🌐United International Journal of Engineering and Sciences🌐
(UIJES – A Peer-Reviewed Journal); ISSN:2582-5887 | Impact Factor:8.075(SJIF)
Volume 5 | Special Issue 1 | 2025 Edition
National Level Conference on "Advanced Trends in Engineering Science & Technology" – Organized by RKCE

Image Quality Enhancement Using Adaptive Techniques of Digital Filters

Dr. Manjunath B E, PhD[1]
Assistant Professor[1], [234]UG scholar
B.ASHOK REDDY[2], G.CH.S.S.V.MURTHY[3], A.V.KOTI REDDY[4], K. TEJA REDDY[5]
Department of Electronics Communication Engineering
R KCollege of Engineering
Vijayawada, India

Abstract – Image enhancement technology is a commonly used way in digital image processing, which can improve image quality, highlight the useful information in the image according to people's actual needs, and suppress the redundant information of the image. Image enhancement technology greatly improves the visual information of people observing images. However, image enhancement technology is also affected by viewing conditions, imaging mode and working tasks, so appropriate methods should be selected appropriately. This paper introduces several commonly used image enhancement algorithms, with emphasis on spatial domain processing. The process of image enhancement is a contradictory one. Image enhancement not only wants to reduce noise interference, but also wants to enhance edge information. However, enhancing the edge information also means increasing the noise, and reducing the noise also makes the edge information blurred. Therefore, when performing image enhancement, it is necessary to make a compromise between these two parts and choose a suitable method to achieve the purpose of enhancement.

I.INTRODUCTION

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too.There are two types of methods used for image processing namely, analog and digital image processing. Analog image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital image processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of data have to undergo while using digital technique are pre-processing, enhancement, and display, information extraction. Since digital image processing has very wide applications and almost all of the technical fields are impacted by DIP, we will just discuss some of the major applications of DIP. Digital Image processing is not just limited to adjust the spatial resolution of the everyday images captured by the camera. It is not just limited to increase the brightness of the photo, etc. Rather it is far more than that. Electromagnetic waves can be thought of as stream of particles, where each particle is moving with the speed of light. Each particle contains a bundle of energy. This bundle of energy is called a photon. The electromagnetic spectrum according to the energy of photon is shown below. In this electromagnetic spectrum, we are only able to see the visible spectrum.

Morphological processing deals with tools for extracting image components that are useful in the representation and description of shape. Segmentation procedures partition an image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing. A rugged segmentation procedure brings the process a long way toward successful solution of imaging problems that require objects to be identified individually. On the other hand, weak or erratic segmentation algorithms almost always guarantee eventual failure.

Representation and description almost always follow the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region (i.e., the set of pixels separating one image region from another) or all the points in the region itself. In either case, converting the data to a form suitable for computer processing is necessary. The first decision that must be made is whether the data should be represented as a boundary or as a complete region. Boundary representation is appropriate when the focus is on external shape characteristics, such as corners and inflections. Regional representation is appropriate when the focus is on internal properties, such as texture or skeletal shape. In some applications, these representations complement each other. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing. A method must also be specified for describing the data so that features of interest are highlighted. Description, also called feature selection, deals with extracting attributes that result in some quantitative information of interest or are basic for differentiating one class of objects from another. Recognition is the process that assigns a label (e.g., "vehicle") to an object based on its descriptors. We conclude our coverage of digital image processing with the development of methods for recognition of individual objects.

II. LITERATURE SURVEY

2.1 Topic: "Manual segmentation"

It involves delineation of the boundaries of tumor manually and representing region of anatomic structures with various labels Manual segmentation requires software tools for the ease of drawing regions of interest (ROI), is a tedious and exhausting task.MRI scanners produce multiple 2-D slices and the human expert has to mark tumor regions carefully, otherwise it will generate jaggy images that lead to poor segmentation results.

2.2 Topic: "Semi-automatic segmentation"

In semi-automatic brain tumor segmentation, human interaction is least as possible. The semiautomatic or interactive brain tumor segmentation components consist of computational part, interactive part and the user interface. Since it involves both computer and human's expertise, result depends on both the combination. Efficient segmentation of brain tumor is possible through this strategy but it is also subjected to variations between expert users and within same user.

2.3 Topic: "Fully automatic segmentation"

In this method, there is no intervention of human and segmentation of tumor is determined with the help of computer. It involves the human intelligence and is developed with soft computing techniques, which is a difficult task. Brain tumor segmentation has various properties which reduce the advantage of humans over machines. These methods are likely to be used for large batch of images in research environment. However; these methods have not gained popularity for clinical practice, due to lack of transparency and interpretability.

2.4 Unsupervised segmentation

If for training input vectors, target output is unknown, training method adopted is unsupervised learning. In the previous years, various unsupervised learning methods such as K-means and fuzzy clustering has gained popularity for brain tumor segmentation. The main aim of this type of segmentation is to segment the image into areas that have similar intensity and has well defined anatomic properties. Unsupervised segmentation of brain tumor achieve its anatomic goal by segmenting the image into atleast two anatomically regions, one is tumor and other is edema. The advantage of this type is that it can handle very difficult tasks such as brain tumor segmentation. It produces an accurate segmentation of different regions present in heterogeneous tumor. Disadvantages of this segmentation are: number of regions is to be known before, tumors may not be specified clearly. This disadvantage can be avoided using skull stripping. Skull stripping is a pre-processing step to wipe out non cerebral tissue such as fat, muscle, skin, skull which are not desired region of interest

2.5 Supervised segmentation

In supervised learning, the network is provided with series of sample inputs and output is compared with expected response. It involves both training phase that uses labelled data that maps features to labels and testing phase is used to map labels to unlabeled data. The advantage of this type is that training set can be changed; it can reduce the manual task by providing labelled data. Irrespective of its advantages, it suffers from disadvantages that it requires patient specific training for brain tumor supervised segmentation and also human variability is also a concern.

2.6 Topic: "Image segmentation via adaptive k-mean clustering and knowledge-based morphological operations"

Image segmentation remains one of the major challenges in image analysis. In medical applications, skilled operators are usually employed to extract the desired regions that may be anatomically separate but statistically indistinguishable. Such manual processing is subject to operator errors and biases, is extremely time consuming, and has poor reproducibility. We propose a robust algorithm for the segmentation of three-dimensional (3-d) image data based on a novel combination of adaptive k-mean clustering and knowledge-based morphological operations. The proposed adaptive k-mean clustering algorithm is capable of segmenting the regions of smoothly varying intensity distributions. Spatial constraints are incorporated in the clustering algorithm through the modeling of the regions by gibbs random fields. Knowledge-based morphological operations are then applied to the segmented regions to identify the desired regions according to the a priori anatomical knowledge of the region-of-interest. This proposed technique has been successfully applied to a sequence of cardiac ct volumetric images to generate the volumes of left ventricle chambers at 16 consecutive temporal frames. Our final segmentation results compare favorably with the results obtained using manual outlining. Extensions of this approach to other applications can be readily made when a priori knowledge of a given object is available.

2.7 Topic: "Medical image segmentation using k-means clustering and improved watershed algorithm"

The use of the conventional watershed algorithm for medical image analysis is widespread because of its advantages, such as always being able to produce a complete division of the image. However, its drawbacks include over-segmentation and sensitivity to false edges. We address the drawbacks of the conventional watershed algorithm when it is applied to medical images by using k-means clustering to produce a primary segmentation of the image before we apply our improved watershed segmentation algorithm to it. The k-means clustering is an unsupervised learning algorithm, while the improved watershed segmentation algorithm makes use of automated thresholding on the gradient magnitude map and post-segmentation merging on the initial partitions to reduce the number of false edges and over-segmentation. By comparing the number of partitions in the segmentation maps of 50 images, we showed that our proposed methodology produced segmentation maps which have 92% fewer partitions than the segmentation maps produced by the conventional watershed algorithm.

2.8 Topic: "A fast parallel using clustering algorithm for large spatial databases"

The clustering algorithm DBSCAN relies on a density-based notion of clusters and is designed to discover clusters of arbitrary shape as well as to distinguish noise. In this paper, we present PDBSCAN, a parallel version of this algorithm. We use the 'shared-nothing' architecture with multiple computers interconnected through a network. A fundamental component of a shared-nothing system is its distributed data structure. We introduce the dR*-tree, a distributed spatial index structure in which the data is spread among multiple computers and the indexes of the data are replicated on every computer. We implemented our method using a number of workstations connected via Ethernet (10 M bit).

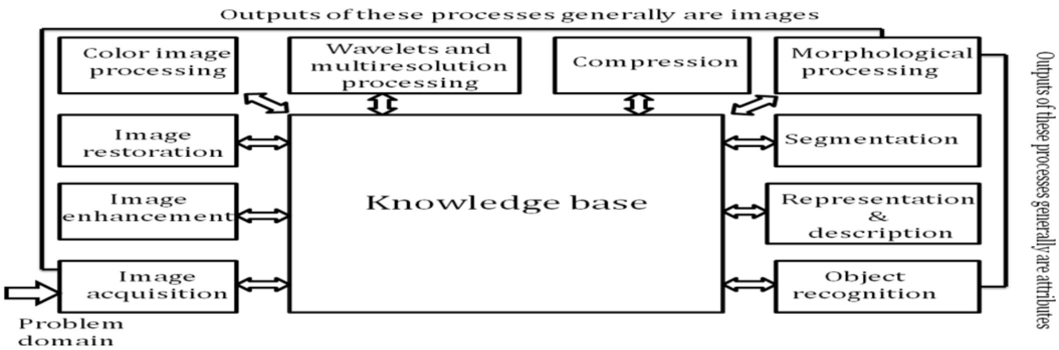


Fig2.5: Fundamental steps in Digital Image Processing

Wavelets are the foundation for representing images in various degrees of resolution. Compression, as the name implies, deals with techniques for reducing the storage required to save an image, or the bandwidth required to transmit it. Although storage technology has improved significantly over the past decade, the same cannot be said for transmission capacity. This is true particularly in uses of the Internet, which are characterized by significant pictorial content. Image compression is familiar (perhaps inadvertently) to most users of computers in the form of image file extensions, such as the jpg file extension used in the JPEG (Joint Photographic Experts Group) image compression standard.

III. EXISTING METHOD

3.1 Image segmentation

Image segmentation is one of the most important steps in image partitioning and their analyses. It can be used for various applications in computer vision and digital image processing. Many of the applications require highly accurate and computationally faster image processing algorithms. The success of any application depends on reliability and accuracy of the image processing used. In this chapter, we have studied, reviewed and analysed important threshold and region based image segmentation techniques and their variations.

Image acquisition digitizes the image captured by camera. Image enhancement is the process of manipulating an image so that the results are more suitable for specific applications. Image restoration improves an appearance of an image which tends to probabilities model of image degradation Morphological processes are the tools of extracting image components that are useful in the description and presentation of an image.

Image segmentation is the most difficult ask in digital image processing which separates objects from the background. Representation makes the decision whether to represent data as boundary or as a complete region. Recognition is the process that assigns label to an object based on information provided by its descriptor.

Image segmentation approaches are commonly based on one of two fundamental properties of intensity values. In discontinuity-based technique image is partitioned by sudden changes in intensity values whereas similarity-based technique partitions an image by grouping together connected pixels in the region which fulfils predefined resemblance criteria. Boundary detection is equivalent to splitting one region into two, hence similarity based and discontinuity-based techniques mirror each other. Segmentation methods based on these approaches are discussed in this section.

3.2 Image Segmentation Techniques

There are various image segmentation techniques. Some of them are:

i. Thresholding based segmentation
ii. Region based segmentation
iii. Watershed segmentation

3.3 Threshold Based Segmentation

Thresholding is one of the simplest approaches for image segmentation based on intensity levels. Threshold based technique works on the assumption that the pixels falling in certain range of intensity values represents one class and remaining pixels in the image represents the other class. Thresholding can be implemented either locally or globally. For global thresholding brightness threshold value is to be selected to segment the image into object and background. It generates binary image from given input image. The pixels satisfying threshold test are considered as object pixels with binary value '1' and other pixels are treated as background pixels with binary value '0'.

$$g(u,v) = \begin{cases} 1 & f(u,v) \geq T \\ 0 & otherwise \end{cases} \qquad (3.1)$$

Where T is predefined threshold. Selection of threshold is very crucial in image segmentation process. Threshold value can be determined either by an interactive way or can be the outcome of automatic threshold selection method. Otsu method is optimal for thresholding large objects from the background. Threshold based approaches are computationally inexpensive fast and can be used for real time applications. A single global threshold partitions image into objects and background, but objects may have different characteristic gray value. In such situations multiple threshold values are needed, for applying over different areas of the image. Threshold value for each region is local threshold and the process is multilevel thresholding which helps to detect different objects in an image separately.

Steps for multilevel thresholding are:

1. Divide image into subparts.
2. Select local threshold for each subpart of image.

3. Compare the pixels for individual subpart and segment the region.
4. Repeat the process for each subpart and stop when all subparts are segmented.

Let us consider an image with two different objects, then identify two thresholds T1 and T2 such that

$T1 \leq f(u, v) \leq T2$ for one object

$f(u, v) \geq T2$ for the other object

$f(u, v) \leq T1$ for the background

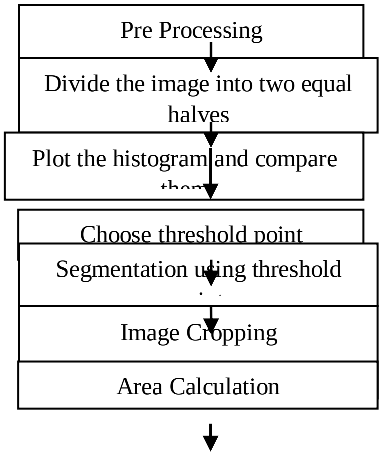


Fig 3.1 Thresholding Based Segmentation Flow

Human brain is symmetrical about left and right side. Divide the brain into two equal halves as shown in Fig 3.2. Plot the histogram and compare them. If the histogram of left part and right part are equal no tumor present in the brain image. If the histogram of left part and right part are not equal then we can conclude that tumor is present in the brain.

IV PROPOSED METHOD

4.1 Clustering:

Clustering is a method of grouping data objects into different groups, such that similar data objects belong to the same group and dissimilar data objects to different clusters. Current research increasing interest in digital image searching, classification, identification, management and storage. Some common but important applications of are person identification in movie clips and festive home videos, recognition in biometric system, natural scene classification for robot vision. The image clustering, an important technology for image processing, has been actively researched for a long period of time and explosive growth of the Web. Clustering approach is widely used in biomedical image segmentation and it is application are used for brain tumor detection as the normal and abnormal to find out the tumor on the brain.

Segmentation is an important process in most medical image analysis and classification for radio logical evaluation or computer-aided diagnosis. Basically, image segmentation methods can be classified into three categories:

1) Edge-based methods
2) Region-based methods
3) Pixel-based methods

k-means clustering is a key technique in pixel-based methods. Because pixel-based methods based on k-means clustering are simple and the computational complexity is relatively low compared with the region-based or edge-based methods, the application is more practicable. Furthermore, means clustering is suitable for biomedical image segmentation as the number of clusters is usually known for images of particular regions of the human anatomy. Many researchers have proposed related research into k-means clustering segmentation. The improvements achieved by researchers have been remarkable.

4.2 Image Classification.

Two major categories of image classification techniques include

- **Unsupervised** (calculated by software)
- Supervised (human guided)

Unsupervised classification is where the outcomes (groupings of pixels with common characteristics) are based on the software analysis of an image without the user providing sample classes. The computer uses techniques to determine which pixels are related and groups them into classes. The user can specify which algorism the software will use and the desired number of output classes but otherwise does not aid in the classification process. However, the user must have knowledge of the area being classified when the groupings of pixels with common characteristics produced by the computer have to be related to actual features on the ground (such as wetlands, developed areas, coniferous forests, etc.).

Supervised classification is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image. Training sites (also known as testing sets or input classes) are selected based on the knowledge of the user. The user also sets the bounds for how similar other pixels must be to group them together. These bounds are often set based on the spectral characteristics of the training area, plus or minus a certain increment (often based on "brightness" or strength of reflection in specific spectral bands). The user also designates the number of classes that the image is classified into. Many analysts use a combination of supervised and unsupervised classification processes to develop final output analysis and classified maps.

4.3 K-Mean Clustering

It is one of the techniques for the clustering concept in the data mining process and is very famous algorithm for the K-means clustering, because it is similar or simpler and easier in computation of an efficient K-means clustering algorithm. It is the simplest unsupervised learning algorithms that solve the well-known clustering problems. K -means algorithm is an unsupervised clustering algorithm that classified in the input data points into multiple classes based on their intrinsic distance from other dataset points of his cluster

K-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. K-means clustering aims to patition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space.

K-means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids,

United International Journal of Engineering and Sciences
(UIJES – A Peer-Reviewed Journal); ISSN:2582-5887 | Impact Factor:8.075(SJIF)
Volume 5 | Special Issue 1 | 2025 Edition
National Level Conference on "Advanced Trends in Engineering Science & Technology" – Organized by RKCE

one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate k new centroids as centers of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done.

4.4 Initialization methods

Commonly used initialization methods are Forgy and Random Partition. The Forgy method randomly chooses *k* observations from the data set and uses these as the initial means. The Random Partition method first randomly assigns a cluster to each observation and then proceeds to the update step, thus computing the initial mean to be the centroid of the cluster's randomly assigned points. The Forgy method tends to spread the initial means out, while Random Partition places all of them close to the center of the data set. The Random Partition method is generally preferable for algorithms such as the k-harmonic means and fuzzy k-means. For expectation maximization and standard k-means algorithms, the Forgy method of initialization is preferable.

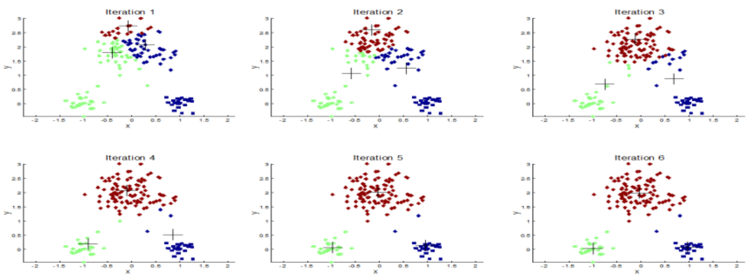
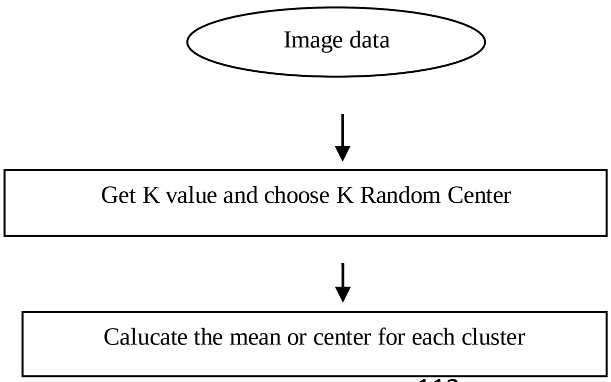


Fig 4.1 Different ways of clustering the same set of points

Fig 4.1 shows the different ways of clustering the same set of points. First choose the number of clusters as three. Choose randomly the three cluster centers.

Calculate the distance between each pixel to each cluster center. If the distance of pixel is near to the center the move to that cluster. Otherwise move to next cluster. Repeat the process until the center doesn't move.



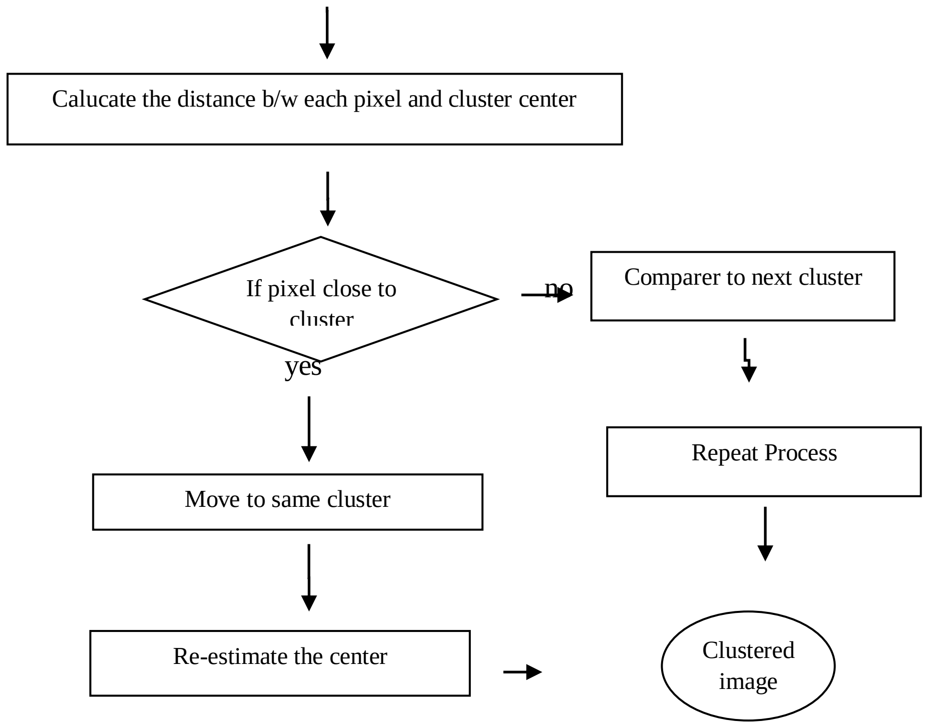


Fig 4.2 Flowchart for k-means Clustering

4.5 Strengths and Weaknesses

K-means is simple and can be used for a variety of data types. It is also a quite efficient, even though multiple runs are often performed. Some variants including bisecting K-means, are even more efficient, and are less susceptible to initialization problems. K-means is not suitable for all types of data, however. It cannot handle non-globular clusters or clusters of different sizes and densities, although it can typically find pure sub clusters if a large enough contains outlier. Outlier detection and removal can help significantly in such situations. Finally, K-means is restricted to data for which there is a notion of a center (centroid)

4.7 Feature Extraction

The feature extraction is extracting the cluster which shows the predicted tumor at the FCM output. The extracted cluster is given to the thresholding process. It applies binary mask over the entire image. It makes the dark pixel become darker and white become brighter. In threshold coding, each transform coefficient is compared with a threshold. If it is less than the threshold value then it is considered as zero. If it is larger than the threshold, it will be considered as one. The thresholding method is an adaptive method where only those coefficients whose magnitudes are above a threshold are retained within each block. Let us consider an image f that have the k gray level. An integer value of threshold T, which lies in the gray scale range of k. The thresholding process is a comparison. Each pixel in 'f 'is compared to T. Based on that, binary decision is made. That defines the value of the particular pixel in an output binary image 'g':

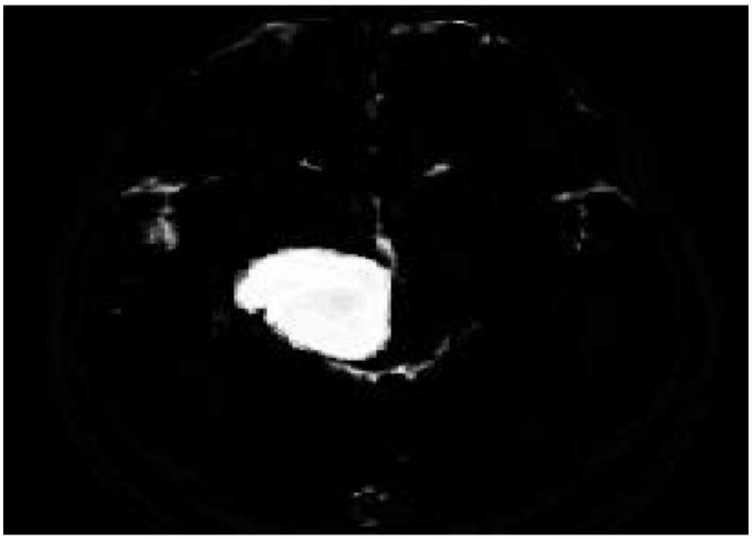


Fig 4.4 Output image of Thresholding

V. CONCLUSION

Image enhancement plays important roles in image processing. In this paper, we give a comprehensive review to analyze image enhancement methods from a supervised and unsupervised perspective. There are three main aspects. We first survey the unsupervised image enhancement methods, including histogram specification, Retinex model, deep learning and visual cortex neural network. Then we introduce supervised image enhancement methods involving deep convolutional neural network. In addition, we also provide main quality evaluation methods for image enhancement. In the future, weakly supervised or unsupervised strategies will probably generate new image enhancement frameworks and bring a rapid progress than state-of-the-art algorithms.

REFERENCES

[1] Bedi SS, Khandelwal R (2013) Various image enhancement techniques-a critical review. Int J Adv Res Comput Commun Eng 2(3):1605–1609

[2] Walter RJ , Berns MW (1986) Digital Image Processing and Analysis[M]. IEEE Computer Society

[3] Chang D, Wu W (1998) Image contrast enhancement based on a histogram transformation of all standard deviation. IEEE Trans Med Imaging 17(4):518–531

[4] Wang Y, Chen Q, Zhang B (1999) Image enhancement based on equal area dualistic sub-image histogram equalization method. IEEE Trans Consum Electron 45(1):68–75

[5] Agaian SS, Silver B, Panetta KA (2007) Transform coefcient histogram-based image enhancement algorithms using contrast entropy. IEEE Trans Image Process 16(3):741–758

[6] Polesel A, Ramponi G, Mathews V (2000) Image enhancement via adaptive unsharp masking. IEEE Trans Image Process 9(3):505–510

[7] Lin S, Wong C, Jiang G, Rahman M, Ren T, Kwok N, Shi H, Yu Y-H, Wu T (2016) Intensity and edge based adaptive unsharp masking flter for color image enhancement. Optik Int J Light Electron Opti 27(1):407–414

[8] Liu L, Jia Z, Yang J, Kasabov N (2015) A medical image enhancement method using adaptive thresholding in nsct domain combined unsharp masking. Int J Imaging Syst Technol 25(3):199–205

[9] Jobson D, Rahman Z (1997) Properties and performance of a center/surround retinex. IEEE Trans Image Process A Publ IEEE Signal Process Soc 6(3):451–462

[10] Jobson DJ, Rahman Z, Woodell GA (2002) A multiscale retinex for bridging the gap between color images and the human observation of scenes. IEEE Trans Image Process 6(7):965–976

[11] Rahman Z, Jobson DJ, Woodell GA (2004) Retinex processing for automatic image enhancement. J Electron Imaging 13(1):100–110

[12] Zhengang S, Liqun G, Kun W (2007) A novel approach to image enhancement and thresholding based on fuzzy theory. In: IEEE Conference on industrial electronics and applications 2201–2205

[13] Kong XW (2007) The fuzzy image enhancement algorithm for iow snr image. Laser J 5:44–45

[14] Li C, Guo J, Porikli F, Pang Y (2018) Lightennet: a convolutional neural network for weakly illuminated image enhancement. Pattern Recognit Lett 104:15–22

[15] Zheng WT, Pu T, Cheng J, Zheng H (2012) Image contrast enhancement by contourlet transform and pcnn, In: International conference on audio, language and image processing 735–739

[16] Singh GMA (2014) Various image enhancement techniques-a critical review. Int J Innov Sci Res 10(2):267–274

[17] Bahmani B, Moseley B, Vattani A, Kumar R, Vassilvitskii S (2012) Scalable k-means++. Proc Vldb Endow 5(7):622–633

[18] D'Andrade RG (1978) U-statistic hierarchical clustering. Psychometrika 43(1):59–67

[19] Dempster AP (1977) Maximum likelihood from incomplete data via the algorithm. J R Stat Soc 39

[20] Wang X, Chen L (2017) An efective histogram modifcation scheme for image contrast enhancement. Signal Process Image Commun 58:187–198

[21] Qiuqi R, Yuzhi R (2013) Digital Image Processing, 3rd edn. Publishing House of Electronics Industry

[22] Le-Peng LI, Sun SF, Xia C, Chen P, Dong FM (2014) Survey of histogram equalization technology. ComputSyst Appl 03:1–8

[23] Zuiderveld K (1994) Contrast limited adaptive histogram equalization. Graphics Gems 474–485

[24] Wang Y, Pan Z (2017) Image contrast enhancement using adjacent-blocks-based modifcation for local histogram equalization. Infrared Phys Technol 86:59–65

[25] Lamberti F, Montrucchio B, Sanna A (2006) Cmbfhe: a novel contrast enhancement technique based on cascaded multistep binomial fltering histogram equalization. IEEE Trans Consum Electron 52(3):966–974

[26] Liu B, Jin W, Chen Y, Liu C, Li L (2011) Contrast enhancement using non-overlapped sub-blocks and local histogram projection. IEEE Trans Consum Electron 57(2):583–588

[27] Kim J, Kim L, Hwang S (2001) An advanced contrast enhancement using partially overlapped sub-block histogram equalization. IEEE Trans Circuits Syst Video Technol 11(4):475–484

[28] Agarwal M, Mahajan R (2017) Medical images contrast enhancement using quad weighted histogram equalization with adaptive gama correction and homomorphic fltering. Procedia Comput Sci 115:509–517

[29] Wang Q, Ward RK (2007) Fast image/video contrast enhancement based on weighted thresholded histogram equalization. IEEE Trans Consum Electron 53(2):757–764

[30] Wong CY, Liu S, Liu SC, Rahman A, Lin SCF, Jiang G, Kwok NM, Shi H (2016) Image contrast enhancement using histogram equalization with maximum intensity coverage. J Modern Opt 63(16):1618–1629

[31] Arici T, Dikbas S, Altunbasak Y (2009) A histogram modifcation framework and its application for image contrast enhancement. IEEE Trans Image Process 18(9):1921–1935

[32] Yun SH, Jin HK, Kim S (2011) Contrast enhancement using a weighted histogram equalization. In: IEEE International Conference on Consumer Electronics

[33] Huang S, Cheng F, Chiu Y (2013) Efcient contrast enhancement using adaptive gamma correction with weighting distribution. IEEE Trans Image Process 22(3):1032–1041

[34] Huang Z, Zhang T, Li Q, Fang H (2016) Adaptive gamma correction based on cumulative histogram for enhancing near-infrared images. Infrared Phys Technol 79:205–215

[35] Kim Y (1997) Contrast enhancement using brightness preserving bi-histogram equalization. IEEE Trans Consum Electron 43(1):1–8