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RESEARCH ARTICLE

MMIFFS: FUSION OF BRAIN IMAGES BASED ON FUZZY SETS-A LIGHTWIGHT APPROACH

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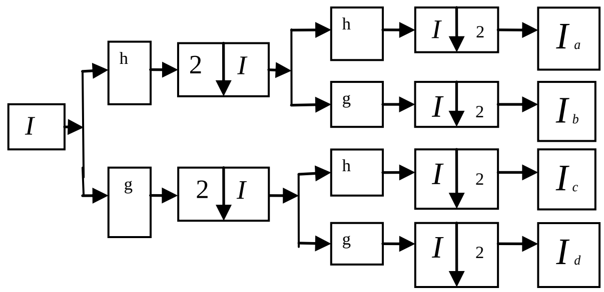
Abstract

The integration of medical images holds substantial clinical relevance. CT scan displays hard tissues, whereas the MRI image illustrates the structure of brain tissue and lacks functional information. Therefore, an ideal merged image must encompass both comprehensiveness and absence of distortion. This work presents a hybrid strategy for the integration of MRI and CT pairs by integrating Fuzzy set theory, and Discrete Wavelet Transform(DWT).The suggested technique amalgam ates the benefits of both DWT and fuzzy methodologies to improve the comprehensive data resultant picture. The analysis of qualitative and Visual demonstrate that the suggested technique proves the efficiency of fusion proves.The proposed approach is superior than the convention al fusion techniques, and the fused output is assessed using the mean, average gradient, and standard deviation.

Introduction:-

The technique of merging pertinent data from multiple sensors into a single resultant picture, called image fusion. Compared to any one of the input photographs, the final image ought to be more informative. The fusion process may be carried out at the signal, pixel, feature, and symbol levels of information representation, which are stored in escalating order of abstraction. Pixel-level fusion involves extracting information after fusing the input images pixel by pixel. Each input image's information is retrieved independently in feature-level fusion, after which the information is combined depending on the input images' characteristics. Decisions are taken for every input channel once the data is retrieved from each input image independently in decision-level fusion [1-4].Medical imaging has been employed significantly in clinical therapy and treatment recently, and a growing variety of image modalities are now accessible. In general, there are two types of medical imaging systems: structural and functional. Functional images like PET (Positron Emission Tomography) and SPECT (Single-Photon Emission Computed Tomography) convey functional details with minimal resolution, whereas structural modalities like MRI (Magnetic resonance imaging) and CT (computed tomography) reveals soft details with sufficient resolution. Anatomical and functional images must be combined to offer significantly more meaningful information since a single image cannot essentially meet clinical demands. The technique of merging multiple modalities of the same location to create a resultant outcome that has more detailed and better visual perception that is necessary clinical application is known as medical image fusion (MIF). The goal of image fusion for most clinical applications is to maximize the relative information while minimizing duplication and ambiguity in the final fused image [5-7]. This study presents gray CT and MRI images. To meet real needs, the fused images must be unique and devoid of inaccuracies and redundancies. This work proposes an integrated fusion strategy using fuzzy logic, discrete wavelet transform (DWT), maximum, and average fusion rules.



Preliminaries:-

DWT:-

The discrete wavelet transform (DWT) [8] offers a paradigm for signal decomposition, where each level corresponds to low and higher frequency bands. Transforms are categorized into two primary groups: continuous and discrete. In one dimension, the wavelet transform aims to represent the signal as a superposition of wavelets. A 2-D DWT involves first executing a 1-D DWT on the rows, followed by the data related to column using distinct filtering and down sampling processes. This transformation addresses the limitations of conventional image processing techniques such as the Fourier transform and Fourier series by using scaling and wavelet concepts. The image may be shown in several resolutions. The DWT converts the image into sub-bands. Each band coefficient has distinct filtering properties. The bands may provide a clear examination of the picture. The diagrammatic representation of 2D-DWT is shown in Fig. 1.

(a) DWT

<table>
<tr><td>LL2</td><td>LH2</td><td rowspan="2">LH1</td></tr>
<tr><td>HL2</td><td>HH2</td></tr>
<tr><td colspan="2">HL1</td><td>HH1</td></tr>
</table>

(b) Decomposition levels

Fig.1. Schematic of DWT

Datasets:-

MIF has become more important due to the advantages of merging multimodal images. This study used the following data sets: MRI-MRA, CT-MRI. Medical photos contain many details: CT (Computerized Tomography) scans may identify the richer in contrast of tissue and provide data on hard structures like bones and fractional details. MRI creates pictures of anatomical structures, disease proximity, and biological capacity, including diseased soft tissues, using a radio frequency signals along with magnetic field. Magnetic resonance angiography (MRA) may promptly detect brain abnormalities. MRA is a technique for imaging interior organs by recording and preserving an electromagnetic wave generated by the organ. MRA is primarily used to identify brain irregularities, and its main value is the ability to distinguish healthy tissue from sick parts. Magnetic resonance may assess both big joints and minor joints of the body. Magnetic resonance imaging can evaluate organs, including the kidneys, spleen, pancreas, and liver for depression in the stomach. Combining CT-MRI and MRI-MRA [9] improves clinical data. One photo cannot convey all. The image fusion is required to incorporate all relevant data, which helps doctors discover anomalies.

Proposed work:-
This section describes the DWT-based bounded measured Fuzzy set method for multimodal medical picture fusion.
System model
The suggested (DWT + Fuzzy set) algorithm system model stages are below:

1. Take the two medical pairs, P1 and P2.
2. Apply fuzzification [10] to the raw pictures using Equation (1).

$$\mu(P) = (P - P(\mathrm{mi}))/(\mathrm{P(ma)} - \mathrm{P(mi)}) \qquad (1)$$

The first image's total range is [0, L-1], L measures the highest pixel value. The image's minimal and maximum gray-level values are Pmi and Pma.

Use Discrete Wavelet Transform (DWT) to obtain Low and high bands. The LF bands are fused with the maximum fusion strategy, and the HF bands are fused with average rule.An inverse DWT creates the fused image from the merged LF and HF bands..Finally, the blended picture is cleared via defuzzification..

$$P(new) = \left(\mathrm{P(ma)} - \mathrm{P(mi)}\right) * \mu(P) + \mathrm{P(mi)} \qquad (2)$$

Working:-
In Fig. 2 for the proposed work i.e. hybrid, including DWT + Fuzzy approach. Two pairs make up the fusion algorithm: fuzzification, decomposition with DWT, LF, HF fusion, and finally reconstruction using DWT. The approach starts with fuzzifying raw pictures, such as CT/MRI scans. After the previous step, a DWT decomposes source pictures into LL, LH, HL, and HH subbands. Next, maximum fusion strategy was used for LL and Average strategy for high components, respectively.

Experimentation and results:-
The experimental configuration includes a 2.2 GHz Intel(R) Core i6 vPro CPU, 16 GB RAM, and 64-bit OS. and was tested using MATLAB 2022a. To gather additional clinical data, proven fusion methods are evaluated for several multimodal medical imaging pairings, such as CT-MRI, and MRI-MRA. Visual quality, edges, soft and hard tissue visibility, and artifacts determine a fused image's subjective rating. The objective fusion performance of a fusion outcome is evaluated with Mean, Standard Deviation (STD), Average Gradient (AG). The fusion metrics are compared to previous techniques, such as simple average, PCA, and DWT. Subjective and objective evaluations indicate improved performance of modern fusion algorithms in combining multimodal information.

Figs. 3(a) and 3(b) observe the medical image pairs. The fusion outcomes of various methodologies are shown in Fig. 3(c) to 3(f), such as Average, PCA, DWT, and the Proposed method (DWT + Fuzzy set), subsequentially. Table 1 displays the fusion findings, which include all objective criteria [10-11] like mean, standard deviation (SD), and average gradient (AG). Table 1 illustrates that the proposed technique surpasses other current methods for several quality criteria.

The second example utilizes a T1- MR scan with MRA picture exhibit pathology as white entities, presented in Fig. 3. The T1- MR scan reveals a clearer understanding of the soft tissues, showing no abnormalities. MRA pictures struggle to detect soft tissue information due to their inadequate spatial resolution. The two pictures have been amalgamated to enhance information in a resultant outcome, facilitating precise diagnosis. Relative to the fused images produced by current methods (simple average, PCA, DWT), the proposed modal generates the outcome has superior spatial resolution. The proposed technique surpasses other current fusion algorithms for quality metrics, since it eliminates uncertainty. The graphical representation of fusion outcomes is displayed in Fig. 4.

Conclusion:-

This study presented the integration of medical pictures with Discrete Wavelet Transform (DWT), fuzzy sets, with avg and max fusion strategies. MMIF is essential in several disease identifications and other tissue related conditions. The issue of blurring effects, a prevalent challenge in pixel-level fusion techniques, has been effectively resolved. This process delineates a 3-steps for the integrating medical pictures via DWT and fuzzy. DWT applies the fuzzified medical photos. Then, the decomposed coefficients were fused by max, and average based fusion strategies. In the last phase, rebuild the decomposed bands and defuzzification process takes place. We presented various combination are carried out to determine the efficacy of the proposed approach and it shows the superiority than other techniques The demonstration of fusion methods uses both visual and quantitative metrics. Employing DWT and Fuzzy, ensuing algorithms are enhanced to achieve superior fusion outcomes across diverse modalities. In future, the research will be carried out with integrating the sophisticated algorithms and appropriate fusion strategies for better diagnosis.

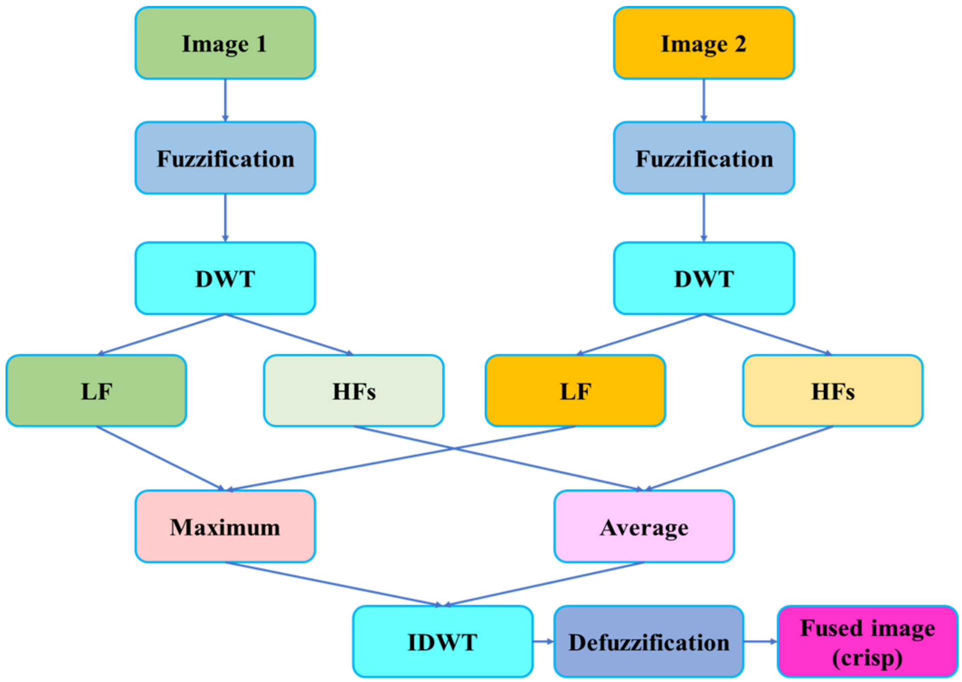


Fig. 2. Schematic diagram of proposed method using DWT+PCA+ Fuzzy set

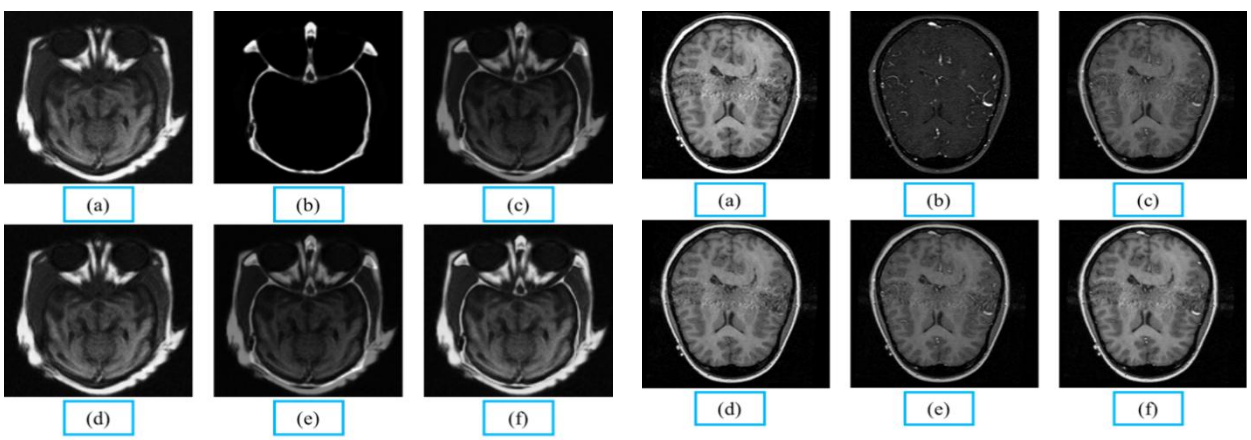


Fig. 3. Subjective analysis of Fusion results. (a) MRI image (b) CT image/ MRA image, (c) Average method, (d) PCA method, (e) DWT method, and (f) Our work (DWT+ Fuzzy set).

TABLE 1 Objective fusion performance

Fusion methods	Medical image pairs					
	MRI-CT			T1-MR - MRA		
	Mean	STD	AG	Mean	STD	AG
Average	32.6739	34.9506	3.8980	45.5719	45.4870	6.4314
PCA	52.7361	54.0957	5.3965	56.5364	57.7863	7.6807
DWT	32.6739	34.9506	3.8980	45.5719	45.4870	6.4314
Our work	**60.6864**	**61.2166**	**7.0651**	**67.6129**	**68.2391**	**9.2021**

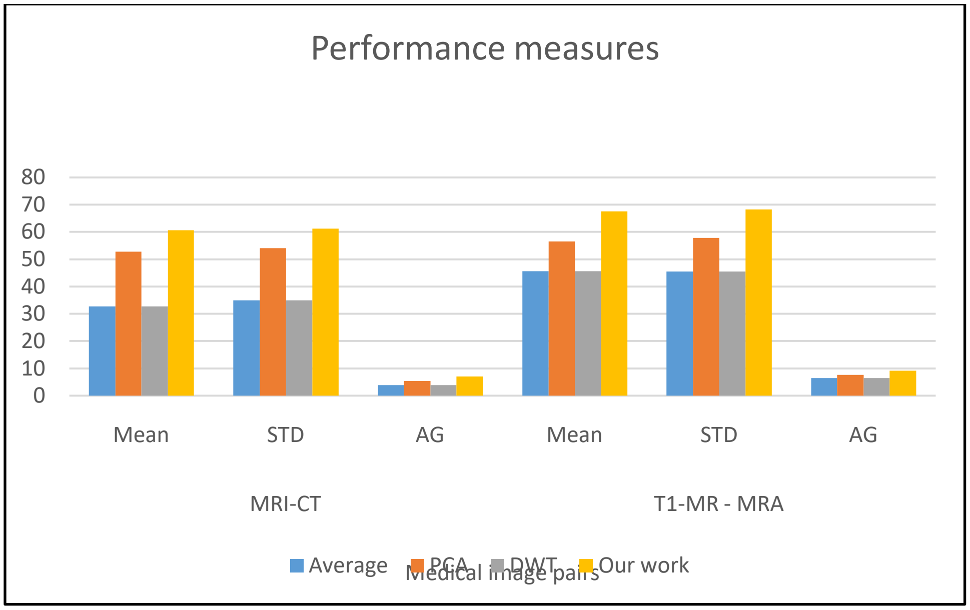


Fig. 4. Graphical analysis of Fusion results.

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