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Design of a Robust Hybrid Fuzzy Method for Medical Image Fusion

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ABSTRACT- In this modern era, medical image processing is an indispensable part of many applications and practices in the medical domain. The images that are used should meet certain criteria, including having more accurate details and information than each individual image, which can help medical scientists with analysis and treatment. Medical image fusion is among the techniques that offer high-quality images, which are combined from different modalities. Multimodal medical image fusion provides remarkable improvement in the quality of the fused images. In this paper, we describe an image fusion method for magnetic resonance imaging (MRI) and computed tomography (CT) utilizing local features and fuzzy logic methods. The aim of the proposed technique is to create the maximum combination of useful information present in MRI and CT images. Image local features are distinguished and combined with fuzzy logic to calculate weights for each pixel. Simulation outcomes show that the proposed method produces considerably better results compared to cutting-edge techniques. The method is also used to detect and highlight tumorous areas, followed by morphology filters used to eliminate any noise and disturbance.

KEYWORDS- Image Fusion, Medical Image Processing, Image Segmentation-Fuzzy C-Mean, Clustering.

I. INTRODUCTION

Clustering is a process for dividing objects or patterns in such a way that samples of the same group are closer to each other than samples belonging to other groups. Different strategies for clustering have been extensively used - hard clustering and soft clustering, which differ from each other in a feature-based way. The regular hard clustering method restricts each point of the dataset (for example, each pixel in an image) to belong completely to just one cluster (or one region in the image). However, in real-life situations, problems like poor and limited spatial resolution, noise, overlapping intensities, and intensity inhomogeneity variations make this hard (crisp) segmentation difficult. Image fusion and fuzzy set theory have produced the idea of decision fusion for detecting objects and partial membership of belonging, which is described by a membership function. Among the fuzzy clustering methods, the fuzzy c-means (FCM) algorithm is the most commonly used method in image segmentation and image fusion decision level because it has robust characteristics for vagueness and can retain much more information than hard segmentation methods. In machine vision, the main function of image segmentation is dividing an image into a set of separated egions with texture, etc. Many different segmentation techniques have been proposed, and detailed surveys can be found in references [1]. Data fusion plays a vital role in modern medical image fields used to gain a better understanding of the human body. Decision-making is an important step in image fusion; thus, a robust and efficient algorithm is always necessary to reduce the number of false detections that may convert to false alarms. In this research, we use a robust method by comparing MRI and CT images with normal brain images to increase confidence in the system's operation. With the advancements in instrumentation and image technology, image fusion has emerged as a powerful tool to enhance image features and improve their quality, resulting in more descriptive and clear outcomes. In an automatic vehicular system, multiple images containing complementary information can be fused together for accurate detection. Likewise, in medical assessment, combining different images with specific qualities can aid in correct diagnosis. Image fusion also enables the detection of high-speed objects, hazardous weapons, and obstacles, and plays a crucial role in tracking vehicle paths during adverse weather conditions like rain or fog. Additionally, it finds applications in detecting airline tracks in hostile climatic conditions as well as in the automation of robotics and machines [19].

The rest of the paper is organized as follows: the next sections discuss related works about image fusion, medical image processing, morphology operators, and FCM. After that, the proposed method as a robust hybrid FCM is illustrated; then, experimental results are presented.

II. A BRIF OVERVIEW OF IMAGE FUSION

Image fusion is an approach to combining two or more images to produce one new image of higher quality than what can be found in the source images. It also improves some features that may be weakened in the original images. Different techniques have been used to integrate images and extract more information from the fused image, especially when there are different images with dissimilar modalities of the same organ. Different modalities have unique characteristics that distinguish them from each other. For example, CT images are used for tissue density while MRI images are typically used to detect brain tumors. There are several algorithms ranging from low-level or pixel-level fusion to high-level or decision-making level, which have different features based on image fusion goals [2]. Different image fusion methods have been shown in flowchart I [3] (see in figure 1).

In this research, we use a multi-view approach at the decision level. The goal is to obtain deeper confidence in correct detector decisions by using our proposed method. Our method could be used in different fields of image fusion, such as remote sensing images, to reach better decisions, but we focus on medical image fusion. Many surveys have been conducted on multimodal fusion for multimedia analysis, like those in [4], which have their own advantages and disadvantages. Our research provides information on some topics discussing the benefits of multimodal fusion and the problems that may occur in this process. Alex James and Belur introduced a review study entitled "Medical Image Fusion: A Survey of the State of the Art" in 2014 [5]. This survey study includes the medical image fusion process, various modalities and algorithms, and organs mostly employed in medical image fusion. These topics are consolidated with a large number of analogous studies in similar subjects. Another review study of "Current Trends in Medical Image Registration and Fusion" by Fatma El-Zahraa El-Gamal and Mohammed Elmogy was offered in 2015 [6]. The study aimed to provide a description of the image fusion steps with special attention to the registration and fusion steps. Then, medical imaging modalities were discussed. Finally, some of the common problems that confront the registration and fusion processes are introduced to improve medical image registration and fusion methods.

Moreover, in [7], important and popular transforms, such as wavelet transform, contourlet transform, stationary wavelet transform, and framelet transform, are mentioned, which are widely used for image fusion. Many researchers have discussed image fusion from different perspectives, such as methods applied in the medical field by K.P. Indira and R. Rani Hemamalini who used curvelet transform for medical applications [8-9]. One of the critical steps in image fusion is image registration, which is defined as mapping input images according to a reference image. This operation is implemented to match images with certain features, helping the fusion process [10]. In other words, image registration means the geometrical alignment of underlying image features, such as points, lines, curves, and regions through a geometrical transformation that explains the underlying deformation between the images. After this alignment, you can add the brightness values (pixel value) to the aligned images through a resembling process. This addition of brightness values can be viewed as a fusion process from a human vision point of view.

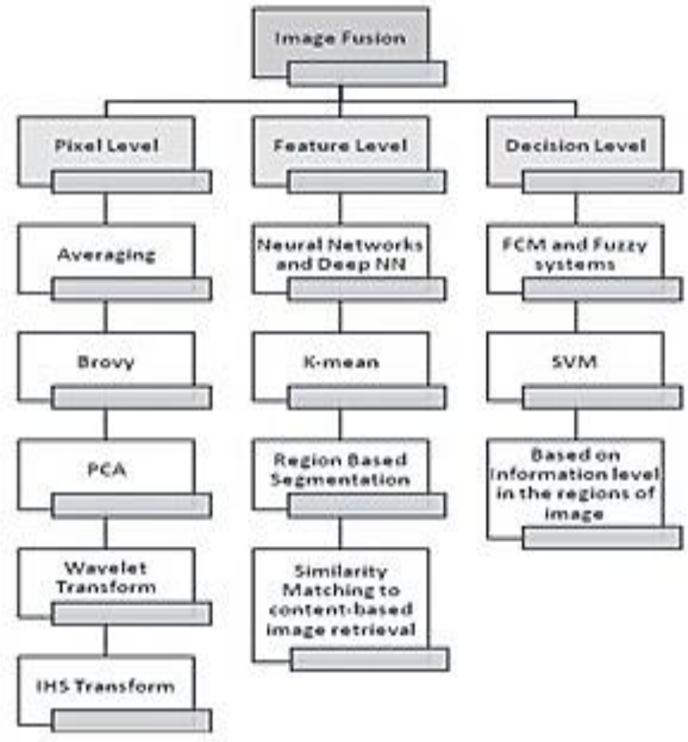

Figure 1: Flow Chart 1- Image Fusion Methods [3]

III. IMAGE MODALITIES

Image modalities are an important part of the clinical setting, offering a key contribution to medical operations and surgeries. Image modalities are considered a must-have in the decision-making process of a treatment plan. A wide range of imaging modalities are used in medical treatment, the most important of which are Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and ultrasound. These techniques can be applied as non-invasive methods to view the inner side of the human body without any surgical intervention. Image modalities like CT and MRI identify structural abnormalities in human body parts, while PET recognizes practical information [11]. Image fusion can utilize other methods to improve its accuracy by combining different modalities. Besides image registration, which is an essential part of the fusion process, image segmentation is used to enhance image quality during image fusion. There are different segmentation methods suitable for different modalities, and therefore, it should be chosen appropriately to achieve maximum efficiency.

A. CT Scan Images

Computed tomography (CT or CAT scan) is a non-invasive diagnostic imaging method that uses a combination of X-rays and computer technology to generate horizontal, or axial, images (often called slices) of the body. When it comes to studying dense structures such as bones with minimal distortions, CT (computed tomography) images are the most suitable option. However, they may not be as effective in detecting physiological changes with the same level of accuracy [16]. A CT scan shows detailed images of any organ of the body, including bones, muscles, fat, and organs. CT scans are more detailed than standard X-rays. (Figure 2).

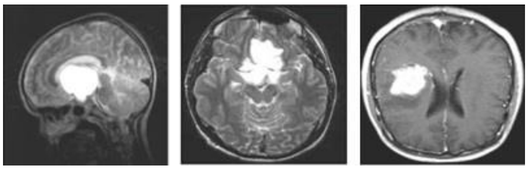

Figure 2: CT-scan Image Samples

B. Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) is a noninvasive medical test that helps physicians diagnose and treat medical conditions. MRI, which stands for magnetic resonance imaging, can reveal details about unhealthy soft tissues. Meanwhile, MRA or magnetic resonance angiography is a useful tool in identifying any abnormalities within the brain [17]. MRI uses a powerful magnetic field; radio frequency pulses and a computer to produce detailed pictures of organs, soft tissues, bone and virtually all other internal body structures. The images can then be examined on a computer monitor, transmitted electronically, printed or copied to a CD.MRI does not use ionizing radiation (x-rays). (Figure 3)

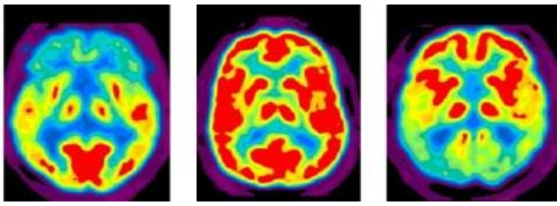

Figure 3: Magnetic resonance imaging Sample

C. PET Scan Image

Positron Emission Tomography (PET) is a nuclear medicine functional imaging technique used to observe metabolic processes in the body, aiding in the diagnosis of diseases. Positron Emission Tomography (PET) can provide highly accurate information about blood flow and pinpoint the precise location of a patient's lesion. This diagnostic method relies on the interaction between positrons and electrons in tissue, which generates photons. By detecting the number of photons produced, PET enables clinicians to gather crucial insights into a patient's condition [18]. The system detects pairs of gamma rays emitted indirectly by a positron-emitting radionuclide. (Figure 4).

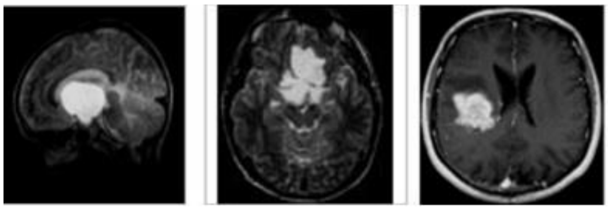

Figure 4: Positron Emission Tomography

IV. FUZZY C-MEAN

Fuzzy clustering in fuzzy logic deals with the degree of belonging of each point to a cluster and is specified in terms of a membership matrix. Several clustering criteria have been proposed for identifying optimal fuzzy c-partitions. The goal of these criteria is to determine the best values for the number of clusters and the corresponding membership function parameters to accurately represent the underlying data distribution. Fuzzy clustering is widely used in various fields such as pattern recognition, image processing, and data analysis.

Let us consider a set of n vectors ($X= (x_1, x_2,\dots,x_n)$ where $2<c<n$) for clustering into c groups. Each vector $x_i \in Rs$ is represented by s real-valued measurements indicating the features of object x_i. A membership matrix called the fuzzy partition matrix is used to represent the degree of membership of each vector to a specific cluster. The set of fuzzy partition matrices (c×n) is described by M_{fc} and is defined in Eq (1):

$$\mathrm{Mf} = \{W \in R^{cn} \mid w_{ik} \in [0,1], \forall i, k; \sum_{i=1}^{c} w_{ik} = 1; 0 < \sum_{K=1}^{N} W_{ik} < n \ \forall i\} \quad \text{where } 1 \leq i \leq c, 1 \leq k \leq n \tag{1}$$

Based on the aforementioned definitions, it can be inferred that members may fit into more than one cluster with varying degrees of membership. The total 'membership' of each member is normalized to 1, and no single cluster can contain all data points. The objective function (Eq. 2) of the fuzzy c-means algorithm is calculated using the membership value and Euclidean distance (Eq. 3).

$$J_m(W,P) = \sum_{\substack{1 \leq k \leq n \\ 0<i<c}} (W_{ik})^m (d_{ik}{}^2) \tag{2}$$

Where

$$(d_{ik} = \|x_k - p_i\| \tag{3}$$

Here, $m \in (1, +\infty)$ is the parameter that controls the fuzziness of the resulting clusters, and d_{ik} is the Euclidean distance from object x_k to the cluster center p_i. The objective function Jm is minimized [14] using the FCM algorithm, which iteratively updates the partition matrix using Eqs. 4 and 5.

$$p_i = \sum_{i=1}^{n} (w_{ik})^m x_k \ / \sum_{k=1}^{n} (w_{ik})^m \tag{4}$$

$$w_{ik}{}^{(b)} = \frac{\sum_{j=1}^{c} 1}{\left[\left(\frac{d_{ik}{}^{(b)}}{d_{jk}{}^{(b)}}\right)^{\frac{2}{m}-1}\right]} \tag{5}$$

The FCM membership function [15] is computed as:

$$\mu_{i,j} = \left[\sum_{t=1}^{c} \left(\frac{\|x_i - v_i\|_A}{\|x_i - v_t\|_A}\right)^{\frac{2}{m-1}}\right]^{-1} \tag{6}$$

μ_{ij} is the membership value of jth sample and ith cluster. The number of clusters is described by c, is the jth sample and v_j cluster center of the ith cluster. $\| \|_A$ shows the norm function.

V. PROPOSED METHOD

In the last few decades, new research and innovations in medicine have improved existing methods and reduced problems that can occur during diagnosis and treatment procedures. In image fusion, suitable regions of input sources are detected and transferred to the output for further operations. Fuzzy logic is one of the best methods for selecting suitable regions by dividing images into classes and allocating membership values. This leads to more accurate categorization of information than crisp methods [12].

In decision-level image fusion, local decisions from weak or partial classifiers are supported, with the goal of achieving comprehensive fusion at this level. To achieve this goal, we need to select regions that are needed for the fused step. We use classifiers such as cascade, HOG, and pre-trained signet, and then propose a hybrid FCM using morphological operators to strengthen composition. This step is known as the main image fusion step and is illustrated in Flow Chart II (see figure 5).

In this research, we introduce our method, which is more effective than some techniques employed in image fusion. We use eigenvalues to create a robust data set instead of a single image for both modalities CT and MRI (Fig. 4). This helps us to have reliable ground truth, which is important for initialization. This way, a source of normal brain images is produced that can be compared with both MRI and CT modalities comprising abnormalities. Before that, we need to register abnormal and normal brain images. We define some key points like the eyes and backbone of the brain and use affine transform, a common method in image registration, to transfer all images to the reference coordinate. This is the first and one of the most important steps because it prepares the input image for low-level image fusion.

We utilize a simple logical operator (XOR) to compare two images - a normal brain and an abnormal brain with tumor (Fig 5). We show the differences between two images of both modalities using red-colored spots. The transformed and result images are then given to a hybrid FCM, mixed with morphology operators. In this part, morphology operators employ various combinations of structure elements. This combined technique can help to remove redundant parts of the image and strengthen essential parts of the result images [13].

A. Eigen values

An image is generally represented as a function of two variables, x and y, with magnitude ranging from 0 to 255 and denoted by f(x,y). The 2D image is divided into rows and columns, and the eigenvalues of these rows and columns matrices indicate the main features of the images. In image processing fields such as image fusion, pattern recognition, and face identification, calculation of eigenvalues and eigenvectors is essential and helpful. The strongest and largest eigenvalue represents the most valuable features of the image, while the weakest and smallest eigenvalue represents less important features that can be neglected. For a brief definition of eigen value and eigenvector in matrix algebra, the following equations illustrate their relationship:

$$A.x = \lambda.x \qquad (7)$$

Where A is a square matrix, x is a vector (will be called eigenvector) and λ is a scalar (will be called eigen value). The equation can be rearranged as follows:

Rearrange: $A.x-\lambda.x=0$

Then factorize and make into a matrix:

$$(A - \lambda. I)\, x=0$$

This form is useful for finding the eigen values and eigen vectors. Multiplying by the identity matrix (I) produces the matrix:

$$\begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix}$$

The last version of the equation shows that there is a trivial solution. To find the eigenvalues (λ), matrix theory tells us to set the determinant of A-λI equal to 0. To find the eigenvectors, we put the eigenvalues back into the original equation and solve for them. When eigenvalues are used for image processing, the vector components represent the brightness of each pixel, and the dimension of this vector space is the number of pixels. The eigenvectors of the covariance matrix associated with a large set of normalized brain pictures provide an example of principal component analysis. They are useful for expressing any brain and modality of brain images as a linear combination of some of them. Research related to Eigen vision systems for determining hand gestures and facial recognition has also been conducted [14].

Similar to the examples above, we use eigenvalues and eigenvectors to combine N images (100) of the same skull, which may have different postures. This helps us to have a more accurate source for preprocessing steps. In the first step, we provide an Eigen normal brain by registering images and using PCA method, which is then used in the next step to compare with a new abnormal brain image. This is an integral part of any processing that requires an undefined input image for further processing. We provide input images with eigenvalues for every single modality such as MRI, CT, PET, and so forth (Figure. 4).

B. Comparing Normal and Abnormal Brain Image

In this part, we compare normal images from different modalities of the brain to images with tumorous growths using affine transformation. We then apply low-level fusion to highlight dissimilarities between normal and abnormal images. The abnormal and reference images are given to the low-level fusion by applying a simple XOR operator, which can merge dissimilarities of input images (the abnormal image) (Figure 6).

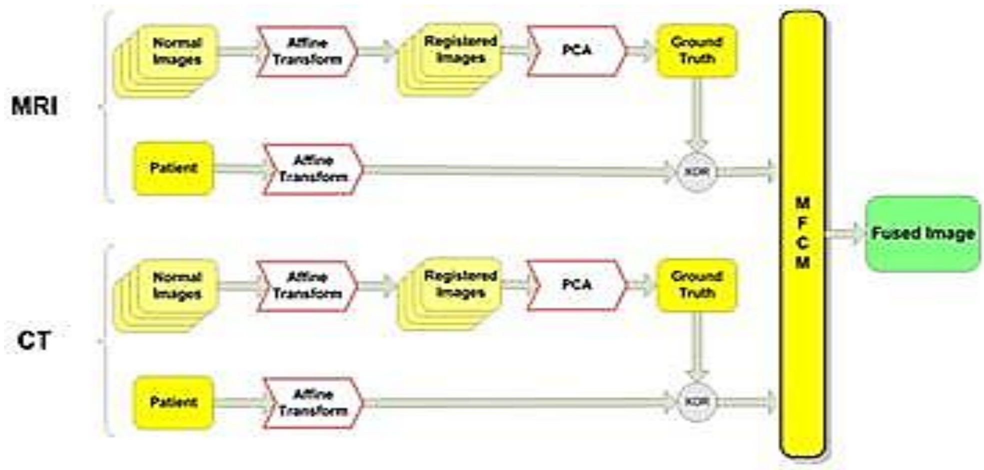

Figure 5: Flow Chart II- Proposed Method

As shown in Fig 6, parts indicating red color demonstrate the results of comparing and adapting normal and abnormal images for both MRI and CT modalities. This step is important because it can highlight similarities between normal and abnormal images, which is beneficial for the next steps in understanding the discussed subject. This step is a prerequisite for the main part of our method, which involves preparing a high-resolution and fused image for the next fusion step. In the following chart II, the entire proposed method with all steps is shown. There are two separate processes that include a similar procedure for both modalities (MRI and CT). This process can be extended to more modalities for more precise fused image results. The process begins by passing both normal and patient images through an affine transform, after which the registered image is given to PCA transform steps. After a comparison between the two images, the resulting image is known as the input for important steps shown with MFCM. The final image will have more details compared to input images. Each separated input image has its own features that are sometimes valuable but not sufficient in some cases for diagnosing abnormalities. Therefore, more assessment by technicians is needed, which is time-consuming with less accuracy.

VI. EXPERIMENTAL RESULTS

MFCM is used for fusion in this section, employing the output of previous steps. Mathematical morphology deals with set theory that represents objects in an image. Morphology is used for the representation and description of region shape. Unlike the previous fusion, which was at the pixel level, we use morphology operators at the decision level. Fig (6) shows the result of brain image fusion of two modalities, CT and MRI. As could be inferred, the difference points of the two input images are shown in red color and include both soft and solid parts of the damaged part of the brain. Morphological operators use the connectedness between pixels to either improve the spatial arrangement of the pixels or to distort them in order to extract useful features from the subset of spatially localized pixel features. The filters designed with morphological operators have been successfully applied to identify tumors. Morphological operators are used to strengthen the fusion of the images from multiple modalities.

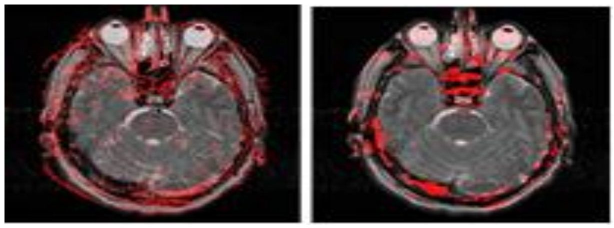

Figure 6: Brain Image Compared between normal and abnormal images

The success of these operators depends on the size and design of the structuring operator that controls the opening and closing operations in morphological filtering. These operators reduce the effect of noise by smoothing uniform regions and sharpening the borders between regions. Post-processing for noise reduction and contrast enhancement of MRI and CT images is of clinical concern because it allows the quality of images taken with faster acquisition times to be enhanced to an appropriate level. The results of this step, particularly in medical applications, are vital for better diagnosis.

The size of the structuring element most importantly affects the degree of noise smoothing by the filter, and both the size and shape influence the preservation of fine details in the image. It should be pointed out that choosing suitable parameters in this method is essential because, for example, selecting large structuring elements can introduce significant distortions to the image and sharpen or highlight some points or boundaries that are not desirable. Inappropriate shape control of the filter can also make false qualitative differences that render filtering useless in some troublesome situations.

Appropriate filtering structures are devised to overcome probable shortcomings in the responses of morphological filters. Both choosing the modality and the right filter are essential because in some situations a chosen filter works properly, but for another modality, it brings false consequences. A combination of operators can also be a beneficial way to improve image quality and enhance resolution, but it is not a comprehensive solution. It is entirely possible that a combined filter works well in one application, such as in the medical field, but not in remote sensing needs.

In Figure 7, it is observed that the image has been divided into two areas, where red points represent abnormalities and green areas represent normal parts. It could be seen that the regions representative of abnormalities are clearly separated from those that are normal regions with high resolution. It is important to have obvious borders between normal and abnormal regions for better diagnosis, which our method achieves by analyzing many different structures and reaching the best algorithm.

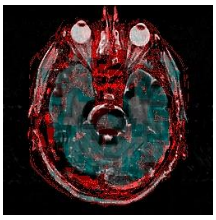

Figure 7: Brain Image fused of CT and MRI

VII. DISCUSSION AND FUTURE WORKS

As mentioned earlier, there are different methods for implementing image fusion, each with its own weaknesses. For example, wavelet and contour methods can produce artifacts that lead to noise in the final results, whereas HIS can cause color distortion. High-frequency methods have high resolution but are categorized as high complexity methods. In comparison, our method has less complexity and good resolution.

The proposed algorithm consists of several parts that could be improved in the future. We could include other modalities such as PET and SPECT, and also explore combinations with other structure operators to achieve better results.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] Er. Anjna, Er.Rajandeep Kaur, "Review of Image Segmentation Technique" Volume 8, No. 4, May 2017 (Special Issue)

[2] Abbas shakeri,Behadmoshiri, hosseingharaee, "Pedestrian Detection using Image Fusion and stereo vision in autonomous vehicles" 2018 9th International Symposium on Telecommunications (IST'2018)

[3] Kumar, Mahendra. (2018). Image fusion based on evolutionary optimization algorithm. 10.13140/RG.2.2.13146.59845.

[4] Pradeep K. Atrey, and M. Anwar Hossain, "Multimodal Fusion for Multimedia Analysis: A Survey", Multimedia Systems, DOI:10.1007/s00530-010-0182-0, Springer Verlag, 2010.

[5] A.P. James, and B.V. Dasarathy, "Medical Image Fusion: A survey of the State of the Art", Information Fusion, vol. 19, pp.4-19, 2014.

[6] Fatma E. El-Gamal, and Mohammed Elmogy, "Current Trends in Medical Image Registration and Fusion", Egyptian Informatics Journal, 2015.

[7] K.P.Indira, and R.RaniHemamalini, "Analysis on Image Fusion Techniques for Medical Applications", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, vol. 3, Issue 9, 2014.

[8] Harmandeep Kaur, Er. Jyoti Rani, "Analytical Comparison of Various Image Fusion Techniques" International Journal of Advanced

[9] Jasmeetkaur, Er. Rajdavinder, "An Evaluation on Different Image Fusion Techniques", IPASJ International Journal of Computer Science (IIJCS), vol. 2, Issue 4, 2014.

[10] Fatma El-Zahraa Ahmed El-Gamal, Mohammed Elmogy *,Ahmed Atwan "Current trends in medical image registration and fusion "Egypt journal August 2015 Volume 17,pp,99 -124

[11] Rudra Pratap Singh Chauhan,Rajiva Dwivedi and Sandeep Negi " Comparative Evaluation of DWT and DT-CWT for Image Fusion and De-noising", International Journal of Applied Information Systems (IJAIS),Volume 4– No.2, September 2012 – ISSN : 2249-0868.

[12] Zhang, H., Fritts, J. E., & Goldman, S. A. (2008). Image segmentation evaluation: A survey of unsupervised methods. Comput Vis Image Underst 110(2), 260–280.

[13] Mahdi Koohi,Abbasshakeri,Mehdi Naraghi, "Edge detection in multispectral images based on structural ", Internationa journal of multimedia & its application Vol.3, No.1 , Feb. 2011.

[14] Runkler, T.A., Katz, C.: Fuzzy clustering by particle swarm optimization. In: Proceedings of2006 IEEE International Conference on Fuzzy Systems, pp. 601–608. Canada (2006).

[15] Huang, M., Xia, Z., Wang, H., Zeng, Q., Wang, Q.: The range of the value for the fuzzifier ofthe fuzzy c-means algorithm. Pattern Recogn. Lett. 33, 2280–2284 (2012).

[16] B. Rajalingama, R. Priya b , R.Bhavanic "Hybrid Multimodal Medical Image Fusion Using Combination of Transform Techniques for Disease Analysis" International Conference on Pervasive Computing Advances and Applications – PerCAA 2019.

[17] T. Tirupal1, B. Chandra Mohan , S. Srinivas Kumar," Multimodal medical image fusion based on yager's intuitionistic fuzzy sets." Iranian Journal of Fuzzy Systems, Volume 16, Number 1, (2019), pp. 33-48

[18] Bing Huang,Feng Yang , Mengxiao Yin, Xiaoying Mo, Cheng Zhong." A Review of Multimodal Medical Image Fusion Techniques". Computational and Mathematical Methods in MedicineVolume 2020, Article ID 8279342, 16 pages.

[19] Munish Rehal , Akhil Goyal," Multimodal Image Fusion based on Hybrid of Hilbert Transform and Intensity Hue Saturation using Fuzzy System". International Journal of Computer Applications (0975 – 8887)Volume 183– No.4, May 2021.