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ESTIMATION OF GLOBAL THRESHOLD OF INFRARED IMAGE BY USING FUZZY GRANULE

Ruchika Rani[1], Munish Vashisht[2] and Shamimul Qamar[3]

[1]Department of Electrical & Electronics Engineering
Krishna Institute of Engineering & Technology
Delhi Meerut Road, NH-58, Ghaziabad-201206, India
ruchika.gzb@gmail.com

[2]Department of Electronics Engineering
YMCA University of Science & Technology
NH-2, Mathura Road, Setor-6, Faridabad-121006, Haryana, India
munish276@yahoo.com

[3]Department of Electronics Engineering
Noida Institute of Engineering & Technology
19, Knowledge Park-II, Institutional Area, Greater Noida-201306, India
drsqmar@rediffmail.com

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Abstract. *Image segmentation is used to recognize objects and their background in computer vision. Thresholding, region growing, region splitting, and merging are different segmentation techniques. Global thresholding is the most popular segmentation technique due to its simplicity and speed, but in control environment. Moreover, precise identification of threshold is not possible in highly un-control environment of sea water, because clumps of intensities of background and ship are merged together and there are no sharp distinctions or clear boundary. Hence the detection of abandoned or the illegally trespassed ship is a very difficult task. Whenever, there is no clear boundary between different entities, then it falls in the territory of granule computing. In the seminal line the concept of granule computing is used to extract ship from background. Consequently, the concept of fuzzy quantifiers 'at least half', 'most', 'as many as possible' are used to automate estimation of global thresholding. The experiments are carried out by taking infrared image of ship. The value of global threshold estimated by heuristic approach is 129, whereas 'most', 'at least half', and 'as many as possible' linguistic quantifiers produce values of global thresholding as 131, 115, and 125 respectively. These results are quite comparable with the heuristic approach.*
Keywords: Linguistic quantifier, Fuzzy granule, Global thresholding, Segmentation

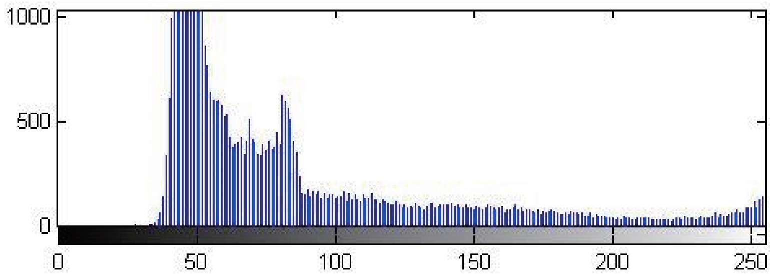
1. **Introduction.** Recognizing objects and their background in real life applications can be managed by segmentation in computer vision. The applications of computer vision range from biometric identification [1] to object recognition [2]. In the seminal line image segmentation is applied in proposed work to detect abandoned ship in sea as a task of computer vision. The problem is rather challenging, since a ship may generate innumerable images with diverse appearances, poses, viewpoints, illumination as well as complicated sea background with flooding waves making it even worse. In the past decades, image semantic segmentation has been usually established by using supervised neural network [3-11]. Techniques based on supervised neural network are not only effort exhaustive but also slow. As a consequence, a promising solution is required to explore segmentation methods with no supervision.

Yuan et al. [6] presented graph-based ranking and segmentation algorithms for traffic sign detection. However, the aforementioned methods are all built on the basis of having sufficient pixel-wise annotated samples for training. As the output of existing automatic systems is far from satisfactory, the vast majority of these annotations are obtained manually, which is labor intensive and time-consuming. Accordingly, the fully supervised networks are typically un-adaptable to general application in reality. On the other side, there are some unsupervised semantic network based segmentation methods that utilize image data without any annotation for training [11]. Instead of the ground truth of each pixel, weakly supervised semantic segmentation approaches [12-14] often required image level annotations for training. Besides, in [13] authors built a model based on convolution neural network with the constraint of putting more weight on the helpful pixels for image classification when training. Among these methods, [14] is an exceptional one since it utilizes object bounding boxes as supervision.

Dai et al. [14] iteratively updated a pool of region proposals and assigned them labels by training convolution networks whereas in [15] inference for a test image is used for the optimal solution. Supervised network is used in [16], and [17] for data representation by using subspace learning, and for large-scale image retrieval. However, their final target is the trained network while our aim is to construct fuzzy granule based method with even less supervision.

Infrared imaging information processing technology has attracted attention and is researched deeply. Thresholding, region growing, region splitting and merging are examples of similarity based segmentation. Global thresholding is the most popular segmentation technique due to its simplicity and speed [18]. One more reason of popularity of thresholding is that it produces a clean segmented image, but in control environment with supervision. In a typical scenario, sea water is highly un-control environment. Hence the detection of abandoned or the illegally trespassed ship is a very difficult task. It is the challenge that attracts the attention of scientists and researchers. Estimation of precise threshold intensity is very critical to segment object of interest from background. One of the simple approaches is heuristically estimating value of global threshold by histogram of image. The histogram of input image is shown in Figure 1(a), along with corresponding input image.

(a) Original image



(b) Histogram of original image

FIGURE 1. Original image with histogram

In proposed work gray levels are ranging from 0 to 255, i.e., black and white. Histogram represents distribution of intensities on horizontal axis whereas vertical axis represents number of pixels that belong to that particular gray level. In the given image targeted ships are brighter as compared to background sea water. Hence the histogram has two clumps of intensities values. The intensities values that lie towards lower side represent background of image. On the other hand intensities values that belong to targeted ship lie towards higher end. When, we looked carefully into Figure 1(b) heuristic threshold intensity lies somewhere 125. However, precise identification of threshold is possible with some supervision, because clumps of intensities of background and ship are merged together and there are no sharp distinctions or clear boundary. In the seminal line the concepts of granule computing and fuzzy quantifiers 'at least half', 'most', 'as many as possible' are used to automate estimation of global thresholding without supervised learning. Furthermore to estimate threshold intensity aggregation process involves sum of product of ordered intensities with weights. These weights are generated by Yager's 'OWA' method [19]. The results generated by the proposed method are quite comparable with the heuristic approach.

Our main contributions are summarized as follows.

1) Histogram of infrared image of ship is used to distinct two clumps of intensities values. The intensities values that lie towards lower side represent background of image.
2) Concepts of granule computing and fuzzy quantifiers are used to automate estimation of global thresholding without supervised learning.
3) We estimate the precise threshold of infrared image by using linguistic quantifiers 'most', 'at least half', and 'as many as possible'.
4) Results produced by 'most', and 'as many as possible' linguistic quantifiers are much closer to visual inspection.

This paper is organized as follows. Section 2, consists of formalization of thresholding, concept of fuzzy granule as well as aggregation. In Section 3, we estimate the threshold of infrared image by using fuzzy linguistic quantifiers 'most', 'at least half', and 'as many as possible', with experimental work results. The final section comprises conclusion.

2. **Proposed Methodology.** Segmentation is one of the image processing methods whose output(s) are attributes extracted from input image(s). Thresholding, region growing, and region splitting and merging are examples of segmentation. Moreover, line detection, boundary detection, and morphological watersheds are also segmentation concepts used in extraction of the image's features. However, 'thresholding' is one of the popular and central concepts among the segmentation methods due to its simplicity and speed. Therefore, in proposed work thresholding based segmentation is done. Further, types of thresholding are global, adaptive, and local. Global thresholding produces minimum segmentation error and is applied frequently in the practical application. Hence, to produce a clean segmented image of targeted ship global thresholding is used.

Global thresholding produces best results in highly control environments, whereas the sea water is highly unstable. Hence there is a requirement of a method that can be specifying threshold 'T'. Consequently, to estimate threshold value concepts of fuzzy granule and linguistic quantifier are used. Subsections 2.1 and 2.2 explained global thresholding and fuzzy quantifier respectively. Moreover Subsection 2.2.5 discussed about proposed algorithm.

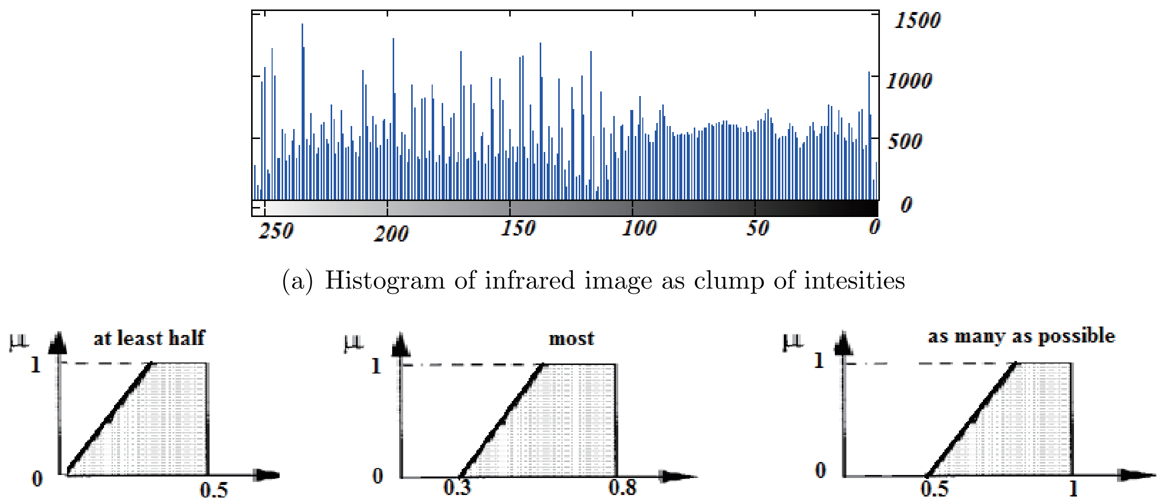
2.1. **Global thresholding.** This thresholding segments the image by using single global threshold 'T'. Suppose that gray level in an image $f(x, y)$, composed of lights objects on a dark background, in such a way that object and background pixels have gray levels grouped into two dominant modes [18]. The objective is to select a threshold 'T' that split up these modes. Then any spatial coordinate (x, y) for which $f(x, y) > T$ is related to object otherwise it is background. A threshold image $g(x, y)$ is defined as,

$$g(x,y) = \begin{cases} L & \text{if} \quad f(x,y) > T \\ 0 & \text{if} \quad f(x,y) \le T \end{cases} \tag{1}$$

When T depends only on $f(x, y)$ the threshold is called global.

2.2. **Fuzzy linguistic quantifier.** Global thresholding is expected to apply in highly control environment to produce promising results. However, to identify targeted ship the image that is to be segmented prevails in un-control environment of sea water. Sometimes, ship submerged in sea water of flooding waves. Hence, the precise estimation of thresholding is not an easier task. To automate precise estimation of threshold concepts of granule computing and linguistic quantifiers are used. A granule is "a clump of similar intensities", which are put together by similarity criteria. Fuzzy quantifiers are applied to estimating global threshold precisely. So that ship and background water can be segmented by using threshold.

Granualization of intensities are shown in Figure 2(a), and these intensities are mapped into a clump of single object as shown in Figure 2(b). To estimate global threshold 'T', all the intensities are orderly multiplied with weights and then sum. These weights are generated by Yager's aggregation operator as discussed in next subsection.



(a) Histogram of infrared image as clump of intesities

(b) Fuzzy membership function of at least half, most, and as many as possible linguistic quantifiers

FIGURE 2. Membership function of fuzzy quantifier

2.2.1. *Aggregation operator.* Yager stated that, "Mapping the aggregation operator R, from $R_m \to R$, (where $R = [0, 1]$), with dimension m, has 'weight vector' $w = (w_1, w_2, w_3, \ldots, w_m)^T$, where $w_j \in [0, 1]$ and $\sum w_j = 1$, the summation of individual weights will always be found to be one. Thus, for the multi-criteria of size m, the input parameter (x_1, x_2, x_3, $\ldots$, x_m), the operator determines the threshold 'T' as follows". The aggregation operator involves subsequent stages.

2.2.2. *Rearrangement of inputs.* Input $x_1, x_2, x_3, \ldots, x_m$ are rearranged in decreasing order $y_1, y_2, y_3, \ldots, y_m$. Here y_i is the ith largest input.

2.2.3. *Estimation of "weight".* The appropriate mathematical function of degree of OR-ness and relative quantifiers are given by Equations (2) and (3) respectively.

$$\beta = \frac{1}{m-1} \sum_{j=1}^{m} w_j (m-1) \tag{2}$$

Here β is degree of OR-ness.

$$Q(r) = \begin{cases} 0 & \text{if } r < a \\ \dfrac{r-a}{b-a} & \text{if } a \leq r \leq b \\ 1 & \text{if } r > b \end{cases} \tag{3}$$

where $a, b, r \in [0, 1]$. Weights w_j are calculated by aggregation from the function Q based on fuzzy quantifier, where 'm' is number of criteria.

$$w_j = Q\left(\frac{j}{m}\right) - Q\left(\frac{j-1}{m}\right) \tag{4}$$

where $j = 1, 2, \ldots, m$ and $Q(0) = 0$.

2.2.4. *Aggregation.* OWA determines the thresholding by using (5), where $(x_1, x_2, x_3, \ldots, x_m)$ is input parameter with the multi-criteria of size 'm'.

$$OWA(x_1, x_2, x_3, \ldots, x_m) = \sum w_j * y_i \tag{5}$$

2.2.5. *Proposed algorithm.* Proposed method is based on algorithm given below.

Proposed Algorithm

START

STEP 1: Read infrared image.

STEP 2: Store all distinct gray levels.

STEP 3: Estimation of threshold 'T'.

(a) Arrange all gray levels in a decreasing order.

(b) Estimate weights by using linguistic quantifiers by using Equations (2) and (3).

(c) Aggregate product of these weights with corresponding gray level inputs by using Equation (4).

STEP 4: Segment the image on the basis of estimated threshold by pixel by pixel analysis of gray level.

(a) If $f(x, y) > T$

(b) Then $g(x, y) = f(x, y)$

(c) Else $f(x, y) == 0$

END

On the basis of proposed methodology experiments are carried out and results along with experimental work are discussed in next section.

3. **Experiments and Main Results.** The experimental work is carried out by taking infrared image of ship as input which is shown in Figure 1. Initially threshold is specified by using heuristic approach based on visual inspection, i.e., 125.

Figures 3 to 5 show results after applying '*at least half*', '*most*', and '*as many as possible*' linguistic quantifiers to estimate threshold respectively.

The value of threshold 'T' estimated by 'at least half' linguistic quantifier is 115 whereas, 'most' and 'as many as possible' linguistic quantifiers produce 131 and 125 respectively. Values of 'T' produced by 'most', and 'as many as possible' linguistic quantifiers are much closer to visual inspection, i.e., 129.

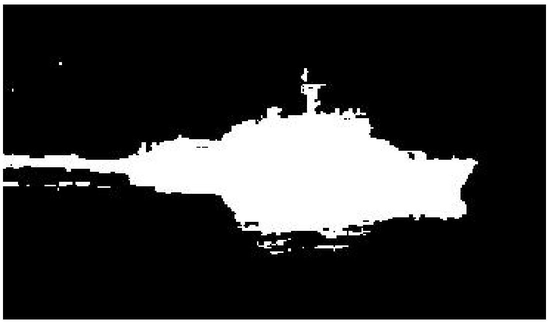


FIGURE 3. Output of 'at least half' linguistic quantifier

FIGURE 4. Output of 'most' linguistic quantifier

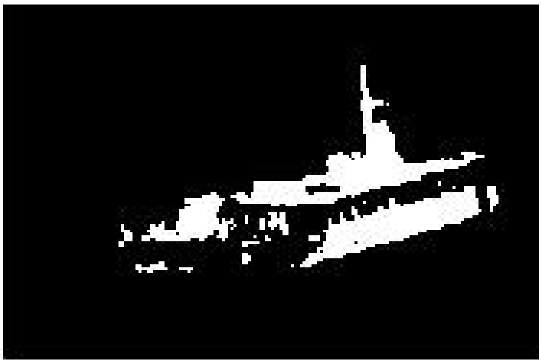


FIGURE 5. Output of 'as many as possible' linguistic quantifier

FIGURE 6. Output of invert image 'as many as possible' linguistic quantifier

In Figure 6 invert image of Figure 5 is shown. The key objective is merely to generate a binary image: black and white relationship could be reverse and targeted ship with dark intensity can be easily detectable in white background.

4. **Conclusions.** In this paper, we have estimated global thresholding to identify the location of ship in sea water. Infrared image is taken as input due to its high heat signature. Threshold value of heuristic approach based on visual inspection is 129. The

value of global threshold produced by 'at least half' linguistic quantifier is 115 whereas 'most' and 'as many as possible' linguistic quantifiers produce 131 and 125 respectively. Results produced by 'most', and 'as many as possible' linguistic quantifiers are much closer to visual inspection. Proposed work is for static positions of ship. In future same methodology can be used for moving ship and it is accepted to produce good results.

REFERENCES

[1] J. Lei, X. You and M. Abdel-Mottaleb, Automatic ear landmark localization, segmentation and pose classification in range images, *IEEE Trans. Systems, Man and Cybernetics: System*, vol.46, no.2, pp.165-176, 2016.

[2] B. Hariharan, P. Arbeláez, R. Girshick and J. Malik, Hyper columns for object segmentation and fine-grained localization, *Proc. of IEEE Conference on Computer Vision & Pattern Recognition*, Boston, MA, USA, pp.447-456, 2015.

[3] W. Zhang, S. Zeng, D. Wang and X. Xue, Weakly supervised semantic segmentation for social images, *Proc. of IEEE Conference on Computer Vision & Pattern Recognition*, Boston, MA, USA, pp.2718-2726, 2015.

[4] N. Pourian, S. Karthikeyan and B. S. Manjunath, Weakly supervised graph based semantic segmentation by learning communities of image parts, *Proc. of IEEE International Conference on Computer Vision*, Santiago, Chile, pp.1359-1367, 2015.

[5] D. Pei, Z. Li, R. Ji and F. Sun, Efficient semantic image segmentation with multi-class ranking prior, *Computer Vision and Image Understand*, vol.120, pp.81-90, 2014.

[6] X. Yuan, J. Guo, X. Hao and H. Chen, Traffic sign detection via graph based ranking and segmentation algorithms, *IEEE Trans. Systems, Man and Cybernetics: System*, vol.45, no.12, pp.1509-1521, 2015.

[7] J. Long, E. Shelhamer and T. Darrell, Fully convolution networks for semantic segmentation, *Proc. of IEEE Conference on Computer Vision & Pattern Recognition*, Boston, MA, USA, pp.3431-3440, 2015.

[8] Y. Li, Y. Guo, J. Guo, M. Li and X. Kong, CRF with locality consistent dictionary learning for semantic segmentation, *Proc. of the 3rd IAPR Asian Conference on Pattern Recognition*, Kuala Lumpur, Malaysia, pp.509-513, 2015.

[9] J. Wang and A. L. Yuille, Semantic part segmentation using compositional model combining shape and appearance, *Proc. of IEEE Conference on Computer Vision & Pattern Recognition*, Boston, MA, USA, pp.1788-1797, 2015.

[10] S. Zheng et al., Conditional random fields as recurrent neural networks, *Proc. of IEEE International Conference on Computer Vision*, Santiago, Chile, pp.1529-1537, 2015.

[11] F. Wang, Q. Huang, M. Ovsjanikov and L. J. Guibas, Unsupervised multi-class joint image segmentation, *Proc. of IEEE Conference on Computer Vision & Pattern Recognition*, Columbus, OH, USA, pp.3142-3149, 2014.

[12] L. Zhang et al., A probabilistic associative model for segmenting weakly supervised images, *IEEE Trans. Image Processing*, vol.23, no.9, pp.4150-4159, 2014.

[13] P. O. Pinheiro and R. Collobert, From image-level to pixel-level labeling with convolution networks, *Proc. of IEEE Conference on Computer Vision & Pattern Recognition*, Boston, MA, USA, pp.1713-1721, 2015.

[14] J. Dai, K. He and J. Sun, BoxSup: Exploiting bounding boxes to supervise convolution networks for semantic segmentation, *Proc. of IEEE International Conference on Computer Vision*, Santiago, Chile, pp.1635-1643, 2015.

[15] Z. Li, J. Liu, J. Tang and H. Lu, Robust structured subspace learning for data representation, *IEEE Trans. Pattern Analysis and Machine Intelligent*, vol.37, no.10, pp.2085-2098, 2015.

[16] L. Bazzani, A. Bergamo, D. Anguelov and L. Torresani, Self-taught object localization with deep networks, *Proc. of IEEE Winter Conference on Applications of Computer Vision (WACV)*, 2016.

[17] J. Tang, Z. Li, M. Wang and R. Zhao, Neighborhood discriminate hashing for large-scale image retrieval, *IEEE Trans. Image Processing*, vol.24, no.9, pp.2827-2840, 2015.

[18] R. C. Gonzalez and R. E. Wood, *Digital Image Processing*, Prentice Hall Publication, 2nd Edition, 2002.

[19] R. R. Yager, On OWA aggregation operators in multi-criteria decision making, *IEEE Trans. Systems, Man and Cybernetics: System*, vol.18, pp.183-190, 1988.