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Under Water Image Using Contrast Limited Adaptive Histogram Equalization

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***Abstract* - This paper describes about the underwater computer vision. Underwater image processing is in general a challenging task, due to its environment, poor sunlight, and the turbidity in itself. Optical, sonar and ultrasound images are captured from the underwater environment. Often optical cameras seem to be a good choice, especially in the case of underwater species identification or counting, coral reefs, pipeline monitoring, mining etc. Underwater images captured from such cameras are poor in contrast, blurred and often contain noise due to the flora and fauna floating in the water. The visibility is limited due to the fact that when light enters the water it is exponentially attenuated. In some cases, underwater images are captured in very low illumination such that object detection itself becomes a challenging task. For accurate object recognition, underwater images must undergo initial pre-processing. This preprocessing must include image enhancement and de- noising as the image suffers from poor contrast, non-uniform lighting, blurring etc. The extracted features must undergo an Artificial Intelligence algorithm for classification. Such automation is often required, as ocean floor is monitored continuously for various applications and manual identification will not help. Artificial neural networks, which exhibit capabilities for adaptation, was used for classifying the objects of interest underwater. The learning algorithms were designed such that features were trained and back propagated to the hidden neurons, until the error was minimized. A stepwise feature selection process was used to determine the subset of features that will optimize the probability of detection and classification. This resulted in accurate object recognition with 96% classification accuracy.**

***Index Terms* - Underwater Imaging, Histogram Equalization & Algorithms.**

1.INTRODUCTION

Underwater imaging is an unexplored area and is gaining importance in the recent years, due to its increase in the use of naval and civilian applications. Continuous monitoring of the sea bed is needed, often in the case of coral reef surveys, marine species counting and monitoring, pipeline maintenance, underwater mines, shipwrecks, etc. Even though, the exploration of planets like Mars, Moon, etc. have been completed to the fullest, only 5% of the Earth's ocean has been explored till now.1, 2 The reason behind this is the limited visibility, and that the sea bed can be reached only after thou-sands of meters' depth under water. Several research concerning ocean science has been done all over the world, in the recent years with the help of Remotely Operated Vehicles/Autonomous Underwater Vehicles (ROV/AUV) deep under the sea.3, 4, 5, 6, 7, 8, 9, 10 Huge volumes of image data are captured every day with the help of ROVs and classifying objects in such images is now challenging. Marine scientists require automated object recognition tools based on image processing techniques. This is because, manual classification is expensive and time consuming. Many image processing techniques are available for real world object classification. But those techniques, might not suit underwater image processing needs due to the following reasons,

1. Images captured are blurred,
2. Feature information is very less,
3. Often object and background have the same intensities.
4. The object shape, orientation and size also vary from picture to picture.

Hence, to resolve all the above challenges and to achieve a better classification accuracy artificial intelligence has to be employed. An intelligent system for object recognition in underwater images has been developed.

1.1 PROBLEM STATEMENT-UNDERWATER IMAGE PROCESSING

Underwater images are highly degraded due to (i) exponential attenuation of light as it travels in the water, (ii) turbidity of water. Because of this, it is often problematic to process the underwater images as compared to the multimedia or land images. Essentially, this problem arises in the pre-processing stage itself which differentiates the underwater image processing from ordinary image processing. Ocean is monitored continuously in search of coral reefs, rare species, pipeline cracks and huge amount of image data is captured every day, which is laborious for trained scientists to recognize, classify and annotate objects manually. Hence artificial intelligence is needed which can improve the contrast of such poor-quality images, segment objects based on texture and annotate objects based on its structure.

1.2 SCOPE FOR UNDERWATER IMAGE PROCESSING

Underwater imaging has been used in many areas of science and technology. It has made a prominent role in civilian and military applications. Computer vision plays a major role for various applications like inspection of pipelines and telecommunication cables, mine detection, shipwrecks, rare underwater species monitoring, archeology etc. Some of them are listed below:

Underwater Inspection: Often inspections are done underwater for oil spillage and maintenance of pipelines and structures underwater. Inspection of ship hulls is a part of the maintenance operations. Ships entering the ports serve as carriers for hazardous materials like nuclear weapons. Hull maintenance is carried out using trained divers which can be replaced by autonomous vehicles. Navy often monitor the seabed in search of mines set by the enemy troop.

Marine Biology and Geology: Underwater imaging systems have been used extensively for marine biological studies. Underwater imaging applications include underwater species behaviour, habitat mapping, study of underwater species, environment condition of seabed (damaged or not) and to separate living corals from dead. It has also been used for marine geology for sediment studies, tidal micro topography, bridge and pipeline inspections, marine archaeology, entertainment, education etc.

Fish-Pond Monitor: Fishpond monitoring is now a new area in which underwater imaging is gaining importance. Zion et al. (2007) in his work describes how an image processing system can help in automatically classifying and sorting live fish in such places.34 Fishes in the pond are trained to collect food by passing through a tunnel made of transparent glass.

Bed-Sediment Microscope: An additional domain that is gaining interest in under-water research is study of sediments in rivers. This area is now of interest to geologists particularly to measure the grains in bed sediments. Grain size analysis is a fundamental step in sediment analysis, and it is often time consuming and expensive in laboratories. Image processing was used for sediment analysis to enable fast measurements and tracking of changes over time. Digital analysis of microscopic images was done to measure grain size of bed sediments in rivers.

1.3 OBJECTIVES

Automated tools for object recognition from underwater optical images are necessary for processing large amounts of image data. The main objective is to develop such auto-mated tool which can pre-process such images and recognize the objects of interest in the images. Underwater object recognition is a challenging problem due to the inherent difficulties in the images like poor contrast, noise, complex spatial borders among classes etc. This work aims to develop fuzzy logic-based algorithms for underwater image enhancement and de-noising. One aim of this thesis when developing such algorithms, was to compare the proposed algorithms with the existing most prominent techniques available in the literature both subjectively and quantitatively. This work also aims to develop artificial intelligence-based learning algorithms for object recognition in underwater images. Development of such automated tool will help in automatic recognition of objects with least computational time. This user-friendly GUI will ultimately help the experts in the field of marine and geology.

2. LITERATURE SURVEY

2.1 UNDERWATER IMAGING MODALITIES

The first underwater image was captured by William Thompson in 1856 with a pole- mounted camera. Later

Louis Boutan in 1893 developed his own camera system and began his work as an underwater photographer. Dr. William Longley in 1926 captured the first colour underwater image using explosive magnesium flash powder as a light source. The invention of the Calypso 35mm underwater film camera and the establishment of The San Diego Underwater Photographic Society, one of the first and largest organizations dedicated to underwater photography, cemented underwater imaging as a mature and viable photographic practice. Since then, underwater photography has developed rapidly to tackle the challenges that come with the unfamiliar environment of the ocean. Currently, underwater images have been captured in numerous ways using different modalities. The popular techniques used for underwater imaging are laser based, sonar and optical systems. Compared with the imagery acquired by digital cameras, the imagery obtained by a sonar system is usually of lower quality. This can be attributed to the complexity of the underwater environment, such as strong reflection from seabed, low cleanliness, and in-homogeneity in the density of water. The strong reflection of seabed makes the detection of objects that are close to the seabed very difficult. Additionally, capturing images using laser and sonar-based methods involves huge cost and currently such images are also not available in huge quantities like digital images. Especially in the case of species classification, sonar and laser images cannot provide more feature information like digital images. Hence digital images were considered for this work.

2.2 UNDERWATER IMAGE PRE-PROCESSING

Recently the use of ROV has led to capturing of underwater images deep under the ocean. Since ROV carry their own light sources with them and objects are captured at various depths, the images captured are often non-uniformly illuminated, poor in contrast, and is corrupted by noise due to the organic matter dissolved in water.13 Even though visibility is augmented by artificial lighting it often forms a beam of light in the center of the image causing object recognition difficult.16 Since there is an exponential decay of the light intensity with distance it leads to a hazy image background. Absorption, forward scattering and backscattering also results in poor quality underwater images. Macroscopic floating particles that float in water creates unwanted signal namely noise on the image. To improve the recognition of objects in underwater images, enhancement techniques are necessary. Many researchers have developed techniques to de-noise and enhance underwater images. The survey on the existing methods is as described in the following sections.

2.3 SOFT COMPUTING FOR UNDERWATER IMAGE PROCESSING

Soft Computing is a collection of methodologies, such as fuzzy logic (FL), evolutionary algorithms (EA), artificial intelligence and machine learning. The capability of these techniques to handle imprecision and incomplete information and to model very complex systems makes them a useful tool in many scientific research areas. The origin of soft computing dates back to 1965 with the introduction of fuzzy set theory by the father of Fuzzy logic Lotfi Zadeh. Image processing is one of the areas where soft computing provides solutions.

Underwater images are captured at various depths and illumination condition and each image vary dynamically in terms of contrast and noise. Traditional techniques for contrast enhancement or de-noising are not effective when there is a dynamic range of intensity information in the images. Fuzzy logic provides solutions to such problems by dynamically analyzing each pixel information and generating the result by forming fuzzy if-then rules. Soft computing differs from conventional (hard) computing in that, unlike hard computing, is it tolerant in handling the vagueness and uncertainty present in data. In effect, the soft computing comprises of tools and technologies that can decide and analyse like a human mind.15The real world problems are pervasively imprecise and uncertain and soft computing provides solutions to these problems in a robust, timely and cost-effective manner. Later neural computing and genetic computing evolved to form core areas of soft computing. Object recognition in such underwater images is also challenging as objects differ in shape, size, and orientation. Statistical features can help in recognition of such objects. But such features need to be trained so that similar features present in the images can be retrieved. Artificial Neural Networks (ANN) are proven to learn features without explicit information of the data that has to be classified.

3. SYSTEM DESIGN

Underwater images are basically characterized by their poor visibility due to the specific transmission properties of light as it travels in the water and hence the captured images appear poorly contrasted and hazy. Artificial light supported by the underwater vehicles often cause a gloom of light on the background of the object, making image processing more challenging. As we know, when light enters the water medium, it disappears due to its restricted wavelength and hence the amount and distance of visibility is limited. Owing to the physical properties of underwater vision sensors, the environment, medium and floating particles, images are deprived of contrast, stained with different kinds of noise, and appear cloudy. Therefore, underwater image enhancement is necessary. Conventional techniques for image processing often involve manual setting of parameters and the image quality is also not uniform under water. Underwater images have dynamic and broad range of uneven intensities which cannot be rectified using straight forward techniques. Thus, there is a need for adaptive techniques that can process and provide consistent results for dynamic low contrast images.99 Implementation of Fuzzy logic has provided clear-cut results in the field of image processing and pattern classification.

3.1 NOISE IN UNDERWATER IMAGES

The noise present in underwater optical images has two major sources: underwater optical vision system and noise caused by natural sources like wind, rain, tides, currents, and biological life. Noise from optical vision system depends on the amount of light exposure underwater, size, type, and temperature of the imaging sensor. Other factors causing noise are sand raised due to the motion of divers and autonomous vehicles, phytoplankton, floating flora, and fauna and dissolved organic matter. This noise typically appears or resembles Gaussian noise. This noise appears arbitrarily as white pixels throughout the image. The probability density function for this noise has the structure of Gaussian or normal distribution. Due to its additive nature, every pixel in a degraded image can be expressed as an addition of the random Gaussian noise to the original pixel.

3.2 OBJECT RECOGNITION USING LEARNING ALGORITHMS

Object recognition is a process for identifying a specific object in a digital image or video. The object recognition problem can be defined as a labeling problem based on models of known objects. To be more specific, given an image containing one or more objects of interest, background, and a set of labels the system should assign correct labels to the region in the image.166 Objects under water vary in size, colour, orientation due to the illumination condition and direction. A structure-based approach will help in retrieving the shape information of the objects. The retrieved structure information can then be compared with other structures and the object can be identified. For such an approach the boundary of the object has to be effectively segmented. An unconnected boundary may not help in object recognition. There can be a little misclassification observed in underwater images when the object resembles the background features. In such cases, morphological operations satisfy the need, by extracting the boundary. The direction of the pixels in the boundary can provide information about the shape of the object. This can be done with the help of chain code. The proposed method will involve three stages. First, the identification of statistical features that uniquely represent the object of interest and background. Second, development of a supervised learning method (ANN) to classify the object of interest from background, based on texture features. Finally, recognition of the object was performed using chain coding and matching. The proposed method will involve three stages. First, the identification of statistical features that uniquely represent the object of interest and background. Second, development of a supervised learning method (ANN) to classify the object of interest from background, based on texture features. Finally, recognition of the object was performed using chain coding and matching. One of the most fascinating features of the human brain is the ability to learn. Artificial neural network mimics the human brain and performs learning with the help of neurons. Learning indicates that the network is capable of changing its input/output behaviour because of the changes in the environment. A machine intelligence algorithm has to be devised, for mapping the extracted features, to the objects under consideration. ANN is an artificial intelligence tool which mimics the human intelligence and is composed of node like structures called artificial neurons. Shallow ANNs are extensively applied in object recognition, image compression, and pattern classification problems involving prediction. Even though there are several approaches available in case of artificial neural networks, a supervised learning approach where the error can be back propagated and minimized will be more suitable. This will help in training the features of the object of interest and the background resulting in effective segmentation.

4. RESULT AND DISCUSSION

Effective pre-processing for underwater images is necessary for accurate object recognition. Here the results of various pre-processing filters after carrying out tests on underwater images are presented. Three diverse filters were compared namely guided filter, bilateral and box filter to rectify the non-uniform illumination present in the underwater images. Illumination normally differs gradually across the image when compared to reflectance component which varies quite sharply at object edges. This steady variation in illumination was improved with the help of bilateral filter, resulting in enhancement of background and edge information which is vital for underwater images.

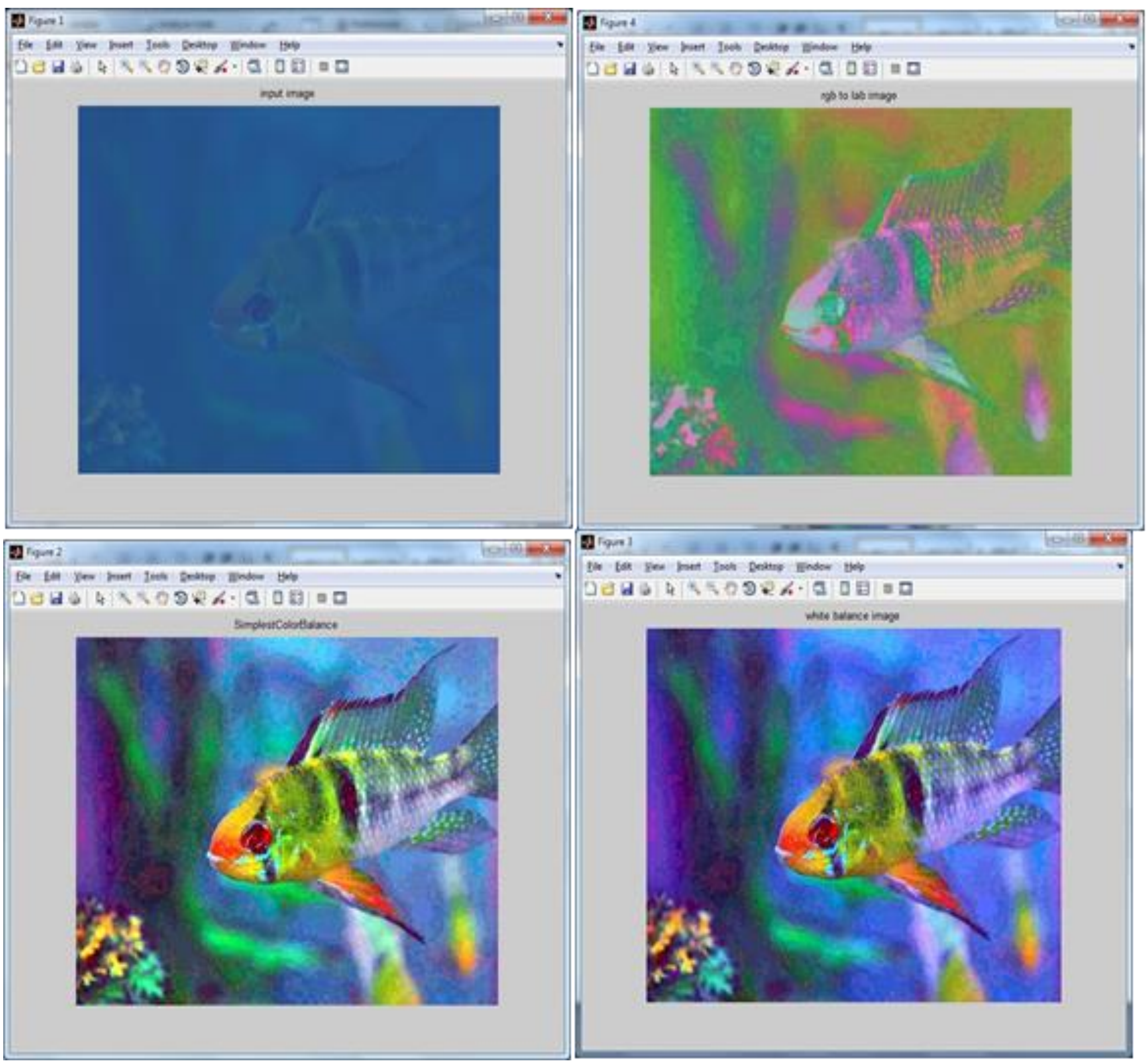


Figure :1 Input and filtered image

Bilateral filter is a sharpening filter, and it tends to increase the low frequencies in the image. the background and fish appear visually clearer than the original image. The black background, the boundary of the fish appears darker and even the blue colour of the fish scales appear enhanced. A similar result was obtained by Stephane and Isabelle. Other filters namely bilateral and anisotropic filter smoothens (blurs) the image while retaining strong edge information It shows the result after applying bilateral filter. Unlike homomorphic filter, bilateral filter is a smoothing filter. Bilateral filter works well for illumination correction in normal atmospheric images. Since image d is already blurred, a smoothing filter like bilateral, might further increase the blurriness. But the resultant image did not appear more blurred, as it performed a weighted average technique and is shown in the right-hand side are shown. But edge structures were not revealed like homomorphic filter. Anisotropic filtering results are shown.

As in the case of bilateral filter, the image did not improve after the application of box filter. Since, this filter also performed a blurring operation, edge structures and background were not revealed. Thus, bilateral and box filter results in a homogenous image with loss of small edge structures. Therefore, to bring uniform brightness in underwater images, homomorphic filter was preferred. To perform de-noising, Haar and Symlet were compared. The threshold for denoising was identified as soft threshold as it will yield a smooth image and hard threshold often result in sudden artifacts in the image, particularly when there is more noise content in the image. The soft threshold value was varied between 1 to 40 and a threshold value5 was set. Setting the threshold very low retained the noise information present in the image. As the threshold value increased, the image appeared blurred resulting in loss of edge information. Hence, the threshold was set.

Since, underwater images are often captured deep under the sea with poor visibility conditions, the contrast of underwater images is very poor. Therefore, these images have to undergo contrast improvement. In order to enhance the contrast in underwater images, contrast limited adaptive histogram equalization was applied. Image d initially had histogram skewed to the left, indicating poor contrast. After applying CLAHE, there was drastic increase in the variation between pixels, and this resulted in a higher IEM of 43.05. A similar observation was made by Arnold bosfor underwater images.85 CNR showed comparatively lower value of 8.94 when evaluated with other techniques indicating better image quality. In order to check the brightness retainment in images.

The integral problems in underwater images were discussed, and existing methods were compared. In order to correct the non-uniform illumination present in the images, box, bilateral and guided filter were evaluated. To improve the contrast, CLAHE was applied on the filtered images. Additionally, to eliminate the noise residuals, Haar and Symlet wavelet de-noising were applied and evaluated. In order to assess the level of contrast improvement, histograms were computed before and after enhancement. ew images used for experimentation. As explained earlier, underwater images suffer from poor contrast and noise. It is necessary to correct such images for further processing. But enhancement on a noisy image resulted in amplifying the noise artifacts.

Hence, contrast enhancement was performed on the images that had a lower estimated noise. The noise estimates (en) of the images as there was relatively less noise on the captured images, to enhance the image, the fuzzy edge amplification method was applied followed by one iteration of de-noising as per eq. (5.10). Here, the approach is adaptive, and hence the de-noising parameters were set as x = 4; = 1 as per eq. (5.7) and (5.9), for retaining more features. To represent the proposed approach more clearly, the method is explained by considering an image with more feature information the original underwater image.

Since, this image has relatively less noise of 2.6, enhancement was applied. The region after contrast enhancement. Further, de-noising was carried out. The level of smoothing is based on the membership function small. The region marked in yellow of the contrast enhanced image. Fig. shows the pixels of the region. In order to perform adaptive smoothing, the mean and standard deviation was computed for every non- overlapping region.

The adaptiveness of the fuzzy de-nosing algorithm was checked by simulating various levels of Gaussian noise on the underwater images. A sample image used for experiment and the noise estimated for each of the images. A similar approach was done for the other underwater images. Here (i) and (ii) shows images with = 0:01 and = 0:03

Gaussian noise.

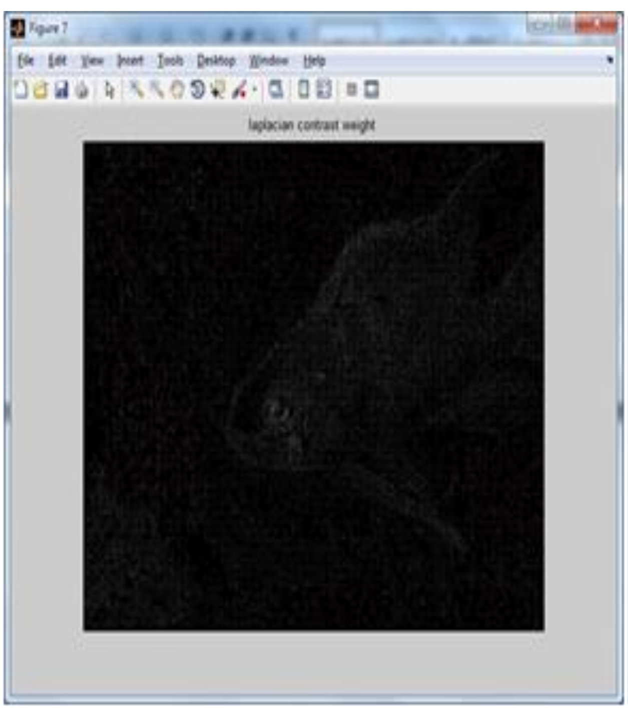
136	146	142	126	107	93	84	78
129	134	128	115	100	89	79	70
114	114	107	97	88	81	73	64
99	95	87	77	75	71	64	55
85	77	71	67	65	61	55	45
77	63	56	57	54	51	45	40
75	64	52	47	46	42	42	45
80	63	49	42	41	40	45	54

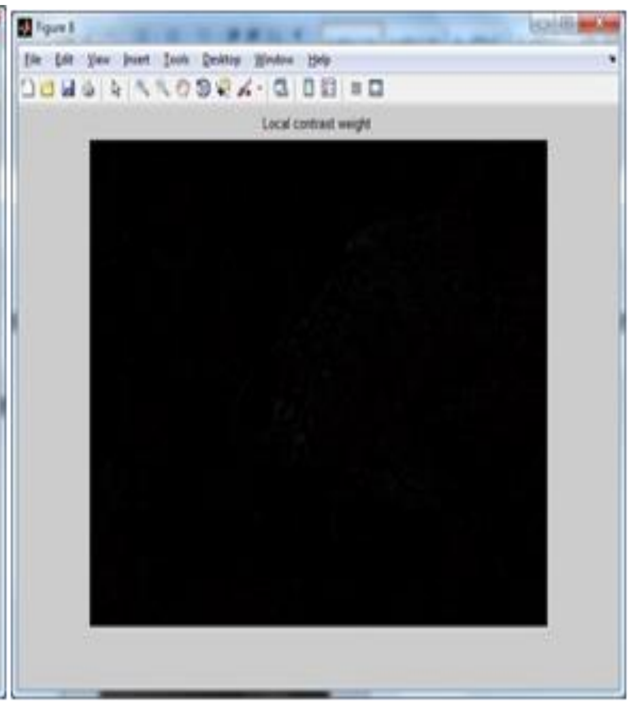
147	158	154	131	113	93	84	77
134	138	131	117	99	87	80	72
118	119	109	93	85	80	77	65
101	95	84	77	77	73	68	56
85	77	68	65	67	62	54	45
77	63	56	54	56	50	45	40
75	62	52	47	45	42	42	45
77	63	49	42	41	40	45	54

Figure 2 De-noising for a pixel block.

Figure 3 Adoptive histogram results

The standard deviation and small (M) values were computed for every 88 region of the entire image and the minimum values obtained for the three colour channels were min [0.49,0.59, 0] and M [0.49,0.59, 0]. As the noise estimate was 2.60 the threshold x was set as 4 and = 1. The estimation of whether a pixel is noise or edge, is explained further. Consider the pixel in 4th row, 4th column with value 77 of Fig. This was identified as noise pixels, due to the following reasons. The fuzzy differential so obtained for the pixel were [8, 16, 32, -10, -12, -9, 0, 7] respectively. Further, the obtained were [0, 0, 0, -19.1, -23.2, -17.1, 1, 0] respectively.





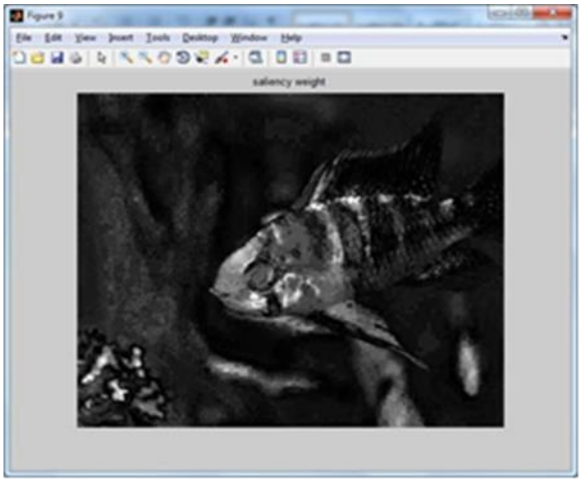


Figure 4 De-noising results of images

Underwater images are captured at various levels of depth under the sea for monitoring of mines, pipelines and underwater species. The challenge in underwater object recognition is visibility, as the images often contain noise due to the flora and fauna floating in water. Even though several algorithms were developed for underwater image de-noising, the feature information and edges present in the image was also removed when removing noise. An effective de-noising method that can classify edge and noise was needed. The level of noise present in the image was also not estimated. This estimation of noise has to be done, as underwater images are captured at various depths and environment conditions. Hence the noise level of each image will vary, and based on the level of noise, the de-noising has to be addressed. Hence an adaptive algorithm was developed based on fuzzy which can distinguish between edge and noise. After performing second iteration of de-noising, the noise estimated was 1.34 showing major amount of noise removed in the image. A similar operation was performed for image with = 0:03 Gaussian noises. The de-noised results for images with Gaussian noise. The edges were also retained after the iterative approach, as the FD method performs smoothing on the noise pixels alone. Apart from that, the FD approach, estimates noise at every iteration and based on the level of noise, it performs adaptive smoothing. This iterative approach was tried with wiener and existing fuzzy filters, they resulted in reduced PSNR as the smoothing operation was done on both edge and noise pixels. From the experimental results, it is found that our FD approach is able to perform both subjectively and visually.

5.CONCLUSION

Ocean is the largest resource that provides the oxygen for survival of the living beings on earth. Even though ocean is rich in terms of its resources it has not been explored to the fullest extent. The use of underwater vehicles is now making the exploration of sea easy and feasible. Underwater vehicles are used for capturing images and videos in benthic environments where light extinct, oxygen is very low and human navigation is impossible. However, such captured images are poor in contrast and huge in volume making manual processing difficult. An intelligent tool which can recognize the objects in such increasing volume of captured images can help in fast automated analysis of aquatic objects used for many applications.

Proposed system an attempt was made using the techniques available for non-uniform illumination correction, contrast enhancement and de-noising of underwater images. For non- uniform illumination correction bilateral filter, anisotropic filter and bilateral filter were compared. For contrast enhancement, CLAHE was used. Wavelet de-noising using Aar and Symlet were compared to remove the noise present in the underwater images. The techniques were compared to identify which best suited underwater images both subjectively and objectively. Noise in underwater images is also a major concern for object recognition. Every image has a different noise level, and traditional techniques require manual change of parameters for every noise level. The level of smoothing also may increase or decreasing each method. Apart from that, the existing techniques perform smoothing on both edge and noise and small features gets destroyed while smoothing using adaptive histogram.

As the image pixels of object and background are often similar in underwater images, texture parameters were extracted for object and background and trained in shallow and deep neural network. Once object was classified from background, morphological parameters were used to resolve 5% of misclassification. Chain coding was used for recognition of objects. The chain code obtained were compared and matched using string matching technique. The chain code which closely matched were labeled as fish and coral. The proposed method resulted in 96% accuracy and was able to perform better than other methods.

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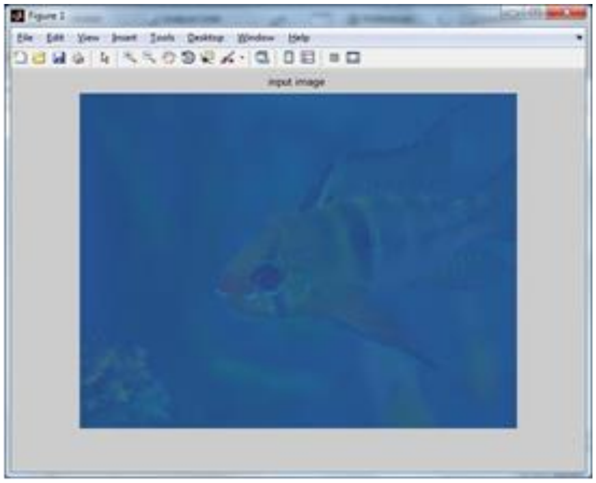
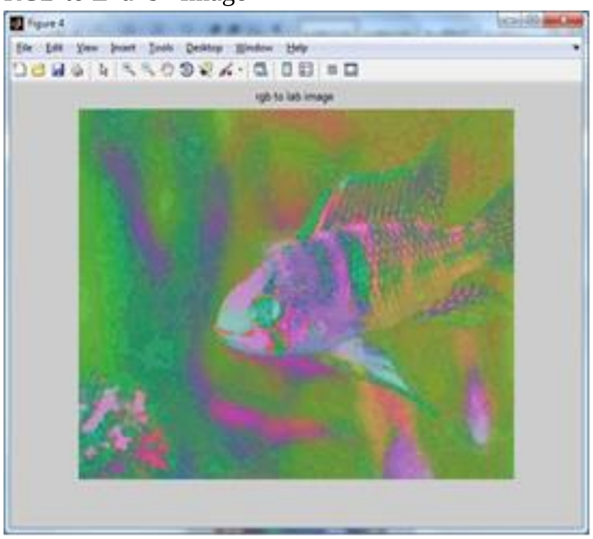
6. SCREEN SHOT

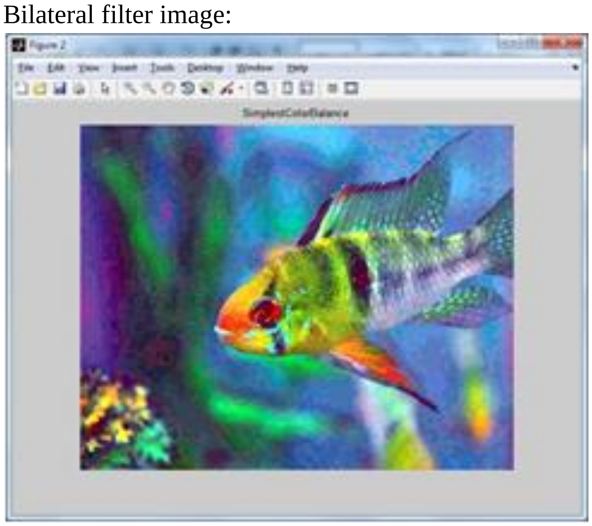
Input image:



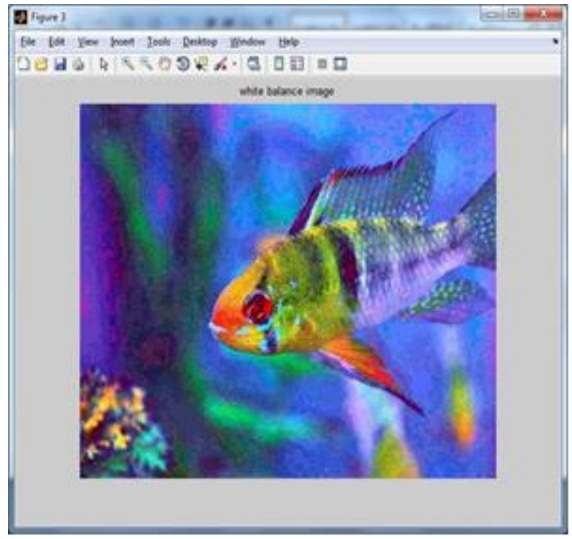
RGB to L*a*b* Image



Bilateral filter image:



White balance filtered image:



Adoptive histogram result:

136	146	142	126	107	93	84	78
129	134	128	115	100	89	79	70
114	114	107	97	88	81	73	64
99	95	87	77	75	71	64	55
85	77	71	67	65	61	55	45
77	63	56	57	54	51	45	40
75	64	52	47	46	42	42	45
80	63	49	42	41	40	45	54

147	158	154	131	113	93	84	77
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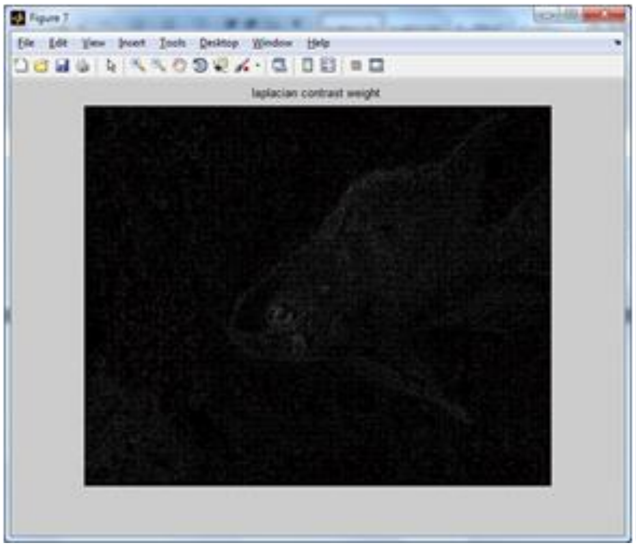
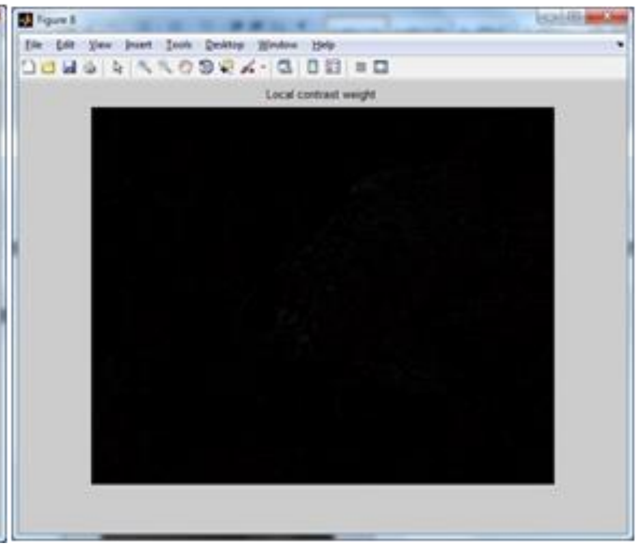
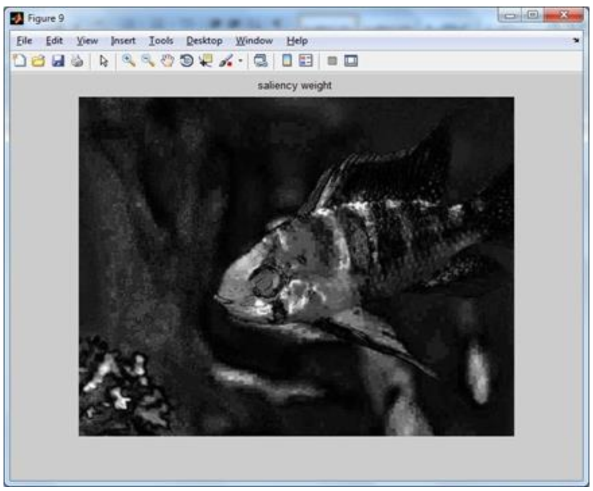
118	119	109	93	85	80	77	65
101	95	84	77	77	73	68	56
85	77	68	65	67	62	54	45
77	63	56	54	56	50	45	40
75	62	52	47	45	42	42	45
77	63	49	42	41	40	45	54

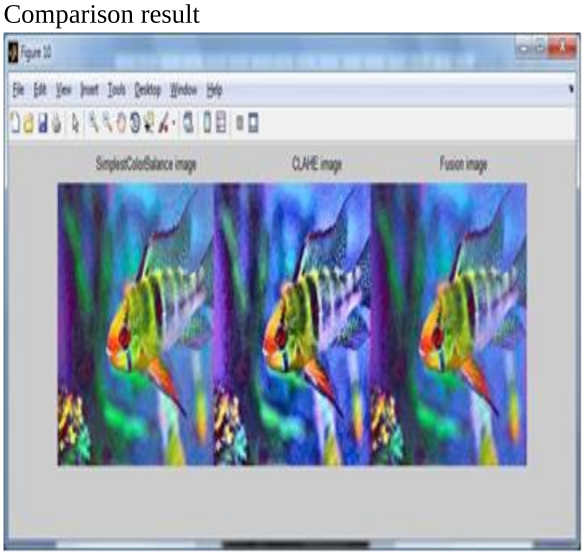
De-noising weighted result results







Comparison result



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