sciendo
ISSN 1335-8871

MEASUREMENT SCIENCE REVIEW

Journal homepage: https://content.sciendo.com

Advanced Computer Vision Techniques for Accurate Measurement in Unmanned Mobile Robots

Bharathi V[1*], Natraj N A[2], Gopinath S[3], Kiruthikaa R[4]

[1]*Kongunadu College of Engineering and Technology, Thottiyam, India,* bharathikncet @gmail.com
[2]*Symbiosis Institute of Digital and Telecom Management, Symbiosis International (Deemed University), Lavale, Pune, India,* natraj@sidtm.edu.in
[3]*Karpagam Institute of Technology, Coimbatore, India,* gopi.vasudev@gmail.com
[4]*Department of Electronics and Communication Engineering, KGISL Institute of Technology, Coimbatore, India,* kiruthikaar27@gmail.com

Abstract: For years, researchers have been studying computer vision, i.e. the ability of artificial intelligence (AI) systems to perceive and interpret visual data like humans. This study is gaining increasing attention as researchers aim to develop tools that automate visual tasks and replicate human visual awareness. However, the interpretation of images is very complex due to the vast amount of multi-resolution information they contain, making the development of AI technologies for visual recognition particularly challenging. This article provides an overview of digital image processing, highlighting the main concepts and introducing key algorithms. These methods are designed to capture, process, and interpret digital images and enable the extraction of important data from real-world environments. We conduct rigorous image processing tests and compare AI-driven recognition systems with human analysis. The results show that computer vision technology significantly outperforms human observation in terms of accuracy and consistency. These results highlight the potential of computer vision to revolutionize various industries by automating complex visual tasks and offer promising future applications in areas such as healthcare, security, and manufacturing. The paper provides valuable insights into current advances in digital image processing and the role of AI in improving visual recognition capabilities, paving the way for further innovation in this area.

Keywords: Computer vision, digital image processing, image recognition, data extraction, artificial intelligence.

1. Introduction

Image processing is used in a variety of applications. It is more dominant in medical image analysis to detect the disease-affected parts. Several algorithms can be used to obtain accurate results via image processing. Multilevel image thresholding finds its application in image segmentation. Certain bee colony algorithms and particle swarm optimization (PSO) algorithms have been analyzed The Friedman rank system was used to rank the analyzed methods based on their performance and the results obtained concluded that IABC/best/1 produces the best results among the methods considered [1]. Fuzzy clustering algorithms can be used to analyze color. Gustafson-Kessel possibilistic fuzzy is a hybrid algorithm that can be used to relate the probabilistic models of prototypes [2]. Ojeda-Magaña et al. have worked with Berkley's glass digital images and database. The results of the proposed algorithm were also analyzed on the minimized regions, which are homogenous.

The image information can be protected from hackers by using the least significant bit method. In this method, the k bits are able to hide the message. The least significant bit substitution can be constructed using a matrix. Shu-Fen Tu and Ching-Sheng Hsu have proposed an improvement for the existing method [3]. Instead of substituting the least significant values, the authors used a fitness function to hide the image. This fitness function is based on human visual system (HVS). It was found that the imperceptibility of the images was improved by the proposed algorithm. Image processing plays a vital role in the medical field. With the help of image processing algorithms, the images can be easily analyzed and accurate results can be obtained. If the image contains too much information, it becomes difficult for the doctors to recognize the disease [4], [5].

2. Literature review

Segmentation in medical computed tomography (CT) images can be done by combining genetic algorithms and large law algorithms. The proposed algorithm can be considered as an immune genetic algorithm. It was found that the efficiency of the image was improved by the proposed algorithm [6]. The existing algorithm achieved a working accuracy of about 75 %, while the proposed algorithm was able to achieve a working accuracy of about 92 %. The accuracy of the immune genetic algorithm was 97 %. It has

DOI: 10.2478/msr-2024-0025

*Correspondingauthor: bharathikncet@gmail.com (Bharathi V)

been shown that the improved genetic algorithm (IGA) algorithm provides better efficiency and accuracy. Image segmentation plays a vital role in image processing. When the threshold value is high, image segmentation faces challenges such as high processing time and lower quality to develop the Cuckoo search algorithm. This algorithm can optimize the size of the steps, provides the optimal solution, and has lower complexity [7]. The fitness function is used to solve the issues related to entropy threshold. Previous researchers have proposed a method to detect the presence of pepper noise in the image. This was done with the help of median filter algorithms. Two median filter algorithms were used for this purpose [8].

The unwanted information was first removed by extracting the center and boundary pixels. The biological image was analyzed in three-dimensional space, and a coordinate system was used to evaluate the pixels of the image. The symmetry, reversing ability, density, and other parameters were determined using appropriate methods [9]. Finally, the image was clustered using the density peak clustering method. After clustering, the image pixels are uniformly distributed over the three-dimensional space. An accuracy of 90 % was achieved with the proposed method. Artificial intelligence (AI) has helped information technology to grow at a faster rate. Its algorithms have been used in recent years to solve problems associated with engineering. AI algorithms take less time to compute large problems due to their stochastic characteristics [10].

The literature review shows the advances in AI-driven algorithms for image segmentation, especially for medical CT images. It highlights the improved accuracy and efficiency of immune genetic algorithms and the Cuckoo search algorithm. Furthermore, AI techniques are not only used in medical imaging, but also in student performance assessment and optimization tasks, demonstrating their broad applicability.

3. Proposed method

The thresholding of the image is used to represent the image in its simplest form. The resulting image is called a segmented image, and the process is called segmentation. In the global thresholding algorithm, the same threshold value is used for the entire image. It is dependent on the histogram values of the image.

Input: Captured image

Output: Binary image after segmentation

Procedure: The first value of the threshold (T) is considered as the average value of all pixels.

The image is divided into smaller parts based on the value of T.

Calculate the value of T again.

$$T_1 = \frac{(mean_1 + mean_2)}{2} \tag{1}$$

Global thresholding can be performed in two ways. It can be performed either by changing the histogram values or by calculating the threshold values. The method of changing the histogram values is sensitive to noise, whereas the method of calculating the threshold values provides better results and is immune to noise.

In the traditional thresholding algorithm, the threshold value is the same for all pixels. The adaptive thresholding algorithm is an improved version of the traditional thresholding algorithm.

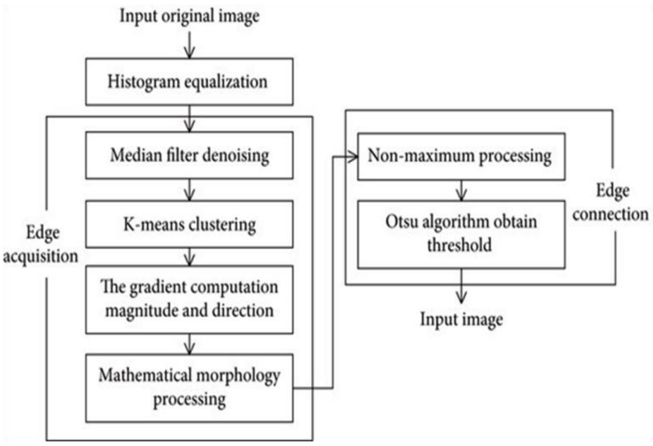

Fig. 1. Flow diagram of an adaptive thresholding algorithm.

Here, different thresholding values are calculated for smaller groups of data. Therefore, the threshold value will be different for different regions. The flow diagram of adaptive thresholding is shown in Fig. 1. The algorithmic steps used in adaptive thresholding are described in the following steps.

Input: Captured image and size of the window

Output: Binary image after segmentation

Procedure: Segment the image using the mean filter or the median filter using the size of the window.

Calculate the threshold value for each smaller segmented part.

Each pixel is analyzed using the threshold value.

The foreground and background are determined based on the threshold value.

K-Means clustering

In the K-means clustering algorithm, the calculation of the centroid takes place until an optimized centroid value is determined. This depends on the number of clusters. In the K-means clustering algorithm, K denotes the number of clusters [11]-[13]. The data points are assigned to the cluster groups in such a way that the square of the distance between the data points and the centroid is as small as possible. As the initial step, the number of cluster centers is determined. Then the starting cluster center is determined at random. The objects are placed near the center of the cluster. The cluster head is then calculated again. The cluster head is selected based on the minimum distance. Finally, the objects are moved into the clusters. The final output is obtained.

In the fuzzy c-means clustering algorithm, the clusters are formed using the pixels present in the image. Each pixel belongs to one of the many cluster groups. The clusters are based on membership functions. The point that is close to the cluster has a high membership value and the point that is away from the cluster has a lower membership value [14].

Image segmentation is a technique in which pixels with similar parameters are combined into a group. The main objective of the expectation-maximization algorithm is to trace the missing data by using the data present in an image. The initial values of the data are determined after capturing the incomplete image. The missing values are guessed using the existing data. This is done in the expectation phase. In the maximization phase, the entire data is generated and the parametric update takes place. The expectation and maximization stages are carried out until complete convergence occurs [15].

This algorithm is used to determine the values within the merging regions. It is used for grouping the pixels that fall under similar parameters. In the image processing application, similarly colored pixels are combined into fewer pixel groups using this statistical region merging algorithm.

4. Results and discussion

The comparative analysis of the different experimental results obtained with different techniques is discussed in this section. The parameters considered for the analysis are sensitivity, accuracy, border error, specificity, Hammoude distance, Hausdorff distance, mean square, peak signal-to-noise ratio (PSNR), and elapsed time.

Table 1. Comparison of sensitivity, accuracy, and border error of various techniques.

S.No	Technique	Sensitivity [%]	Accuracy [%]	Border error [%]
1.	Global thresholding	91.08	96.14	21.26
2.	Adaptive thresholding	46.15	78.53	81.58
3.	K-means clustering	83.15	91.58	27.89
4.	Fuzzy C-means	90.12	96.63	14.61
5.	Expectation maximization	92.16	96.49	16.89
6.	Statistical region merging	84.87	94.58	17.58
7.	Active contour model	91.26	81.64	63.67
8.	Spectral clustering	91.53	95.28	12.91

Table 1 compares the sensitivity, accuracy, and border error of the different techniques. It can be seen that the expectation-maximization algorithm has the highest sensitivity, which is 92.16 %. The adaptive thresholding algorithm has a lower sensitivity of 46.15 %.

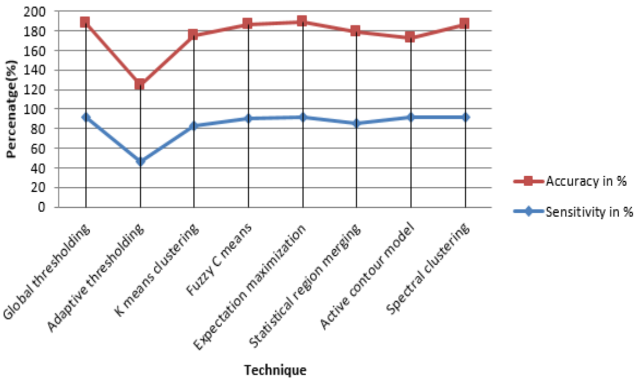

Fig. 2. Graphical representation of accuracy and sensitivity of various techniques.

The accuracy of global thresholding, adaptive thresholding, and k-means clustering is 96.14 %, 78.53 %, and 91.58 %, respectively. The accuracy of the fuzzy c-means algorithm, the expectation maximization algorithm, and the statistical region merging algorithm is 96.63 %, 96.49 %, and 94.58 %, respectively. The accuracy of the active contour model and the spectral clustering model is 81.64 % and 95.28 %, respectively.

Fig. 2 shows the graphical representation of the accuracy and sensitivity of the different techniques. The border error of global thresholding, adaptive thresholding, and k-means clustering is 21.26 %, 81.58 %, and 27.89 %, respectively. The accuracy of the fuzzy c-means algorithm, the expectation maximization algorithm, and the statistical region merging algorithm is 14.61 %, 16.89 %, and 17.58 %, respectively. The accuracy of the active contour model and the spectral clustering model is 63.67 % and 12.91 %, respectively.

Table 2. Comparison of specificity, Hammoude distance, and Hausdorff distance.

S.No	Technique	Specificity [%]	Hammoude distance [%]	Hausdorff distance [%]
1.	Global thresholding	95.48	7.35	4.23
2.	Adaptive thresholding	94.36	38.42	8.64
3.	K-means clustering	92.57	17.84	5.57
4.	Fuzzy C-means	98.93	6.64	4.84
5.	Expectation maximization	96.87	7.72	4.69
6.	Statistical region merging	98.64	7.27	5.25
7.	Active contour model	99.35	29.54	6.67
8.	Spectral clustering	98.27	6.68	4.82

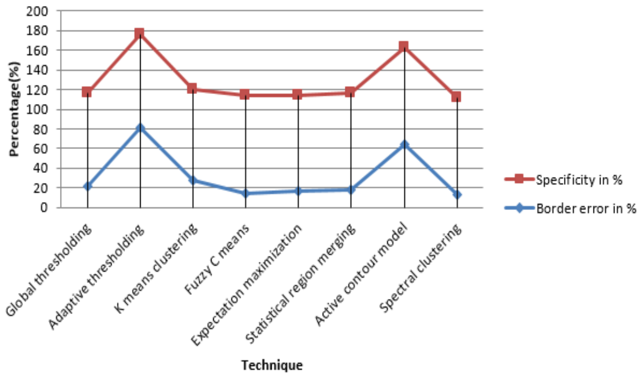

Fig. 3. Graphical representation of specificity and border error in percentage.

Table 2 compares the specificity, the Hammoude distance, and the Hausdorff distance, and Fig. 3 shows the graphical representation of the specificity and the border error in percent. The active contour model has a specificity value of 99.35 %, which is the highest among all other algorithms. The specificity of the K-means clustering is 92.57 %, which is the lowest among the other algorithms. The specificity of the other methods, namely global thresholding, adaptive thresholding, and the fuzzy C-means algorithm, is 95.48 %, 94.36 %, and 98.93 %, respectively. The specificity of the expectation maximization model, the statistical region merging model, and the spectral clustering method is 96.87 %, 98.64 %, and 98.27 %, respectively.

Table 3. Comparative analysis of mean square error, PSNR, and elapsed time.

S.No	Technique	Mean square error [%]	PSNR [%]	Time elapsed [sec]
1.	Global thresholding	0.04	63.08	1.14
2.	Adaptive thresholding	0.24	55.23	0.10
3.	K-means clustering	0.08	60.54	0.21
4.	Fuzzy C-means	0.03	63.87	0.21
5.	Expectation maximization	0.03	63.51	1.86
6.	Statistical region merging	0.04	62.53	0.76
7.	Active contour model	0.17	56.42	0.34
8.	Spectral clustering	0.03	64.05	22.72

Table 3 shows the comparative analysis of mean square error, PSNR, and elapsed time. The Hausdorff distance of global thresholding, adaptive thresholding, and the k-means clustering is 4.23 %, 8.64 %, and 5.57 %, respectively. The Hausdorff distance of the fuzzy c-means algorithm, the expectation maximization algorithm, and the statistical region merging algorithm is 4.84 %, 4.69 %, and 5.25 %, respectively. The Hausdorff distance values of the active contour model and the spectral clustering model are 6.67 % and 4.82 %, respectively.

Fig. 4 shows the graphical representation of the mean square error of the different methods. The mean square error of global thresholding, adaptive thresholding, and the k-means clustering is 0.04 %, 0.24 %, and 0.08 %, respectively.

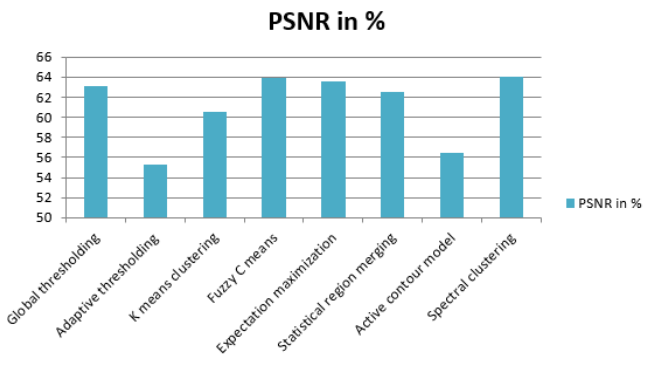

Fig. 4. Graphical representation of PSNR in percent.

The mean square error of the fuzzy c-means algorithm and the expectation-maximization algorithm is 0.03 % for both techniques. The statistical region merging algorithm has a mean square error of 0.04 %. Similarly, the Hausdorff distance values of the active contour model and the spectral clustering model are 0.17 % and 0.03 %, respectively. Fig. 5 shows the graphical representation of the elapsed time of the different methods.

The PSNR of global thresholding, adaptive thresholding, and the k-means clustering is 63.08%, 0.24 %, and 55.23 %, respectively. The mean square error of the fuzzy c-means algorithm and the expectation-maximization algorithm is 60.54 % and 63.87 %, respectively. The statistical region merging algorithm has a mean square error of 62.53 %. Similarly, the Hausdorff distance values of the active contour model and the spectral clustering model are 56.42 % and 64.05 %, respectively.

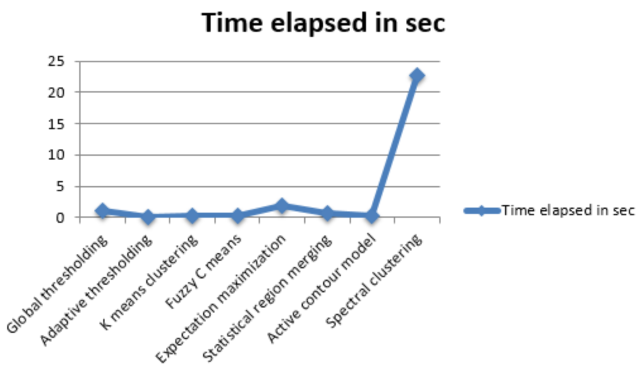

Fig. 5. Graphical representation of elapsed time in seconds.

5. CONCLUSION

There are many different contexts in which image processing can be helpful. In the segmentation stage of image processing, the region of interest in the image is separated from the rest of the image by using various parameters. There are numerous algorithms to choose from, and each is dependent on the attributes used for segmentation. This article gives an overview of the various algorithms used in image processing, including global thresholding, adaptive thresholding, K-means clustering, fuzzy logic, maximization expectation, statistical region merging, adaptive contour method, and spectral clustering algorithm. The results obtained with these algorithms were compared and analyzed.

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Received May 09, 2024
Accepted September 04, 2024