edges, edge preserving filters should be utilised. The filtering methods satisfy several processing steps for correcting non-uniform lighting, suppressing speckle noise, improving contrast and correcting colours.

The underwater image carries huge volumes of data, so we represented the image coefficient using sparse representation theory, so that details are not lost and the computation time for object recognition is reduced. We adopted here clustering based sparse representation algorithm (Zheng Zhang et. al. 2015). Gray Level Coocurrence matrix features are extracted from the clustered based sparse representation image. GLCM functions represents the texture of an image by calculating he occurence of pairs of pixel with specific values and specified spatial relationship, and then extracting statistical features from the image matrix. The object is identified using Support vector machine classifier through the extracted GLCM features.

2. LITERATURE SURVEY

Pooja Sahu, et. al. (2014) used Median Filter to enhance the colour contrast of the target object in underwater and to remove different noise such as gaussian noise, speckle noise. Dr.G. Padmavathi et. al., (2010) compared the performance of the Homomorphic, Anisotropic, Wavelet denoising filters and analyzed their performance by the Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) Imen mandhouj et.al. (2012) used Wavelet filters for reducing Gaussian noise which improved the image quality. Prabhakar C J. et. al., 2011 obtained the comparison results for Homomorphic filtering, Wavelet denoising Bilateral filtering, and constant stretching. The proposed preprocessing technique enchance the quality of the degraded under water images which suffers from non uniform light illumination and diminished colors. Ali A. Yassin, Rana, et. al. (2013) used Discrete Wavelet transform (DWT) and Hue Saturation Value (HSV) in their proposed work. The compensation between the original image and resulting image is very high. Sachin D Ruikar, et. al, (2011) proposed Visu Shrink, Universal Sure shrink, Normal Shrink, Bays Shrink, New Threshold Circular Kernel, This paper may be useful for other Denoising scheme for evaluating suppression of noise. S. Kumari, et. al., (2012) showed the denoising effect of symlet filter on still images. P. Mohanaiah, et. al., (2013) proposed Image texture feature extraction using GLCM.

3. PROPOSED WORK

The proposed work involves the methods adopted for the spotting of the object in underwater sonar images which is shown in the Figure 2.

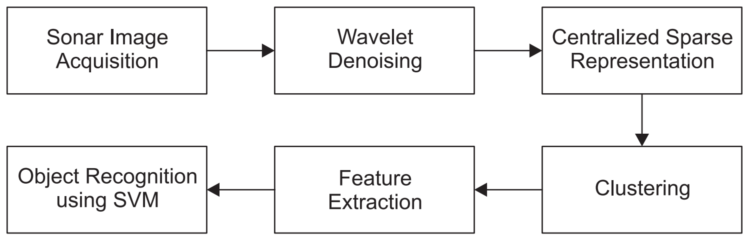


Figure 2: Block Diagram for the Object Recognition

Image Acquiring

We have used the sonar images from the EDGETECH database for our work. The images used are captured using side scan sonar equipment, Series 4125, Ultra high resolution portable, lightweight and is operating at a frequency range of 400-900 KHz. The images acquired is of low resolution and affected with speckle noise, hence it has to be processed for removing noise, improving the resolution.

Preprocessing-Wavelet Filtering

The Sonar image has to be preprocessed since it has speckle noise. Speckle noise is considered as the noise which is multiplicative in nature, that degrades the quality of sonar images. Due to random fluctuations in the return signal from an object, speckle noise occurs. It increases the mean grey level of a local area. Speckle noise makes image interpretation difficult and it follows a gamma distribution. Wavelet filtering is used to remove speckle noise, since it preserves edges and it has high Peak signal to Noise Ratio. Wavelet filter is used to reduce the speckle noise present in the SONAR images. It is found that among the wavelet families, symlet wavelet gives good performance for natural images (S. Kumari et. al., 2012). Symlet wavelets have their properties similar to Daubechies wavelet. There are 7 different Symlet functions from sym2 to sym8. N is the order in symN. In our work we used sym 4 because its an intermediate wavelet.

Centralized Sparse Representation for Super Resolution

Sparse representation from redundant dictionaries helps to capture and reveal the structures in object detection. It reduces the model complexity and avoids overfitting. It also reduces the computation time. We have represented the image in a sparse way to enhance the resolution. After preprocessing, the low resolution sonar Image is converted to a super resolution image by using Non locally Centralized sparse representation algorithm, which outperforms the existing methods (Weisheng Dong et. al. 2011). The low resolution image is obtained first by blurring the high resolution image with a blur kernel. Then it is down sampled by a scaling factor. Hence, recovering the High Resolution image from a single Low Resolution image is severely underdetermined. The Low Resolution image (which is simulated) is generated by first blurring the High Resolution image with a (7×7) Gaussian kernel with standard deviation of 1.6, and then down sampling the blurred image by a scaling factor of 3 in both the (horizontal and vertical) directions. Since human eye is more sensitive to changes in the luminance, we apply the Image Restoration methods to the luminance component and then apply the simple bicubic interpolation methods for the chromatic components.

K Means Clustering

We extracted the image patches from the super resolution image and clustered the patches into K clusters by using K means clustering (where $k = 70$) method. Since the patches in a cluster are same, for each cluster we created a dictionary of PCA bases and used this compact PCA dictionary for coding the patches in the cluster (W. Dong et. al., 2011). These PCA sub-dictionaries construct a large over complete dictionary to represent all the possible local features of natural images. We first checked which cluster the given patch falls into, by calculating its distances to means of the clusters, and then selected the PCA sub-dictionary of this cluster to code it. To evaluate, the PSNR and SSIM results for a sample of sonar images are calculated.

Gray-Level Co-Occurrence Matrix (GLCM) Features

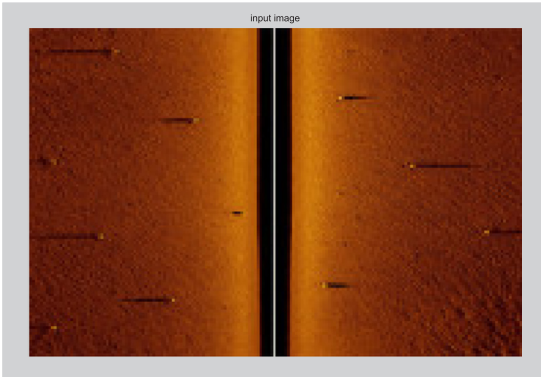
Gray-Level Co-Occurrence Matrix (GLCM) features extraction is a method which uses statistics to analyse the texture that considers the spatial relationship between pixels. It is also known as the gray-level spatial dependence matrix. This function characterise the texture of an image by calculating the occurrence of a pairs of pixel with exact values and spatial relationship, creating a GLCM, and then extracting statistical measures from GLCM matrix. In the sonar image we have extracted the features such as contrast, energy, correlation and homogeneity, which characterises the texture.

Object Recognition using Support Vector Machine (SVM)

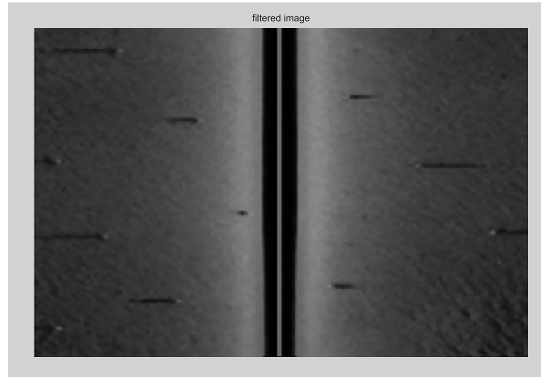
Sidescansonar equipment scans large area of the seabed at once, the objects of target are very difficult to identify. The objects lying on the seabed, seems to appear like a faint spot of shadow adjacent to a bright highlight region. In addition to this sidescan sonar images are very sentient to the grazing angle, which makes the object to appear differently depending on its surrounding scene. We have preprocessed and improved the resolution of the sonar image and now we have used Support Vector Machine (SVM) to identify the object. Since SVM has good generalization ability and accuracy so we have used in our work. We have trained three sample characteristics of images using support vector machine algorithm and then we input the test image for object recognition. The object has been well recognized as ship wreck, mining, pipeline using SVM algorithm.

4. RESULTS

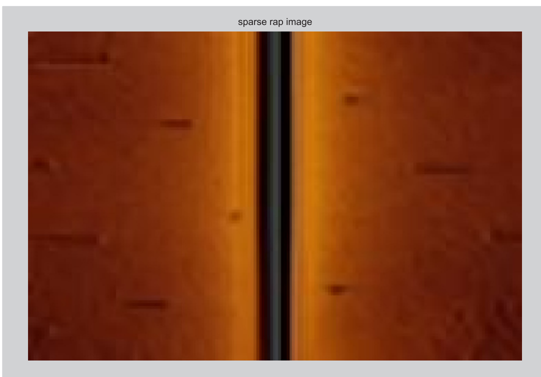
Figure 3 (from left to right) shows the acquired sonar images (3a) from Edgetech website. The image is filtered using symlet wavelet filter in order to remove the speckle noise which usually occurs due to back scattering of acoustic signals. The filtered image (3b) resolution is enhanced using centralized sparse representation algorithm which we obtain as sparse representation image(3c). In order to evaluate the performance of the sparse representation we have found the Peak Signal to Noise Ratio (PSNR) and Structural Similariy Index (SSIM) value which is reported in Table 1 as well as in Figure 3(d). PSNR and SSIM is one of the image quality metrics. The computation time is also calculated reported in Table 1. The Gray level cooccurence matrix features are extracted from the sparse representation image which is reported in Table 2 as well as in Figure 3(e). Then we have applied the Support Vector Machine algorithm to recognize the object as mining Figure 3(f). For this we have trained a sample of sonar images with object such as mining, pipeline, ship wreckage characteristics. The then we input the test image and recognized as mining. The below Figures (4 & 5 series) also shows similar steps described above and the image recognized as pipeline and ship wreckage.



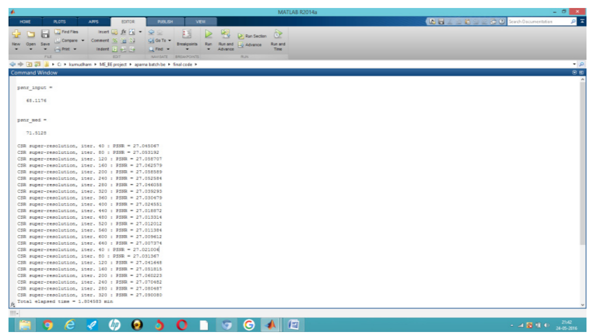
(3a)



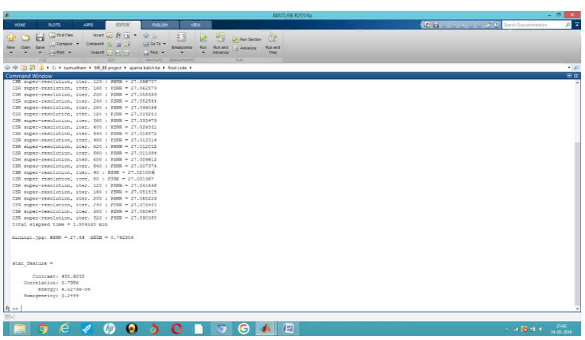
(3b)



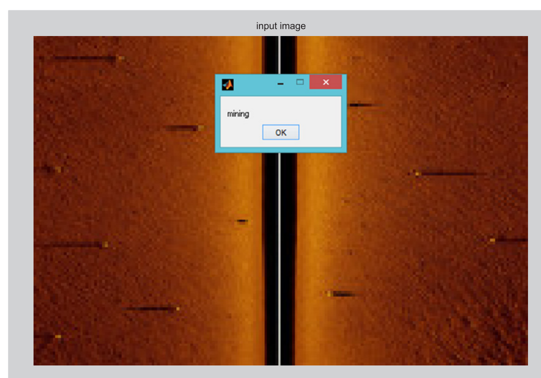
(3c)



(3d)



(3e)

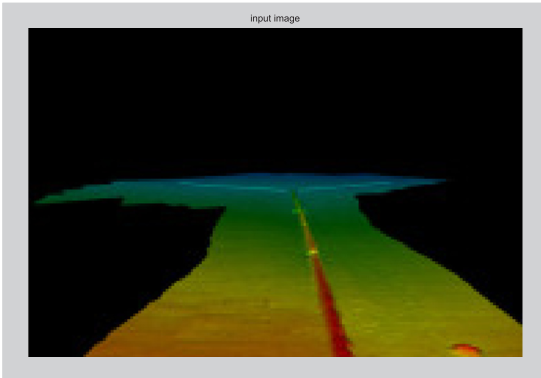


(3f)

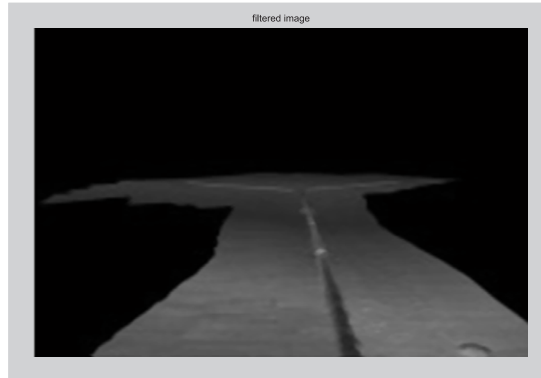
Figure 3: (Left to right) (3a) Acquired Sonar Image (3b) Symlet Wavelet Filtered Image (3c)Sparse Represented Image (3d) (3e) output for PSNR, SSIM values using Centralised sparse representation Algorithm, GLCM Features (3f) Output showing object recognized as Mining

Table 1
Performance Metrics of Centralised Sparse Representation Algorithm on Sonar Image

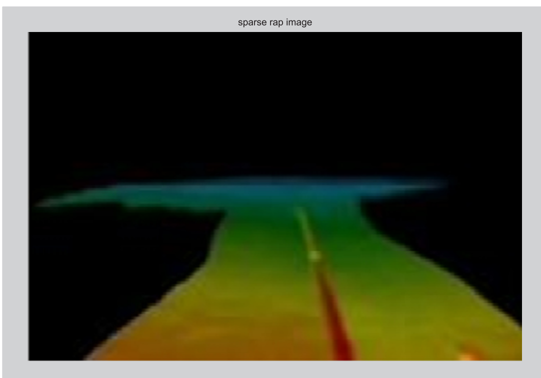
S.No.	*Sonar Images*	*PSNR*	*SSIM*	*Total Elapsed Time (min)*
1	mining1.jpg	27.09	0.762356	1.804583
2	pipe-line-1.jpg	40.59	0.971845	1.843383
3	shipwreck.jpg	26.76	0.676879	2.370683



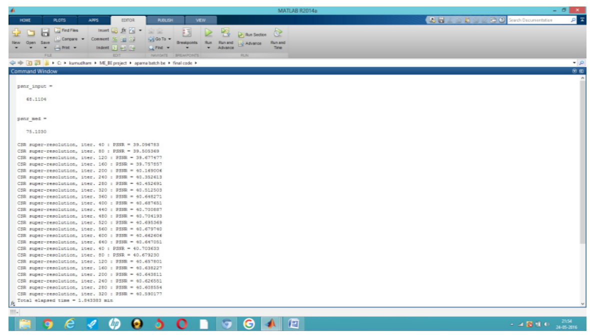
(4a)



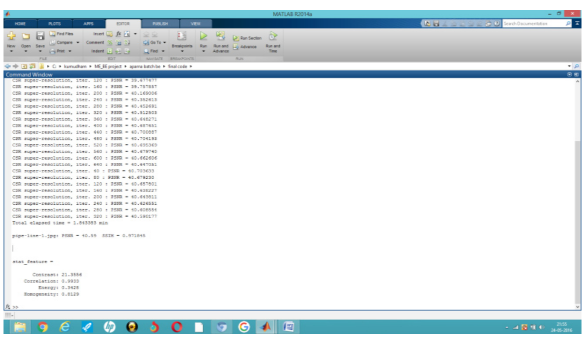
(4b)



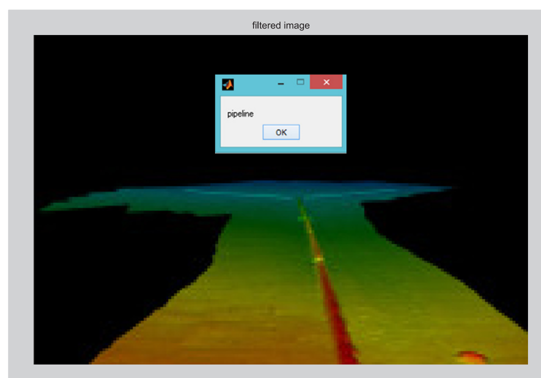
(4c)



(4d)



(4e)



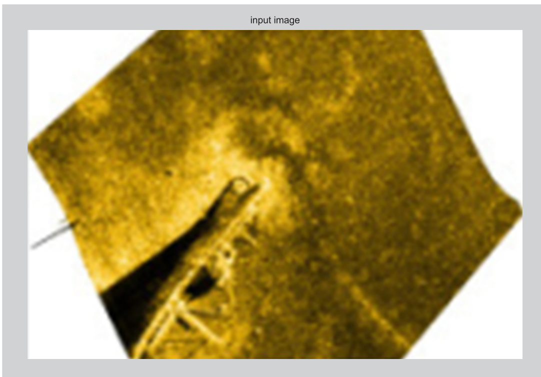
(4f)

Figure 4: (Left to right) (4a) Acquired Sonar Image (4b) Symlet Wavelet Filtered Image (4c) Sparse Represented Image (4d) (4e) output for PSNR, SSIM values using Centralised sparse representation Algorithm, GLCM Features (4f) Output showing object recognized as Pipeline

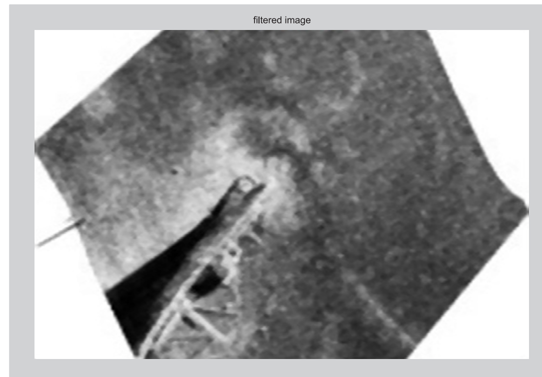
Table 2
GLCM Features Extracted from Sonar Images

S.No.	*Sonar Images*	*Texture (GLCM) Features*
1	mining1.jpg	Contrast: 488.9038 Correlation: 0.7356 Energy: 6.5273e-04 Homogeneity: 0.2499

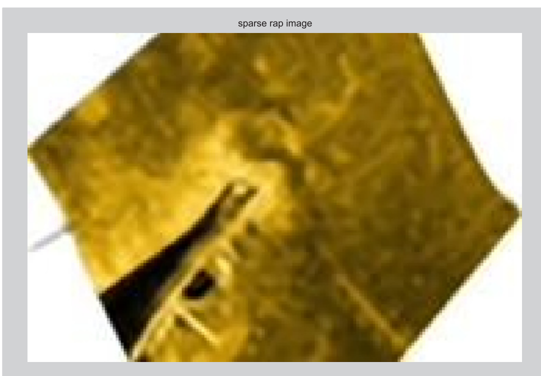
S.No.	*Sonar Images*	*Texture (GLCM) Features*
2	pipe-line-1.jpg	Contrast: 21.3556 Correlation: 0.9933 Energy: 0.3428 Homogeneity: 0.8129
3	shipwreck.jpg	Contrast: 558.4439 Correlation: 0.9479 Energy: 0.0322 Homogeneity: 0.2986



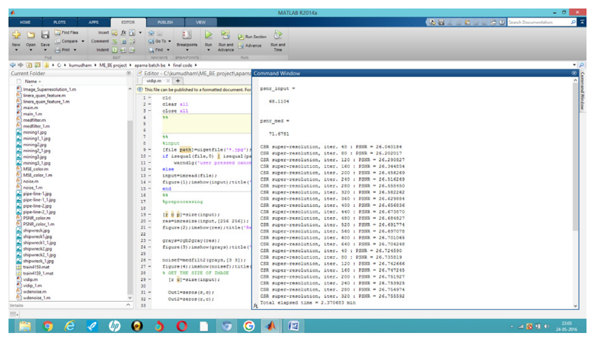
(5a)



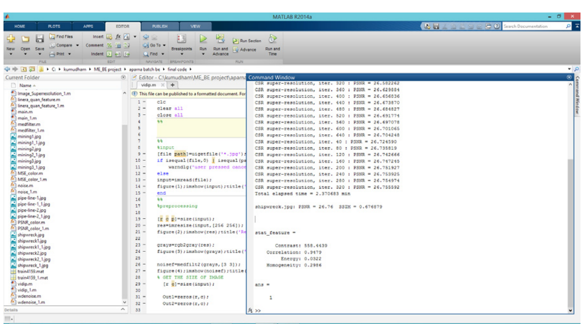
(5b)



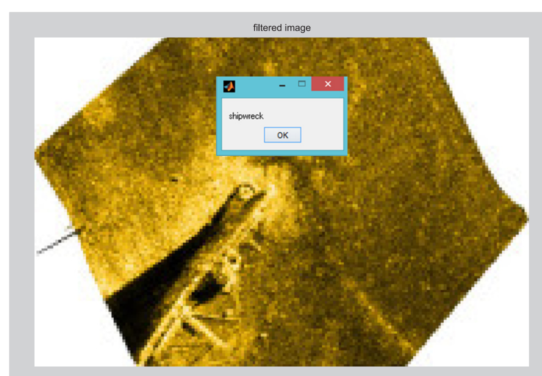
(5c)



(5d)



(5e)



(5f)

Figure 5: (left to right) (5a) Acquired Sonar Image (5b) Symlet Wavelet Filtered Image (5c) Sparse Represented Image (5d) (5e) output for PSNR, SSIM values using Centralised sparse representation Algorithm, GLCM Features (5f) Output showing object recognized as Pipeline

5. CONCLUSION AND FUTURE WORK

In our proposed work we adopted methods for recognizing the object in the Underwater sonar image. We used symlet wavelet filter for denoising that is removing the speckle noise, which is found to give high Peak Signal to Noise Ratio. Then we used centralized sparse representation algorithm to exploit the sparsity in the image. GLCM features are extracted from the sparse represented image patches. Then the object in the image is recognized as mining, ship wreckage or pipeline. We trained three sample characteristics of image and identified using support vector machine algorithm. To evaluate the performance of the algorithm we have calculated the metrics such as PSNR, SSIM values and computation time. In future we have planned to work for more number of image characteristics for object recognition and to work in real time application.

REFERENCES

[1] Sowmyashree M S, Sukrita K Bekal, Sneha R, Priyanka N, "A Survey on the various Underwater image enhancement techniques", International Journal of Engineering Science Invention, Volume 3, Issue 5, May 2014, pp. 40-45.

[2] Naveen Kumar, Qun Feng Tan, Shrikanth S. Narayanan," Object classification in sidescan sonar images with sparse representation techniques", IEEE-ICASSP 2012.

[3] Zheng Zhang, Yong Xu,Jian Yang, Xuelong Li,David Zhang, "A Survey of Sparse Representation: Algorithms and Applications", IEEE Access, May 20, 2015.

[4] Pooja Sahu, Neelesh Gupta,Neetu Sharma, "A survey on underwater image enhancement technique," Vol. 87, No. 13, 2014.

[5] Dr. G. Padmavathi, Dr. P. Subashini and Suresh kumar thakur, "Comparison of filter used for underwater image pre-processing," Vol. 10. No. 1, January 2010.

[6] Prabhakar C. J. Praveen Kumar, "An image based technique for enhancement of underwater image," Vol. 3, 2011, pp. 217–224.

[7] Ali A. Yassin, Rana, M. Ghadban, Salah F. Saleh, "Using discrete wavelet transformation to enhance underwater image,". Vol. 10, No. 2, 2013.

[8] Sachin D Ruikar, Dharmpal D Doye, "Wavelet based image denoising technique," Vol. 2, No. 3, 2011.

[9] S. Kumari, R. Vijay, "Effect of symlet filter order an denoising of still images," Vol. 3, No. 1, 2012.

[10] M.S. Sowmyashree, R. Sneha, "A survey on various underwater image enhancement technique," Vol. 3, 2014.

[11] P. Mohaniah, P. Sathyanarayana, "Image texture feature extraction using GLCM," Vol. 3, 2013.

[12] S. Kumari, R. Vijay , "Effect of Symlet Filter Order on Denoising of Still Images", Advanced Computing: An International Journal (ACIJ), Vol. 3, No. 1, January 2012.

[13] Weisheng Dong, Lei Zhang, and Guangming Shi, "Centralized sparse representation for image restoration", IEEE Int. Conf. Computer Vision (ICCV), 2011.

[14] W. Dong, L. Zhang, G. Shi, and X. Wu, "Image deblurring and super-resolution by adaptive sparse domain selection and adaptive regularization," IEEE Trans. On Image Processing, Vol. 20, No. 7, pp. 1838-1857, July 2011.

[15] Kumar, N.; Mitra, U.; Narayanan, "Robust Object Classification in Underwater Sidescan Sonar Images by Using Reliability-Aware Fusion of Shadow Features", S.S. Oceanic Engineering, IEEE Journal of Year: 2015, Volume: 40, Issue: 3, Pages: 592-606, DOI: 10.1109/JOE.2014.2344971, IEEE Journals & Magazines.