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Fuzzy logic-based automatic contrast enhancement of satellite images of ocean

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Abstract In this paper, we evaluate the conventional contrast enhancement techniques [histogram equalization (HE), adaptive HE] and the recent gray-level grouping method and the fuzzy logic method in order to find out which of these is well suited for automatic contrast enhancement for satellite images of the ocean, obtained from a variety of sensors. All the techniques evaluated were based on the principle of transforming the skewed histogram of the original image into a uniform histogram. The performance of the different contrast enhancement algorithms are evaluated based on the visual quality and the Tenengrad criterion. The inter comparison of different techniques was carried out on a standard low-contrast image and also three different satellite images with different characteristics. Based on our study, we advocate that a modified fuzzy logic method elucidated in this paper is well suited for contrast enhancement of low-contrast satellite images of the ocean.

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1 Introduction

Contrast enhancement which is a fundamental subset of image enhancement seeks to enhance the apparent visual quality of an image as well as the specific image features for further processing and analysis by a computer vision system or for visual perception of human beings. Image contrast is useful for segmentation and identification of objects and features in a scene as edge points can be thought of as pixel locations of abrupt gray level changes. The commonly used techniques for contrast enhancement are (i) spatial domain techniques—involving convolutions with high-pass filter masks, un sharp masking, inverse contrast ratio masking, local adaptive contrast enhancement and histogram transformations; and, (ii) frequency domain techniques involving—filtering through the manipulation of Fourier transforms, Weiner filters, homomorphic filters [1–10]. Although, the techniques of contrast enhancement perform quite well with images having a uniform spatial distribution of gray values, difficulties arise when the object to be recognized and the background assume a broad range of gray tones or when the background has a non-uniform distribution of brightness, as is common in satellite images covering land and ocean. Display systems and satellite images having low contrast with weak edges pose challenges in the fields of computer vision and pattern recognition. Extraction of these weak edges needs an efficient tool, which should also suppress noise. The aim of this study is to compare the recent methods of contrast enhancement and elucidate an automatic method for contrast enhancement of low-contrast satellite images which enables

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improvement of visual quality of image as well as aid in extraction of the spatial features present in the satellite image.

2 Conventional techniques for contrast enhancement in satellite images

Contrast enhancement techniques are widely used in the area of satellite image processing for the enhancement of low-contrast satellite images. A large amount of valuable information can be extracted from the enhanced satellite images for further analysis. The techniques for contrast enhancement include gray-level transformation-based techniques (*viz.,* logarithm transformation, power-law transformation, piecewise-linear transformation, etc.) and histogram processing techniques (*viz.*, histogram equalization (HE), histogram specification, etc. [1]). For gray scale image enhancement, the most popular method is HE, which is based on the assumption that a uniformly distributed gray scale histogram will have the best visual contrast. Some other methods are the variants of HE. The HE techniques like bi-histogram equalization (BHE), block-overlapped HE, multi-scale adaptive HE, shape preserving local histogram modification are also derivatives of conventional techniques [2–10]. Conventionally, the contrast enhancement is manually performed using spatial domain methods, as there is generally a necessity to select specific parameters for enhancement. Therefore, conventional contrast enhancement techniques have an inherent inability for automation and also cannot be applied for broad variety of images, especially satellite images. Moreover, if the images are originally of low contrast—like those pertaining to satellite images, then additional limitations which arise out of employing the conventional contrast enhancement techniques include the washed out effect, inability to preserve edges, amplification of background noise, subjective manual manipulation, non-preservation of brightness and the inability to discern localized intensity changes. Recent studies [11–13] stress on the importance and necessity of having automatic methods for contrast enhancement and suggest that the gray-level grouping (GLG) and fuzzy logic-based methods are better suited for automatic contrast enhancement of images. The real world applications of automated image contrast enhancement techniques are many and encompass varied fields like medical imaging, geophysical prospecting, seismic exploration, astronomy, camera and video processing, aerial and ocean imaging, sensors and instrumentation, optics, and surveillance.

3 Gray-level grouping

Like HE, the basic objective of GLG is to achieve a uniform histogram for an image having discrete histograms, i.e., the histogram components are to be redistributed uniformly over the gray scale. However, unlike the conventional HE, which is likely to leave too much empty space on the gray scale thus resulting in an under or over-contrast image, the main task in GLG technique is to utilize the gray scale in a more controlled and efficient manner and spread the components of histogram by grouping the components into a proper number of gray-level bins according to their amplitudes ensuring a reduction in the number of gray bins, and allowing the redistribution of the histogram components in a set of gray-level bins whose amplitudes are close to each other. This also ensures a quasi-uniform distribution of the histogram components. The histogram components in different segments of the gray scale can be grouped using different criteria, so they can be redistributed differently over the gray scale to meet specific processing purposes, e.g., certain applications may require different parts of the histogram to be enhanced to different extents.

In GLG, the basic procedure is to first group the histogram components of the image into a proper number of bins according to a selected criterion, then redistribute these bins uniformly over the gray scale, and finally ungroup the previously grouped gray-levels. To reduce the time as well as number of iterations, a default value can be used for the total number of gray level groups, e.g., 20, as the dynamic range of human eye in relatively low light condition is about 1 million (approximately 2^{20}) [14].

Therefore, there is no need of constructing the transformation function and calculating the average distance between pixels on the gray scale for each set of gray level bins, thus making the computation faster. Following Chen et al. [12], the algorithm of the Fast GLG technique [12] is described as represented in Fig. 1.

4 Fuzzy-based contrast enhancement techniques

In recent years the fuzzy set theory was applied to develop new techniques for non-linear control systems [15, 16], image noise removal, image contrast improvement, etc. Fuzzy image processing has three main stages: image fuzzification, modification of membership values, and, if necessary, image defuzzification. The coding of image data (fuzzification) and decoding of the results (defuzzification) are steps that make possible to process images with fuzzy techniques.

The main power of fuzzy image processing is in the middle step (modification of membership values). After the image data are transformed from gray-level plane to the membership plane (fuzzification), appropriate fuzzy techniques modify the membership values. This can be a fuzzy clustering, a fuzzy rule-based approach, a fuzzy integration approach and so on. In the commonly used fuzzy rule-based techniques, the histogram is used as the basis for fuzzy modeling of images

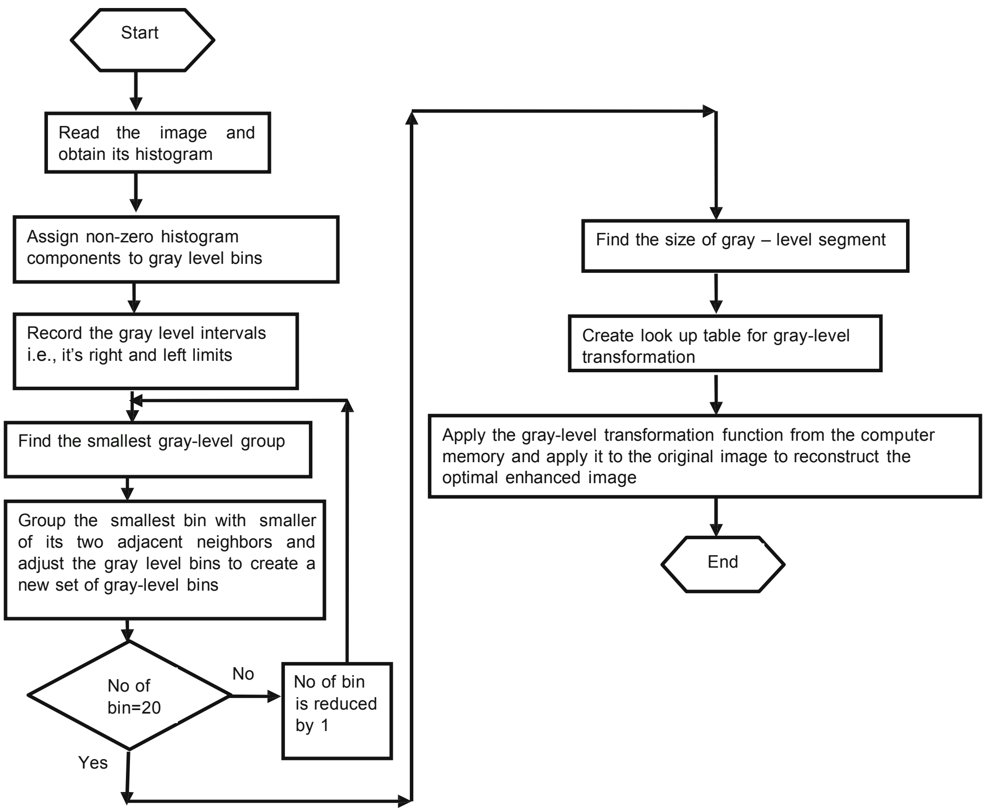

Fig. 1 Flow chart of fast GLG, *after* [12]

and entropy measure is used as the basic criterion for contrast enhancement. Two major contributions in the field of image enhancement using the fuzzy framework have been established in recent years. The first contribution deals with basic fuzzy rules for image enhancement [17–19], where in a set of neighborhood pixels forms the antecedent and the consequent clauses that serve as the fuzzy rule for the pixel to be enhanced. The second contribution relates to a rule-based smoothing [20] in which different filter classes are devised on the basis of compatibility with the neighborhood.

In the fuzzy method [21] gray tone, is modeled into a fuzzy set using a membership function. Here the image is considered as an array of fuzzy singletons having a membership value that denotes the degree of some image property in the range. Applying an intensification operator globally modifies the membership function. Li and Yang [22] have demonstrated an efficient way of contrast enhancement based on the fuzzy relaxation technique with improved speed and quality. Different orders of fuzzy membership functions and different statistics were tried out by various researchers in order to improve the speed and quality of contrast enhancement based on the fuzzy logic method. While Hanmandlu et al. [23] have proposed a new intensification operator, NINT, which is a parametric sigmoid function for the modification of the Gaussian type of membership on the basis of optimization of entropy by a parameter involved in the intensification operator which is suitable for gray level images; Hanmandlu and Jha [13] proposed a Gaussian membership function to fuzzify the image information in spatial domain by introducing a global contrast intensification operator which contains three parameters, t, the intensification parameter, f_{h}, the fuzzifier and μ_{c} the crossover point—for enhancement of color images.

Fuzzy contrast depends on how far the membership functions are stretched by an operator with respect to the crossover point μ_{c}. This turns out to be the cumulative variance of the difference between the membership function and the crossover point over all pixels. The desired appearance of image is controlled by a fuzzy contrast-based quality factor and entropy-based quality factor. Hanmandlu and Jha [13] calculated the global contrast intensification operator parameters t, f_{h}, and μ_{c} globally by minimizing fuzzy entropy of the image information with respect to the quality factors. Accordingly, an image of size $M \times N$ with intensity values in the range (0 to $L-1$) can be considered as a collection of fuzzy singletons in the fuzzy set relation,

$$I = U\{\mu(x_{mn})\} = \{\mu_{mn}/x_{mn}\},$$
$$m = 1, 2, \ldots, M; \quad n = 1, 2, \ldots, N.$$

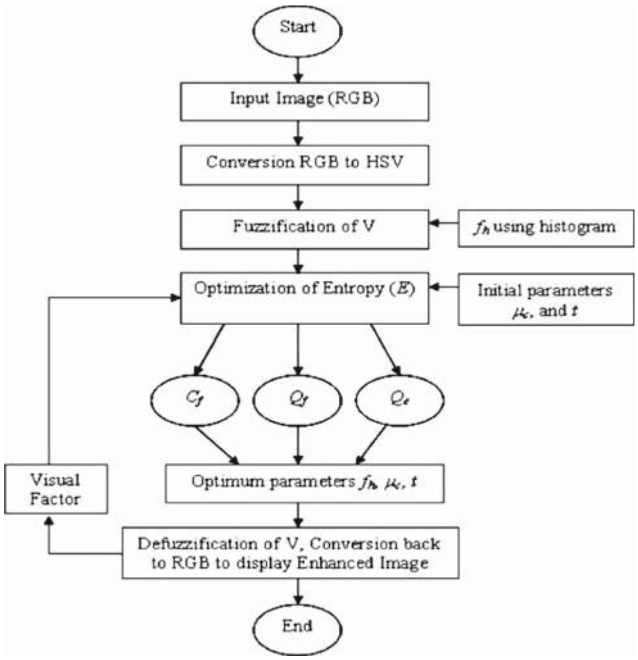

Fig. 2 Flow chart of fuzzy logic method, *after* [13]

where μ_{mn}/x_{mn} represent the membership or grade of some property μ_{mn} of x_{mn}, x_{mn} is the color intensity at the (m, n)th pixel.

The fuzzy logic method proposed by Hanmandlu and Jha [13] for contrast enhancement is presented in Fig. 2.

5 Inter-comparison of histogram-based techniques for contrast enhancement and performance analysis

Given the plethora of algorithms available for contrast enhancement, the impetus for the present study was to identify which is the most suitable algorithm for use with satellite images from a cross section of satellite sensors having varying characteristics. The quality of an image is traditionally measured by objectively computing the sharpness of the image. Statistically sharpness measures were developed based on various categories: gradient-based, variance-based, correlation-based, histogram-based, and frequency domain-based methods [24, 25]. Sharp images usually involve scattered grey levels in a large dynamic range, suggesting a large variance. Elimination of noise and computational complexity of the algorithm are two primary concerns. Gradient-based sharpness measures, especially the Tenengrad measure, are known for their effectiveness and low computations. Moreover, their pixel-based computations facilitate the differentiation between edge and noise pixels. Therefore, in order to evaluate the efficacy of a particular method against existing contrast enhancement techniques, the most well-known benchmark image sharpness measure, the Tenengrad criterion is used to compare the results of contrast enhancement methods. The Tenengrad criterion is based on gradient magnitude maximization, and is considered one of the most robust and functionally accurate image quality measures. The Tenengrad value of an image, I is calculated from the gradient $\nabla I(x, y)$ at each pixel (x, y), where the partial derivatives are obtained by a high-pass filter, e.g., the Sobel operator, with the convolution kernels i_x and i_y. The gradient magnitude is given as

$$S(x, y) = \sqrt{(ix \otimes I(x, y))^2 + (iy \otimes I(x, y))^2}$$

and the Tenengrad criterion is formulated as

$$\mathrm{TEN} = \sum_x \sum_y S(x, y)^2 \quad \text{for } S(x, y) > T$$

where T is a threshold. The image quality is usually considered higher if its Tenengrad value is larger. However, for some images, even though Tenengrad value for HE is larger visual degradation can occur due to enhancement of noise also.

Lakshmanan et al. [26] made an inter-comparison of the various variants of the histogram-based GLG methods and the fuzzy logic method of Hanmandlu and Jha [13] to know whether any one specific algorithm can be used for automatic contrast enhancement of images from a wide variety of sensors and therefore evaluated the results of the analysis on three different images in order to ascertain which of the algorithms are better suited across a variety of images from different sensors and having varying characteristics. Based on the visual quality and the Tenengrad criterion, Lakshmanan et al. [26] concluded that the Fast GLG method may be applied for automatic contrast enhancement across a wide variety of images.

6 The role of crossover value (μ_c) in contrast enhancement

In order to understand the role of μ_c in contrast enhancement using the fuzzy-based technique on low-contrast images, we have considered a standard low-contrast image of 'Mineral' available from the IDL image processing software package (version 6.3). The 'mineral' Image is a low-contrast image with many spatial features which after enhancement can be used for segmentation purposes for determining the various constituents present in the 'mineral' image. The results of contrast enhancement as a function of the μ_c values and the corresponding histograms are presented in Fig. 3. The computed quality measure represented by Tenengrad values as a function of the crossover values (μ_c) are presented in Fig. 4. It becomes evident that the choice of μ_c strongly determines the final outcome of the contrast enhancement with smaller values yielding a washed out or blurred image and higher

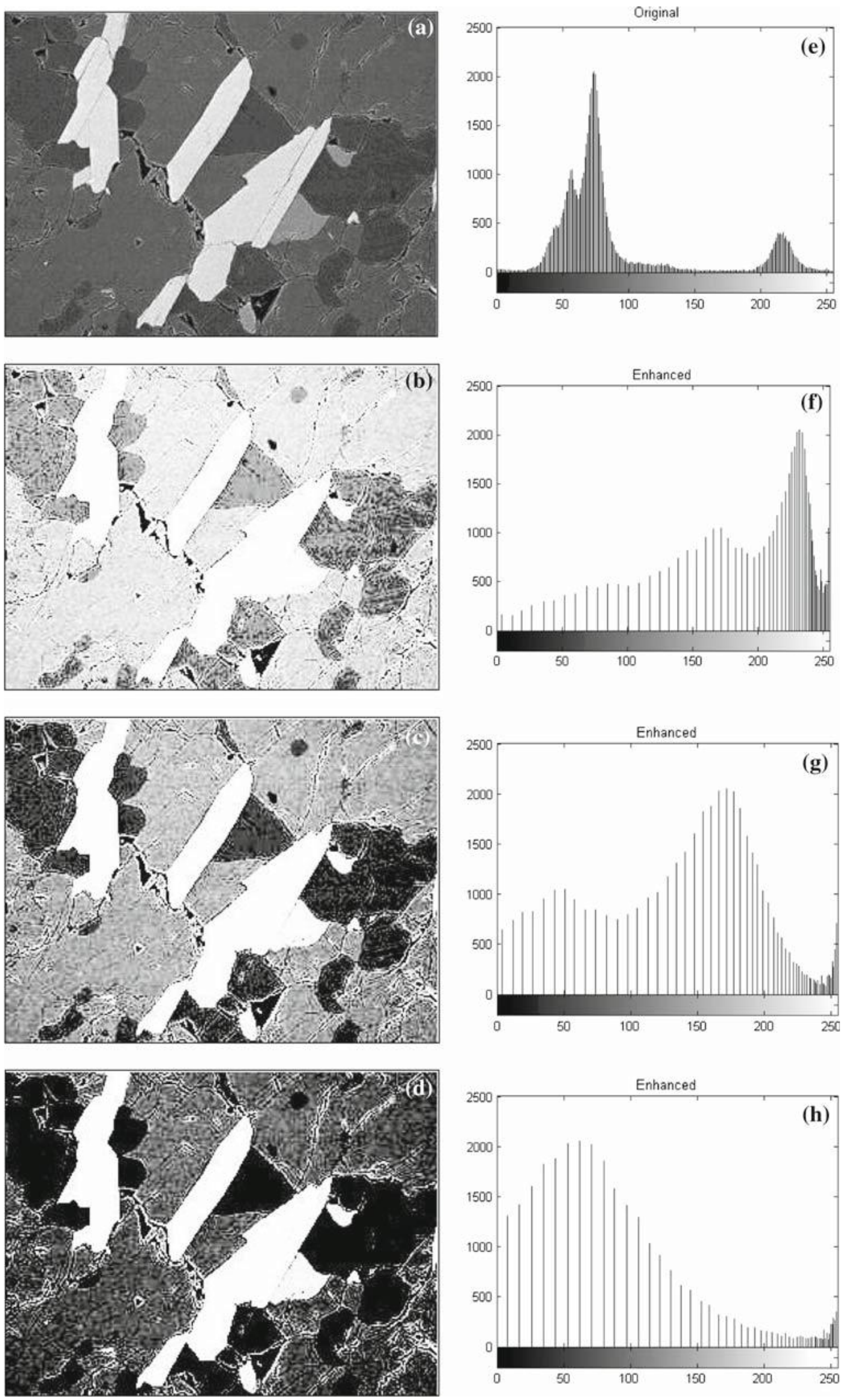

Fig. 3 **a** Plot of the original image. **b–d** The fuzzy logic-based enhanced images of low-contrast 'Mineral' image with crossover point (μ_c) values of 0.3, 0.36, and 0.42, respectively. Subplots **e–g** represent their corresponding histograms, respectively

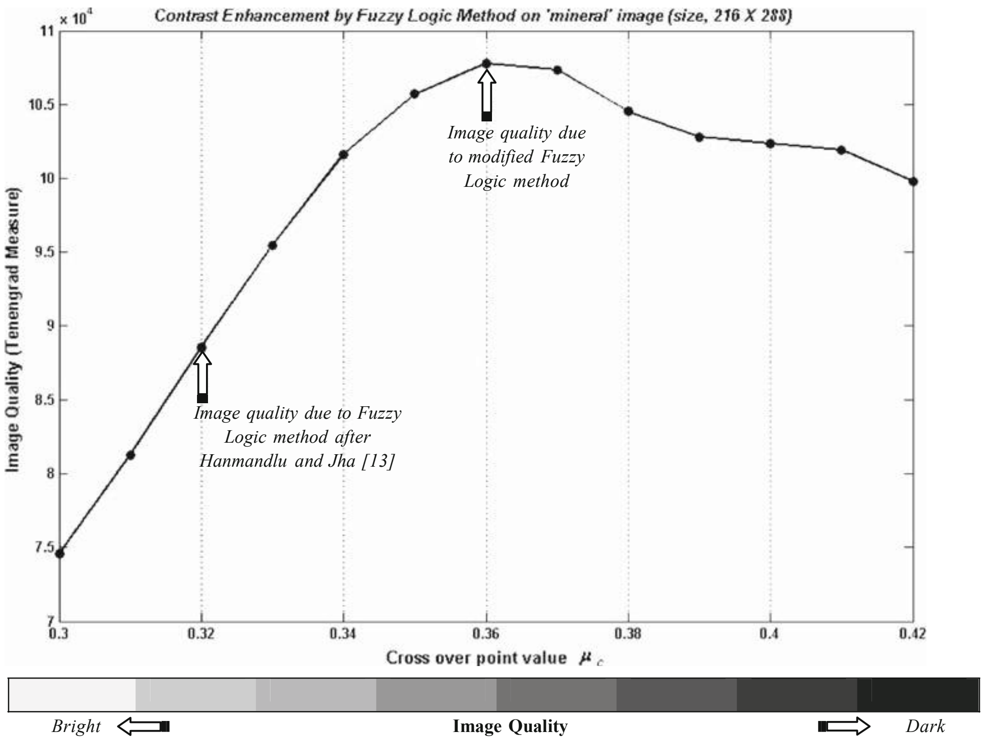

Fig. 4 Plot of the Tenengrad values obtained after applying the fuzzy logic method on a standard low-contrast 'Mineral' image with different crossover point (μ_c) values

values yielding a darker image devoid of many of the important image features (Fig. 4).

The uniformly distributed histogram obtained for the corresponding optimal μ_c value of 0.36 is also consistent with the basic philosophy of histogram-based techniques for contrast enhancement. As can be observed there were no empty regions in the histogram corresponding to the value of 0.36, and also there are fewer extreme peaks and valleys in the histogram of the enhanced image compared to the original image (Fig. 3). We therefore advocate that the optimal μ_c value to be chosen based on the maximum Tenengrad value and then given as input for further processing in the modified fuzzy-based method (shown in Fig. 5) by initially determining the optimal values of t and f_h iteratively, and then selecting the optimal value of μ_c corresponding to the highest Tenengrad measure obtained during the optimization process. In order to arrive at the optimal algorithm for ocean images from satellite sensors, we therefore advocate a modified method for arriving at the membership values in the Fuzzy logic method. The modification is that, unlike the iteratively determined values of t, f_h and μ_c as suggested by Hanmandlu and Jha [13], we determine an optimal μ_c by considering the maximum of the resultant Tenengrad values and utilize the same for improving the image quality.

In this paper, therefore, we suitably modified the algorithm whose details are elucidated below:

1. Choose a starting point $P_i = (t, \mu_c, f_h)_i$ and set $i = 1$.
2. Find the search direction S_i as

$$S_i^T = \begin{cases} (1, 0, 0, 0, 0, \ldots); & i = 1, n+1, 2n+1, \ldots \\ (0, 1, 0, 0, 0, \ldots); & i = 2, n+2, 2n+2, \ldots \\ & \ldots \\ (0, 0, 0, 0, \ldots, 1); & i = n, 2n, 3n, \ldots \end{cases}$$

3. For the current direction S_i, find whether the function value decreases in the positive or negative direction. For this a small probe length, ε, also called learning factor, and evaluate

$$J_i = J(P_i),\ J_i^+ = J(P_i + \varepsilon S_i),\ \text{and}\ J_i^- = J(P_i - \varepsilon S_i).$$

If $J_i^+ < J_i^-$, S_i will be the correct direction for decreasing the value of J_i, and if $J_i^+ > J_i^-$, $-S_i$ will be the correct direction. If both J_i^+ and J_i^- are less than J_i, then the minimum of the two is taken as P_i.
4. Set $P_{i+1} = P_i + \varepsilon S_i(\partial J_i/\partial P_i)$.
5. $J_{i+1} = J(P_{i+1})$.
6. Set $i = i + 1$ and go to step II. Continue this procedure until no significant change is observed in the value of the objective function.

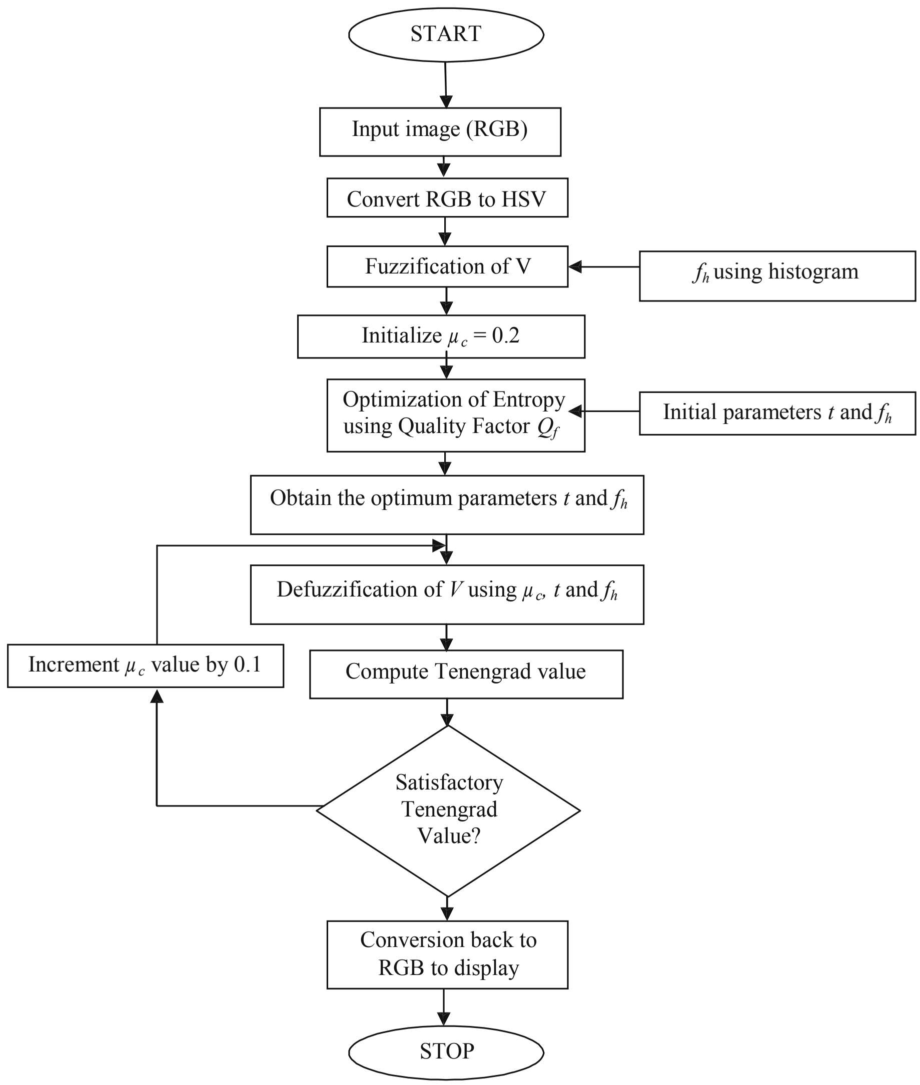

Fig. 5 Flow chart of modified fuzzy logic method as suggested and implemented in this study

Our modified fuzzy logic method for contrast enhancement is elucidated by means of a flow chart in Fig. 5.

7 Results and discussion

The aim in satellite image processing for oceanic applications is to extract important features from an image data, from which a description, interpretation or understanding of the scene can be provided by the machine or by human perception. Automatic enhancement of features in images from satellite sensors is crucial from an operational perspective as voluminous data are required to be processed in the shortest possible time. Among the various features present in an image the gray levels, their joint probability distributions and spatial distributions characterize spatial features of an object. In oceanic images the spatial features are the signatures left by natural changes (like the changing wind pattern) or by some moving platform like ship. A problem of fundamental importance in ocean image analysis is extraction of these signatures efficiently and quickly. The impetus for this study therefore was to evaluate the various histogram-based algorithms available for contrast enhancement in order to arrive at an optimal algorithm which is capable of extracting the spatial features from such low-contrast images. In this paper we applied the various methods for contrast enhancement, i.e., standard HE, adaptive HE, fast GLG method, fuzzy logic method, and the modified fuzzy-based technique on typical low-contrast satellite images of the ocean obtained from different sensors.

As we were interested in inter-comparison of the conventional contrast enhancement techniques with the recent GLG and fuzzy-based techniques on low-contrast images, and as there no standard low-oceanic images available, we initially applied all the techniques on a low-contrast standard gray scale image pertaining to the picture of a 'Mineral' image taken from the image processing package IDL (version 6.3). The original 'mineral' image is shown in Fig. 3a.

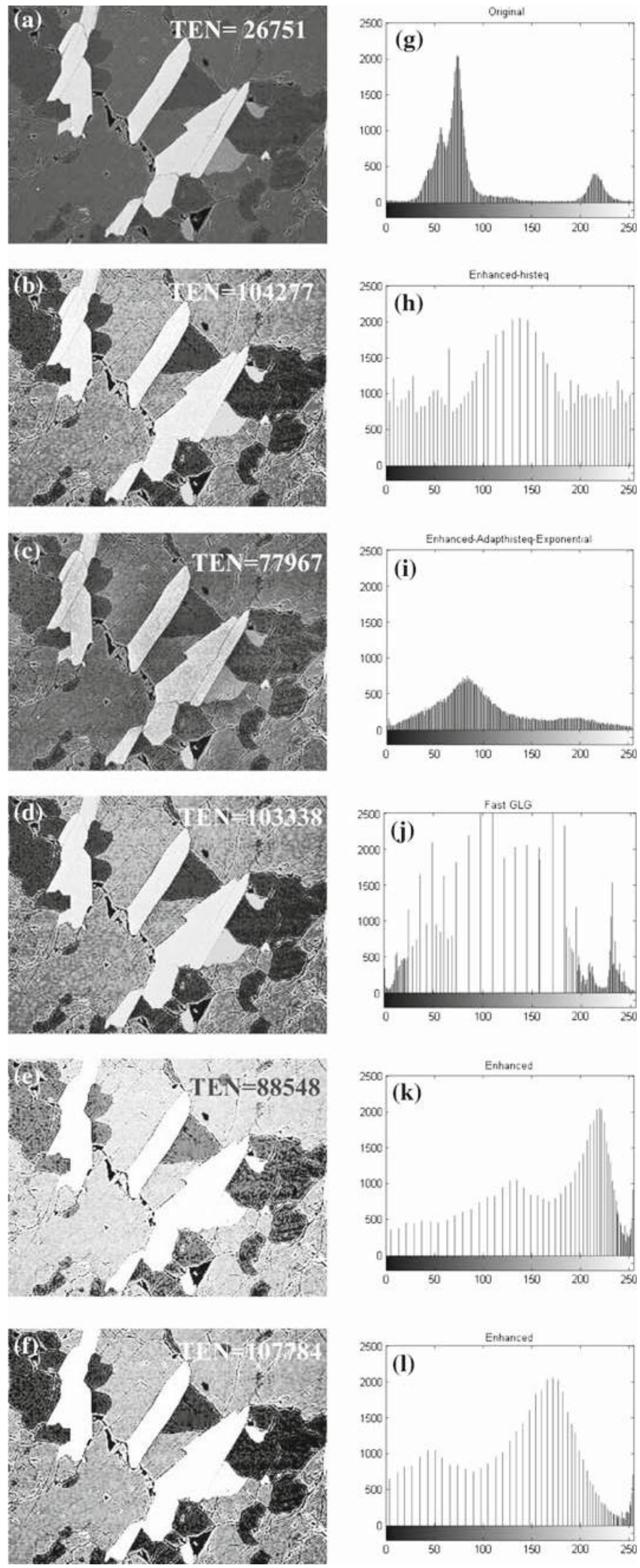

Fig. 6 **a** The original image of size 216 × 288. **b–f** The enhanced images of Mineral Image after applying the histogram equalization, adaptive histogram equalization with exponential distribution, GLG, fuzzy method [13] (with optimal $\mu_c = 0.32$) and the modified fuzzy methods (with optimal $\mu_c = 0.36$), respectively. **g–l** The corresponding histograms, respectively. Tenengrad values are shown in the *top right corner* of each image. As can be seen from the Tenengrad values the visual quality is best for the modified fuzzy-based method with an improvement of 22% as compared to the fuzzy method of [13], and 5% as compared to the FGLG method

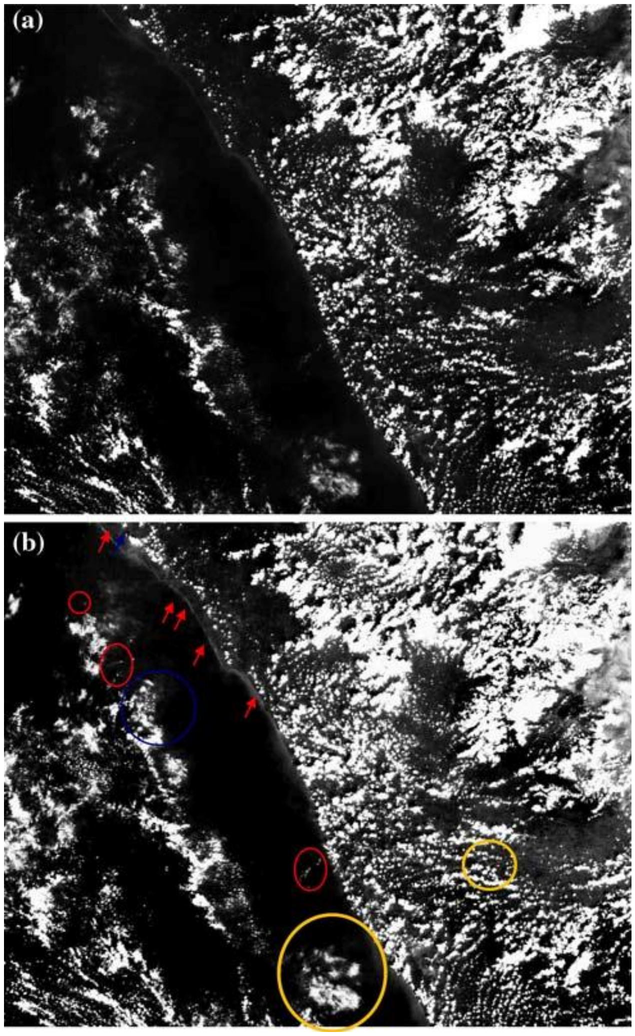

Fig. 7 **a**, **b** The original and fuzzy logic-based ($\mu_c = 0.4$) enhanced images of low-contrast Satellite Image I, respectively. Features that became evident after contrast enhancement are (i) shoreline and beach (represented by *red arrows*), (ii) ships at sea (represented by *red circles*, the second *red circle* from the *left* also shows the wake of the moving ship), (iii) cloud cover over sea (represented by *yellow circle*) and (iv) part of a road (represented by *smaller yellow circle* on the land). The quality of the image (Tenengrad value) improved by 23% with a computation time of approx. 8 s on the original satellite sub-image of size 940 × 1267. The satellite sensor was IRS 1C pan CCD. The image was of the west coast of India

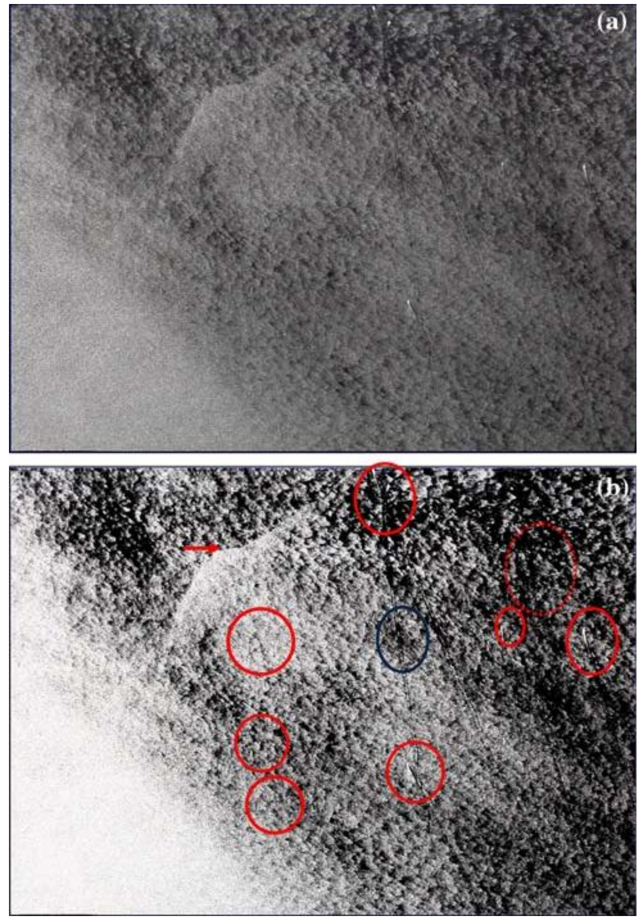

Fig. 8 **a**, **b** The original and fuzzy logic-based (optimal $\mu_c = 0.4$) enhanced images of low-contrast Satellite Image II, respectively. Features that became evident after contrast enhancement are (i) oceanic front (represented by *red arrow*), (ii) ships at sea (represented by *red circles*), (iii) the wake of the moving ship (represented by *blue circle*) and (iv) an almost invisible ship with its wake (represented by *dashed red circle*). The quality of the image (Tenengrad value) improved by 228% with a computation time of approx. 6 s on the original satellite sub-image of size 806 × 1127. The satellite sensor was ERS SAR. The image was of the Gulf of Oman

In addition to visual quality, the criterion employed for performance analysis is the Tenengrad measure. Figure 6 shows the results of contrast enhancement on the original along with their respective histogram distributions and Tenengrad values for the various methods compared. As is apparent from Fig. 6 the visual quality and the Tenengrad quantification results indicate that the modified fuzzy-based technique yields better results for automated contrast enhancement.

Figure 7a shows the original low-contrast sub-image from IRS P4 OCM satellite sensor with a medium resolution. The image pertains to the West Coast of India and is predominantly covered by clouds making visual interpretation very difficult as most of the features remain invisible. This is a typical image due to environmental degradation and is very common for most seasons of the year. The image looks under exposed with low signal to noise ratio (noise assumed here is cloud cover). As such images are most common from optical satellite sensors the utility of extraction of features from such images becomes very important. Figure 7b shows the results of the automatic contrast enhancement using the modified Fuzzy logic method, indicating a visual quality improvement and also an increase in the Tenengrad value by 23%. As explained in the figure many important features in the image can now be discerned enabling more meaningful information extraction.

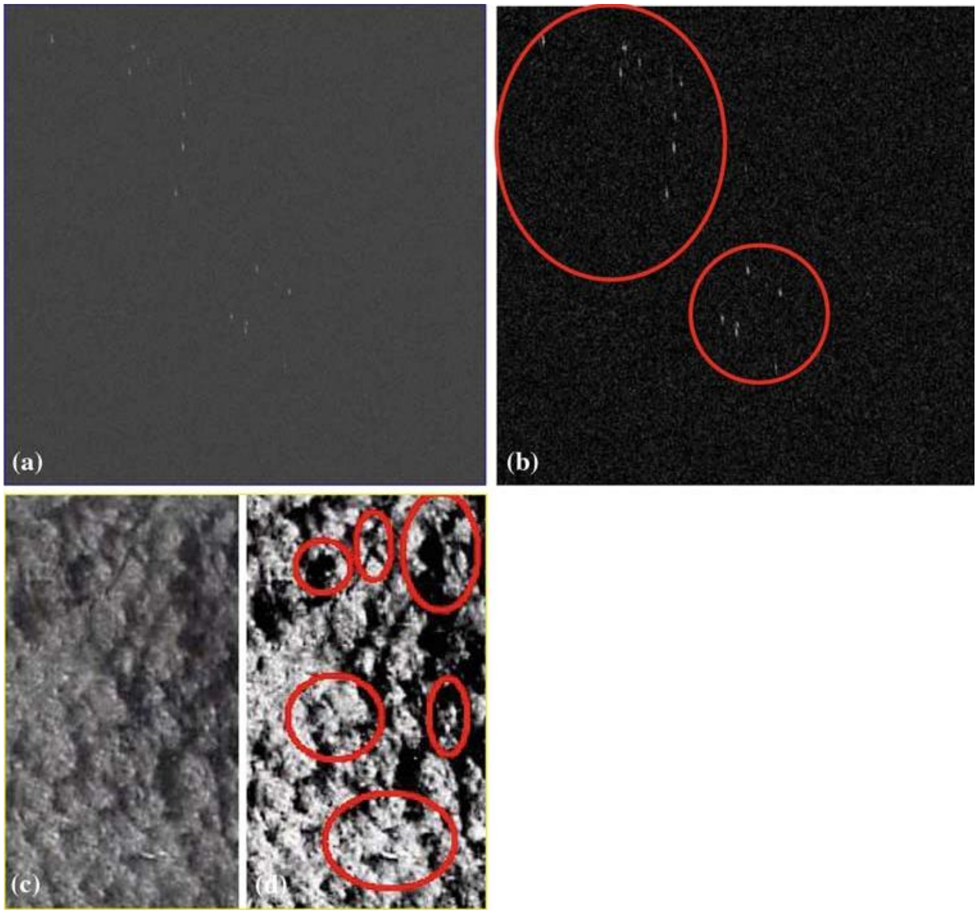

Fig. 9 **a**, **b** The original and fuzzy logic-based (optimal $\mu_c = 0.5$) enhanced images of low-contrast Satellite SAR Image, respectively, during relatively calm sea conditions. Features that became evident after contrast enhancement were the small fishing vessels (ships) circled in red and the quality of the image. (Tenengrad value) improved by 289%. The image was taken over Arabian Sea by a RADRSAT SAR sensor. **c**, **d** The original and fuzzy logic-based (optimal $\mu_c = 0.4$) enhanced images of low-contrast Satellite SAR Image, respectively, during relatively rough sea conditions (i.e., during the presence of strong winds which generate rough sea and high waves). The original image in this case is sub-image of 155 × 272 pixel size, cropped from the *upper right corner* of the image shown in Fig. 8. It is generally believed that rough sea gives rise to worsening specular reflections in a SAR image and therefore greater difficulty in detection of moving targets at sea (ships). However, one can observe that **d**, even when strong sea swell is prevailing the contrast enhanced image in **d** clearly enables one to detect the ships and the ship wakes (*circled* in *red* with ship appearing as a bright reflection and the wake appearing as a *dark line*). The quality of the image (Tenengrad value) improved by 228% with a computation time of approx. 6 s on the original satellite sub-image of size 806 × 1127. The satellite sensor was ERS SAR. The image was taken over the Gulf of Oman

Synthetic aperture radar (SAR) is a coherent imaging sensor, recording both the amplitude and the phase of the back-scattered radiation. Because of this, it suffers from a noise-like phenomenon known as speckle. Each resolution cell of the system contains many scatterers; the phases of the return signals from these scatterers are randomly distributed and speckle is caused by the resulting interference, which gives the images a grainy appearance. This imposes a significant limitation on the accuracy of the measurements that can be made: the brightness of a pixel is determined not only by properties of the scatterers in the resolution cell, but also by the phase relationships between the returns from those scatterers. In single-look images, the uncertainty is equal to the expected value, and the problem is generally overcome to some degree by averaging to produce multi-look images.

Synthetic aperture radar images can also be de-speckled using advanced filtering techniques. Each pixel in a SAR image represents the back-scattered radiation from an area in the imaged scene. A large pixel value (bright) represents a strong received signal. The strength of the received signal depends on many parameters, including the radar wavelength and the relative size of the scatterers, incidence angle and polarization of the radar pulses, topography and water content of the area being imaged, and the direction of the flight path of the SAR sensor. Ship detection by SAR has become a very important endeavor in the past few years and numerous algorithms to assist in identification have been developed. The appearance of ship or ship wakes in radar images depends on various parameters: the shape of the platform, the sea state, the observation geometry and the characteristics of the radar, like the carrier frequency, the polarization, and the observation configuration. Depending on the configuration, one or several of the following features are visible. First, the wake is nearly always characterized by a dark streak behind ships in SAR images. This dark trail originates from the turbulent vortex created by the ship, which reduces the roughness of the sea. The linear features are of primary importance when wake detection is considered, because they allow for the use of line detection algorithms. However, the detection task is complicated by the presence of multiplicative noise (speckle), which is prominent when the sea state is high, since it hides the features to be extracted (i.e., the wake and, or the ship).

Most of the algorithms used begin with the Radon transform, since its properties make it particularly suitable to line detection in speckle noise. The Radon transform is applied to the raw, noisy image, and the features visibility is then optimized by using subsequent processing methods such as Wiener filtering. Other approaches rely on multi-scale analysis, such as the wavelet transforms, which enable in extracting features by assuming that objects such as wakes display a certain correlation between adjacent scales, unlike noise. Another approach may be to use the Hough transform, which is related to the Radon transform in its principle and can be faster to compute, but which is not as robust to noise; and the approach requires de-speckling the image beforehand. SAR is useful in ship detection on development of sophisticated algorithms for image analysis and information that can be extracted from SAR includes location of ships, their speed, heading and sometimes their size class and approximate type.

In recent years, however, in order to preserve the full resolution and extract information regarding smaller areas of interest, SAR speckle in marine single look complex images is investigated by means of a physically consistent model [27], with the belief that marine speckle contains information that can be exploited once an appropriate physical model is established, thus helping in the detection of small dark areas (oil spill) and small dominant scatterers (ships).

Against this background, we wished to see whether a simple contrast enhancement of a SAR or an optical image can result in any incremental improvement of the visual quality (*and in speckle noise reduction*) vis-à-vis the ship (and or wake) detection problem without resorting to any sophisticated algorithms and speckle modeling.

Figure 8a shows the raw sub-image of ERS 1 satellite SAR sensor with a medium spatial resolution. The image is covering the ocean in Gulf of Oman. The raw image is featureless with low contrast and partially noisy especially in the lower left corner of the image, an artifact of the sensing mechanism

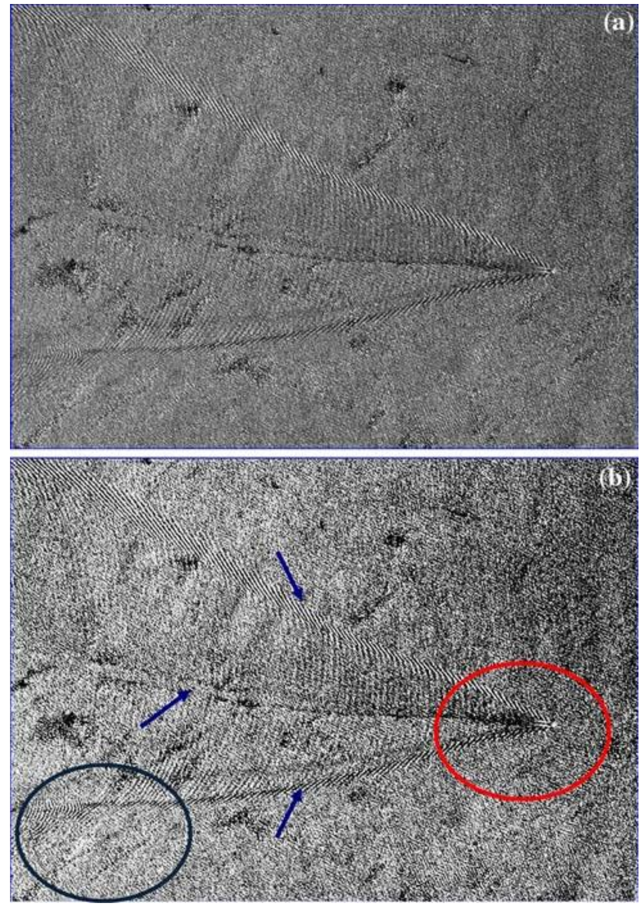

Fig. 10 **a**, **b** The original and fuzzy logic-based *(*$\mu_c = 0.45$*)* enhanced images of low contrast but high-resolution Satellite Image III, respectively. Features that have become more prominent after contrast enhancement are (i) the transverse waves and the turbulent stern wake in the lee side of the moving ship (represented by *blue arrows*, (ii) small ship at sea (represented by *red circles*), (iii) the clear Kelvin wake structure due to the moving ship (represented by *blue circle*) and (iv) an almost invisible ship with its wake (represented by *dashed red circle*) and (iv) the divergent cusp waves (represented by the *blue circle*).The quality of the image (Tenengrad value) improved by 22% with a computation time of 5 s on the original satellite sub-image of size 691 × 978. The satellite sensor was high-resolution IKONOS Pan CCD. The image was of the east coast of India

and the subsequent processing. Figure 8b shows the visually improved image where many features are discernible. The Tenengrad value has also considerably increased by 228%. Again, as explained in the figure many important features in the image can now be discerned enabling more meaningful information extraction.

Figure 9a shows the raw sub-image of Radarsat SAR sensor with a medium spatial resolution. The image is covering the ocean in Arabian Sea. The raw image was featureless with low contrast taken during calm sea conditions. Figure 9b shows the visually improved image where many small fishing vessels (ships) are discernible. The Tenengrad value has also considerably increased by 289%. Figure 9c shows the raw ERS SAR sub-image taken during stormy weather (with more speckle noise) and 9d shows the visually improved image where both ships and their wakes are discernible inspite of the higher speckle noise in the raw image. The Tenengrad value has also considerably increased by 228%.

Figure 10a shows the original sub-image from a high-resolution optical satellite sensor, IKONOS. The image covers the Bay of Bengal region and the quality of the image is good. Figure 10b shows the contrast enhanced image with substantial improvement in visual quality as well as the Tenengrad measure by 22%. As explained in the figure many important features in the image can now be discerned enabling more meaningful information extraction.

Therefore, our study clearly indicates that the modified fuzzy logic method can be used for automatic contrast enhancement of low-contrast satellite images from different sensors to extract meaningful information on features present in the images.

8 Conclusion

An inter comparison of the conventional histogram-based contrast enhancement techniques (like HE, adaptive HE) along with the recent histogram-based GLG method (after [12]), the Fuzzy Logic method (*after* [13]) and the modified fuzzy logic method as suggested in this paper was carried out to ascertain which of these methods is better suited for automatic contrast enhancement of satellite images of the ocean. The different methods were applied on a variety of oceanic images and it is concluded that the modified Fuzzy Logic method as elucidated in this paper has improved the visual quality as well yielded a higher Tenengrad measure of quality.

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References

1. Gonzalez, R.C., Woods, R.E.: Digital Image Processing, 2nd edn. Prentice-Hall, Englewood Cliffs (2002). ISBN: 0-201-18075-8
2. Kim, Y.-T.: Enhancement using brightness preserving bi-histogram equalization. IEEE Trans. Consumer Electron. **43**(1), 1–8 (1997)
3. Wan, Y., Chen, Q., Zhang, B.-M.: Image enhancement based on equal area dualistic sub-image histogram equalization method. IEEE Trans. Consumer Electron. **45**(1), 68–75 (1999)
4. Pizer, S.M., Amburn, E.P., Austin, J.D., Cromartie, R., Geselowitz, A., Greer, T., Romeny, B.H., Zimmerman, J.B., Zuiderveld, K.: Adaptive histogram equalization and its variations. Comput. Vis. Graph. Image Process. **39**, 355–368 (1987)
5. Caselles, V., Lisani, J.-L., Morel, J.-M., Sapiro, G.: Shape preserving local histogram modification. IEEE Trans. Image Process. **8**(2), 220–230 (1999)
6. Chang, D.-C., Wu, W.-R.: Image contrast enhancement based on a histogram transformation of local standard deviation. IEEE Trans. Med. Imaging **17**(4), 518–531 (1998)
7. Chen, S.-D., Ramli, A.R.: Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation. IEEE Trans. Consumer Electron. **49**(4), 1301–1309 (2003)
8. Chen, S.-D., Ramli, A.R.: Minimum mean brightness error bi-histogram equalization in contrast enhancement. IEEE Trans. Consumer Electron. **49**(4), 1310–1319 (2003)
9. Jin, Y., Fayad, L., Laine, A.: Contrast enhancement by multi-scale adaptive histogram equalization. In: Proceedings of the SPIE, vol. 4478, pp. 206–213, 2001
10. Kim, J.-Y., Kim, L.-S., Hwang, S.-H.: An advanced contrast enhancement using partially overlapped sub-block histogram equalization. IEEE Trans. Circuits Syst. Video Technol. **11**(4), 475–484 (2001)
11. Chen, Z., Abidi, B.R., Page, D.L., Abidi, M.A.: Gray-level grouping (GLG): an automatic method for optimized image contrast enhancement—part I: the basic method. IEEE Trans. Image Process. **15**(8), 2290–2302 (2006)
12. Chen, Z., Abidi, B.R., Page, D.L., Abidi, M.A.: Gray-level grouping (GLG): an automatic method for optimized image contrast enhancement—Part II: the variations. IEEE Trans. Image Process. **15**(8), 2302–2314 (2006)
13. Hanmandlu, M., Jha, D.: An optimal fuzzy system for color image enhancement. IEEE Trans. Image Process. **15**(10), 2956–2966 (2006)
14. Blackwell, J.: On human vision. Opt. Soc. Am. **36**, 624–643 (1946)
15. Rajesh, R., Kaimal, M.R.: Variable gain Takagi–Sugeno fuzzy logic controllers. Informatica Int. J. Lith. Acad. Sci. **17**(3), 427–444 (2006)
16. Rajesh, R., Kaimal, M.R.: T-S fuzzy model with nonlinear consequence and PDC controller for a class of nonlinear control systems. Appl. Soft Comput. J. **7**(3), 772–782 (2007)
17. Zadeh, L.A.: Outline of a new approach to the analysis of complex systems and decision processes. IEEE Trans. Syst. Man. Cybern. **SMC-3**(1), 28–44 (1973)
18. Jimmermann, H.J.: Fuzzy Set Theory and its Applications, 2nd edn. Kluwer, Norwell (1991)
19. Russo, M., Ramponi, G.: A fuzzy operator for the enhancement of blurred and noisy images. IEEE Trans. Image Process. **4**(8), 1169–1174 (1995)
20. Choi, Y.S., Krishnapuram, R.: A robust approach to image enhancement based on fuzzy logic. IEEE Trans. Image Process. **6**(6), 808–825 (1997)
21. Pal, S.K., King, R.A.: Image enhancement using smoothing with fuzzy sets. IEEE Trans. Syst. Man. Cybern. **SMC-11**(7), 494–501 (1981)
22. Li, H., Yang, H.S.: Fast and reliable image enhancement using fuzzy relaxation technique. IEEE Trans. Syst. Man. Cybern. **19**(5), 1276–1281 (1989)
23. Hanmandlu, M., Tandon, S.N., Mir, A.H.: A new fuzzy logic based image enhancement. Biomed. Sci. Instrum. **34**, 590–595 (1997)
24. Krotkov, E.P.: Active Computer Vision by Cooperative Focus and Stereo. Springer, New York (1989)
25. Santos, A. et al.: Evaluation of autofocus functions in molecular cytogenetic analysis. J. Microsc. **188**, 264–272 (1997)
26. Lakshmanan, R., Nair, M.S., Wilscy, M., Tatavarti, R.: Automatic contrast enhancement for low contrast images: a comparison of recent histogram based techniques. In: IEEE International Conference on Computer Science and Information Technology, ICCSIT 2008, Singapore, pp. 269–276, August 2008
27. Migliaccio, M., Ferrara, G., Gambardello, A., Nunziata, F., Sorrentino, A.: A physically consistent speckle model for marine SLC SAR images. IEEE J. Ocean. Eng. **32**(4), 839–847 (2007)