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Image Fusion Techniques: A Review

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ABSTRACT

Image Fusion is being used to gather important data from such an input image array and to place it in a single output picture to make it much more meaningful & usable than either of the input images. Image fusion boosts the quality and application of data. The accuracy of the image that has fused depending on the application. It is widely used in smart robotics, audio camera fusion, photonics, system control and output, construction and inspection of electronic circuits, complex computer, software diagnostics, also smart line assembling robots. In this paper provides a literature review of different image fusion techniques in the spatial domain and frequency domain, such as averaging, min-max, block substitution, Intensity-Hue-Saturation (IHS), Principal Component Analysis (PCA), pyramid-based techniques, and transforming. Different quality metrics for quantitative analysis of these approaches have been debated.

Keywords: *Fusion, IHS, PCA*

I. Introduction

The concept of fusing a sequence of images in to a single object began in the past in the 1950s and 1960s by examining useful amalgam image approaches starting with different devices with its most common system called sensor to give a compound image can be used to identify real and artificial enterprises well. [1].Issue such as amalgamation, Alteration, fusion, integration, and many extra terms which have since emerged in the fiction to guide more or less the analogous notions [2] The following definition was adopted in the application of remote sensing communal:"A formal framework in which means and tools for expressing the alliance of data are originating from different sources called data fusion. It aims to obtain information of greater and better quality; the exact definition of 'greater quality' will depend upon the application" [3] In general, fusion is a process through which two or more images or images are connected together in a sole image that contains the substantial structures and network topologies for each of the originating images[4]. For photographs of similar prospects or individuals obtained from specific process modalities or acquired methods; the fusion of images is often essential [5].Important applications for image fusion include medicinal image processing for improved disease detection and understanding, Image research, remote sensing, engineering, computer science like deep learning and robots in the context of microscopic information analysis.

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Aim of the fusion image:

The basic objectives of the fusion image can be represented in the illustration in Figure 1[6].

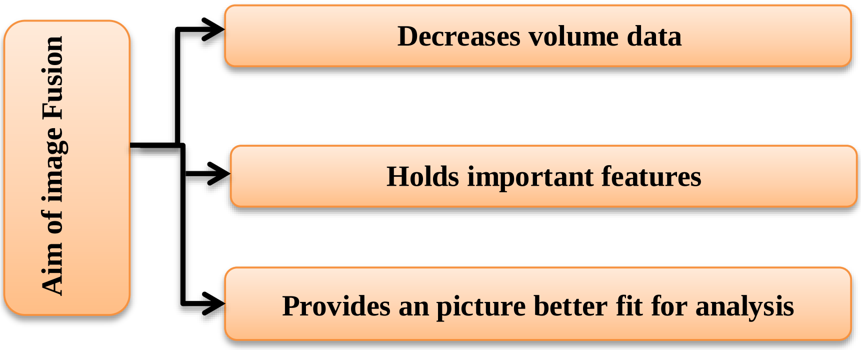

Figure 1: Aim of image fusion [6]

1.1 **Decreases volume data**

The goal of image fusion, particularly in medical imaging, is to create new images which are more appropriate for human visual perception purposes. The easiest technique for images fusion to take the combination of 2 images data. Directly applied, this leads to a reduction in contrast features. A solution to this technique gives an image fusion based on the Laplacian pyramid [2].

1.2 **Holds important features**

The image fusion is designed to obtain a fused image which contains the most important information in all input images captured from same scene by different configurations. The fusion process will, in particular, increase the contrast and preserve the integrity of significant features from the input images [7].

1.3 **Provides an picture better fit for analysis**

Uses multi-focus image fusion for obtain valuable and essential information for input images with different emphasis depths to generate an output image that ideally contains all the input image information [1][8].

II. Image Fusion Systems

There will be two major types of imaging fusion systems, seen in Figure 2.

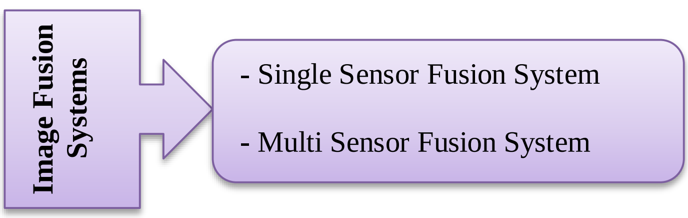

Figure 2: Image Fusion Systems

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2.1 Single Sensor Fusion System (SSFS):

The case in which only one sensor exists, images are obtained and processed using a single object, images are processed in a sequence of the particular scene, as well as the image sequence would then be fused in to a single image[9].Using the single sensor has a major drawback as it is based on sensor efficiency so that problems can occur using a single sensor [10].

2.2 Multi-Sensor Fusion System (MSFS):

Several sensors are used in the case of an MSFS to track and record images [12]. Different sensors record a series of images These are then combined in to a single image showing it all in the picture focus. Essentially, Multi-Sensor Fusion System images were implemented to the address Single sensor fusion system limitations and thus offers several advantages more than a single sensor image fusion system[13].

III. Literature Review:

When we investigate the field for image fusion they can see considerable work has been done in a the image fusion perspective, starting from image fusion method can be broadly classified into two groups From the temporal domain to a spatial realm. On possibility of image fusion. Starting with one of the most popular image fusion application**:Remote Sensing Image Fusion With Deep Convolutional Neural Network** , In (2018), Zhenfeng Shao, the dataset were taken from The Quick Bird and Gaofen-1 images satellites , A mapping object fusion method which might accurately extract spectrum and spatial characteristics of origin images is suggested based on both the deep convolutionary neural network. The major innovation of this study is that the proposed fusion approach involves a two-branch network with a deeper structure capable of separately capturing salient features of the MS and Pan-chromatic (PAN) frames. In addition, our network adopts residual learning To be meticulous research the relationship In all MS images of high and low resolution, Computational Efficiency Comparison It is clear that Remote Sensing Image Fusion With Deep Convolutional Neural Network (RSIFNN) running speed is only slower than Wavelet Transform (WT)and much faster than Convolutional Neural Network (CNN) based Pan-sharpening (PNN) or deep learning based Super-Resolution Convolutional Neural Network (SRCNN), indicating small kernel size computing efficiency, In the test phase. Comparison of various fusion approaches running time Sparse Representation (SR) ~20 min, Bayes SR ~10 h [15]. So the If you don't have a good Graphics Processing Unit (GPU) they are quite slow to train for complex tasks and they use to need a lot of training data.**Hyper spectral and Multispectral Image Fusion via Deep Two-Branches Convolutional Neural Network, In 2018** Yong-Qiang Zhao, the **dataset** were taken The Air assault Visible / Infrared Imaging Spectrometer (AVIRIS) dataset and the Environment Map and Analysis Program (EnMAP) both apply the Hyperion-Sentinel data fusion approach to real space. By Building a deep CNN with two dedicated divisions to Hyper Spectral Images (HIS) ,And the characteristics of Multi-Spectral Images (MSI), we are proposing a fusion process with HSI-MSI. The extract features of each pixel spectrum in low-resolution HSI as well as its corresponding spatial neighborhood in MSI in order to leverage spectral similarity and fuse the MSI with the two CNN divisions. The extracted characteristics will then be concatenated and fed onto Fully Connected (FC) layers where HSI and MSI data could be fused completely. Our fusion result is found to result in competitive classification accuracy to both Support Vector Machine (SVM) and Canonical Correlation Forests (CCF) classifiers in SVM the two CNN is 0.86% and the CCF the two CNN is 0.47% [16] but this method is high expensive. **A novel convolutional neural network based fault recognition method via image fusion of multi-vibration-signals ,** In 2018 Huaqing Wang, the dataset were taken Voice and variable images, paper proposed a new, multi-sensor data fusion and bottleneck layer-optimized convolutional neural network Memristive Binary Convolutional Neural Networks (MB-CNN) approach for rotating machinery. It is suggested to use a conversion approach to translate vibration signals from multiple sensors to images that can combine data to achieve richer features than single sensor vibration signals The prediction uncertainty matrices of three CNN models are, the prediction accuracy of the single-channel sensor model is 81%, MB-CNN's prediction accuracy is 97.25%, which is much better than other models predictions. In the other two models of CNN [17], the disadvantage lack of performance under real-life conditions, limited usability (which mostly applies to wearable and smartphone-based fall detectors).**Multi-focus image fusion via morphological similarity-based dictionary construction and sparse representation**, in 2018, Guanqiu Qi1, the dataset is Variable images from Lytro 10 pairs of grey level images and 20 pairs of color images, the classified image bases are used by concept element analysis to establish corresponding sub dictionaries. All built sub dictionaries are merged into one dictionary of information. Compressive sampling matched pursuit algorithm is used based on a constructed dictionary to obtain corresponding sparse coefficients for origin object representation.Live box Max (L1 MAX) fusion rule first fuses the obtained sparse coefficients and then inverts them to form the final fused image, the relative increase in the rate of the suggested solution is convincing compared to the other four existing solutions. The rate of increase in all comparative solutions varies from 0 to 4.3 percent [18], so These methods generate blurred output that in effect affects image contrast.**Local binary pattern metric-based multi-focus image fusion,** In 2019, Weiling Yin, **data set** used Variable images " Lytro", a simple yet efficient multi-focus fusion method based on Local Binary Pattern (LBP) is presented to address these two challenges. Using the LBP metric, we calculate the consistency in our algorithm and construct the initial weight graph. And then the connected field decision strategy Connected Area Judgment Strategy (CAJS) is used to reduce the noise in the initial map, The results of the experiment confirm that perhaps the proposed algorithm outclasses government-of - the-art image fusion algorithms both in qualitative and quantitative assessments, particularly when dealing with low contrast and edges data environments. The objective performances it can be obviously seen that the Guided Filtering based Fusion (GFF) method and our LBP metric-based method beat the other two transition domain methods on all the metric. Compared with the GFF method, our LBP metric-based method has larger quality indexes for Quality of Marriage Index (QMI); and Average Gradient (AG) Some images. The QMI consistency index tests the similarities between images from the source and fused images. Which means our approach can effectively retain focused source picture knowledge from different databases. That index represents the edge information retention power. AG represents information about the edge of the picture. That means our system will effectively inherit the edge information[19],**They produce** rather long histograms, which slow down the recognition speed especially on large-scale face database. **TWO-STREAM MULTI-FOCUS IMAGE FUSION BASED ON THE LATENT DECISION MAP** , In 2019 Weihong Zeng, 39 pairs of multi focus image ,19 pairs of These are gray images from either the multi-focus image fusion dataset, other 20 pairs are RGB images from either the "Lytro" dataset, Focusing on learning the deep seated decision spatial map. The map of the decision shows the degree of each pixel centered. We using ResNet blocks to obtain object characteristics then combine low-level features with high-level semant data to increase the fusion efficiency, Boundary Finding (BF) has achieved the best performance and improvement over visually and metrically by 0.716 from other methods, as a result Comparison of results on all 39 images inside both datasets between our system as well as other methods. the fusion quality metrics calculated using QMI "Image Fusion Performance Measure" The third one is Information Entropy (IE) "Visual Information Fidelity (VIF)" The best result 1:192 0.712 7:401 0:888 [20], **sugge** that ResNet did not solve the vanishing gradients problem for very long paths.**Spatiotemporal Satellite Image Fusion Using Deep Convolutional Neural Networks** , in 2018 Huihui Song, Under the application background of massive remote sensing dataset, a novel spatiotemporal fusion method based on deep CNNs. We are building two five-layer CNNs in the training stage to deal with complicated correspondence issues and large spatial resolution gaps between The Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat images, The quantitative evaluations for the fusion results in terms of Root-Mean-Square Error (RMSE), Erreur Relative Global Adimensionnelle De Synthese (ERGAS), Structural SIMilarity Index (SSIM) and Spectral Angle Mapper (SAM) indicate that Spatiotemporal Fusion Using Deep Convolutional Neural Networks (STFDCNN) performs better than Spatiotemporal Fusion Super-Resolution (STFSR) in all fusion results bands [21], By conducting experiments on two datasets featured by spatial heterogeneity and temporal dynamics. **Remote Sensing Image Fusion With Deep Convolutional Neural Network ,** in 2018 Zhenfeng Shao,images the data set taken, Remote sensing object fusion Approach said that the spectral and spatial characteristics can be reliably extracted from source images. The key novelty of this study is that the suggested solution to fusion includes a two-branch network with such a deeper structure able to independently capturing salient features of the Multispectral (MS) and Panchromatic (PAN) frames, We review the Adaptive Intensity Huesaturation (AIHS), Wavelet Transform (WT), Sparse Representation (SR)+WT, Super-Resolution Convolutional Neural Network (SRCNN), Super-Resolution Convolutional Neural Network Gram Schmidt (SRCNNGS), CNN-based Pan Sharpening (PNN), and Remote Sensing Image Fusion With Deep Convolutional Neural Network (RSIFNN) methods on the photos, And the time it runs is transparent RSIFNN's running speed is only slower than WT and much faster than PNN or SRCNN, indicating small kernel size computing efficiency the running time of these methods are AIHS 2.902, WT 0.196, WT+SR 14.91, SRCNN -4.295, SRCNNGS 4.354, PNN 4.365, RSIFNN 0.655 [15], for better result Disregard that redundant information and only concentrate on the features that are important for MS image spatial resolution.**CNN – based multi-focus image fusion with light field data** in 2019 Zicheng Nian and Cheolkon Jung **,** the dataset taken for their ground truth Multi-focus image fusion is primarily investigated using display technology data and CNNs for network planning, using light field data. Followed the light field data to generate all-clear images & focus maps by refocusing. The proposed approach works better than the others in term of two metrics, our value of structure similarity metric is the same as the best results. This is because proposed method used light field data to generate precise focus maps with fusion at pixel level, particularly along object boundaries[22], there is no qualified dataset with focus images, all-clear images & focus maps. **Multi-scale convolutional neural network for multi-focus image fusion**, in 2019 Hafiz Tayyab Mustafa, state-of-the-art image fusion methods used, we are presenting a new approach for fusing multi-focus objects with Deep Learning (DL). Current approaches to Multi-Focus Image Fusion (MFIF) based on DL methods view MFIF primarily as a classification function. These methods use a CNN to identify pixels as focused or defocused pixels as a classifier. Nonetheless, due to the lack of marked data available for train networks, existing supervised MFIF DL-based models incorporate Gaussian blur in focused images to generate training data the The image's getting too dark or are too bright. Multi-Exposure Fusion (MEF) techniques are applied in this case for fusing images with varying exposure. MEF problem is similar to MFIF problem, excluding variable exposure to source images than variable focus. It is used for fusemulti-exposure photos to exploit the generalizability of CNN without fine tuning of already qualified network.That our proposed system successfully fuses variable images of the exposure. This proves that the CNN model is generic that can be used in digital photography image fusion applications[23], our proposed CNN model can be used in other image fusion applications like multi-exposure fusion and fusion of infrared and visible images, the aim to make our model more robust and generic which be applied to fuse more than two images. **Multi-focus image fusion with a natural enhancement via joint multi-level deeply supervised convolutional neural network,** in 2018 Wenda Zhao, the source image on Multi-Focus Images With Common Unfocused Areas (MfIWCUA) dataset used, a novel end-to-end multi-focus object fusion with a natural method of enhancement based on Deep Convolutional Neural Network (DCNN). Many end-to-end CNN architectures were planned and researched first, which are explicitly tailored to this mission. Based on the assumption that low-level extraction of features can capture low-frequency information, whereas high-level extraction captures high-frequency data effectively, we further combine multi-level outputs to isolate, fuse, and enhance the most visually distinctive features, to demonstrate our design's superiority; we provide Siamese Network (SN), Pseudo-Siamese Network (PSN), and Multi-Level Deeply Supervised Convolutional Neural Network (MLCNN) evaluation metrics. The number of layers in SN and PSN (8 layers) is the same as the number of Number Of Levels Convolutional Neural Network (NLCNN) rates, And other hyper-parameters are same, so different image fusion methods with consistency metrics on Multi-Focus Images With Perfect Registration (MfIWPR) = 11.8887 and Multi-Focus Images With Misregistration (MfIWMR) = 13.1836. In terms of all measurement parameters, MLCNN achieves better performance than SN and PSN [24]. It is suggested that the combination of multi-level features will improve image fusion quality and enhancement. In developing a more stable CNN-based fusion system, the emphasis will be on enhancing the efficiency of fusing multi-focus images with severe misregistration.**Image Fusion Using Convolutional Neural Network with Bilateral Filtering,** in 2018, P. Mathiyalagan Suvitha N, the method Lytro dataset taken, to derive data from the two source images from the high frequency.A focus map is developed after multiple convolution as well as max-pooling layers which contain the data on both the source image clarity. A fixed threshold is added to the target map to construct a binary segmented map, which correctly classifies that pixels belonging to a centered regions. Binary segmentation results involve some misclassified pixels that are improved by using a broad area elimination technique to get the initial map of the decision Quality evaluation metrics Fused Image use Bilateral Filtering Structural SSIM: 0.568767, Standard Deviation (STD): 1.48814, Edge Strength (EI): 47.5367, Average Gradient (AG): 2.97405[25], we remember Fused image focusing on all parts of a single image can be applied to various fields such as medical diagnosis to detect tumors and to look for a detailed representation of tumors. **Convolutional Neural Network Based Multi-Focus Image Fusion,** in 2018, Huaguang Li**,** the dataset were taken VCO2012 datasets**,** the emphasis is mainly Use CNN to boost the clarity of both the multifocal picture and the fusion effect. First, set up a collection of image data for objects and assign mark tags to the dataset for binary objects. Using the CNN network to then train the datasets that have been established, The article also includes IE, Average Gradient (AG), STD, Spatial Frequency (SF), The experimental results were four objective indices for evaluation of the suggested algorithm below for DWT 7.0576IE, 3.4230 AG, 41.0685 STD, 8.2859 SF, to make it more intuitive, the bar graph is included, the IE algorithm can be seen in this paper Is considerably higher than other algorithms. Hence, this algorithm's fusion is stronger [26], Rich contextual knowledge in a fused picture, fusion quality is good than most other state-of **-** the-art methods both for subjective and objective assessment, but not enough.

Multi-scale Visual Attention Deep Convolutional Neural Network for Multi-focus Image Fusion, in 2017, Rui Lai, the data set were taken “Lytro”, The innovative Deep Convolutional Neural Network (DCNN) multi-focus fusion unit Introduces a Multi-Scale Feature Extraction (MFE) device to capture as well as fuse more compatible features from various spatial scales into a more spatial data. The framework is designed to help the network identify the targeted region more reliably and select more useful features for piecing the information perfectly throughout the fusion process. Experimental findings show that the proposed system exceeds most existing multi-focus image fusion methods in terms of both subjective special effects and objective output measures, we compute cost comparisons on the dual-focus image fusion task (520*520) and then list the findings in process parameters CNN 4.93, Ensemble Convolutional Neural Networks (ECNN) 1.58, Multi-Scale Visual Attention Deep Convolutional Neural Network (MADCNN) 0.17 as can be seen, CNN and ECNN patch-based methods need to recurrently calculate the Repair and consume enormous computing ressource. The MADCNN method, on the other hand, significantly outperforms the other methods based on deep learning in computing and model parameters. The MADCNN needs the Shortest running time to fuse the dual-focus image that benefits from either the lower complexity of both the model[27], so our model can be optimized and computational load minimized by using the newly proposed parallel depth with better real-time efficiency with low power consumption. **Brain CT and MRI medical image fusion using convolutional neural networks and a dual-channel spiking cortical model**, in 2018, Ruichao Hou1, Computed Tomography (CT) and MRI medical images dataset used, Models a novel fusion approach based on CNNs and a dual-channel Cortical Spiking Technique (DCSCM) of clinical images through CT and MRI. Only, Non-Sampled Shear Let Transformation (NSST) is being used to decompose the source image into a coefficients of low frequency and a range of coefficients in frequency.Additionally, the low frequency coefficient is fusion by the CNN model, in which the weight map is generated by a series of feature maps as well as an adaptive selection law, and afterwards the high frequency coefficient are fused by DCSCM, where the frequency input stimulus adopts the modified average gradient of both the high frequency frequencies.Eventually, the fused image is replicated by the reverse NSST; the results are more helpful to assist doctors in accurate disease diagnosis dependent on the proposed procedure. The deep learning scheme are currently implementing to extract multiplayer functionality and generate the low-frequency fusion weight that achieves great performance, However, the choice for deep features is also based on the theory of artificial design[28], this approach is complex throughout the algorithm of fusion. Strong fusion technique needed for better outcome. **Panchromatic and Multispectral Remote Sensing Image Fusion Using Particle Swarm Optimization of Convolutional Neural Network for Effective Comparison of Bucolic and Farming Region,** in 2018, P. S. Jagadeesh Kumar, dataset taken is containing 50 panchromatic image and 50 multispectral image from various sensors like Worldview, Emphasizes the integrated combination of high-resolution panchromatic and low-resolution multi-spectral images with particle swarm optimization of the CNN in the bucolic and agricultural groups. For assess the eminence of the fused objects with and without the reference object, qualitative and quantitative analysis methods were used. The practical consequences show that, the test results indicate that assessment metrics have been found to be important and quantitative analysis is the best way to simulate and evaluate the entire dataset for the performance of the optimized fused picture. Concerning the overall accuracy and kappa index, the comparison of bucolic and farming region is evaluated The ROI-based quad tree classification of bucolic and farming region demonstrates higher efficiency both in terms of overall accuracy and kappa index, which clearly and accurately represents the farming area, road map, bucolic region and land cover [29], Although the proposed fusion framework provides higher precision and productivity, it suffers from halfway hopefulness and can't work out the issues of scattering**. Robust Sparse Representation Combined With Adaptive PCNN for Multifocal Image Fusion,** in 2018, YONG YANG, used data from Lytro dataset, a Robust Sparse Representation (RSR) and adaptive Pulse-Coupled Neural Network (PCNN) The image fusion process is described as multi-focus. In order to obtain a sparse matrix of coefficients and a residual matrix, each source image is rest decomposed with RSR. Second, the spatial frequency of the residual matrix is measured as the incentive for PCNN neurons, and an origin object salience map is suggested as the PCNN's adaptive linking force. Through comparing the ignition frequency maps of the origin images obtained via PCNN, the initial decision map is acquired. Then, through morphological opening and closing operations, the nail decision map is achieved. Lastly, the image is fused obtained by employing a weighted fusion rule [16], the disadvantage is must will focus on improving the efficiency of the method.**Diagnosis of Diabetic Retinopathy Using Deep Neural Networks**, in 2019, ZHENTAO GAO1, the method used Methods to Evaluate Segmentation and Indexing Techniques in the field of Retinal Ophthalmology (MESSIDOR) dataset, Diabetic Retinopathy (DR) in patients with diabetes is a common eye disease and a sign cant cause of blindness. The most effective way to manage the disease is routine screening with fundus photography and prompt intervention. The large population of diabetic patients and their huge screening criteria has generated interest in computer-aided and fully automatic DR diagnosis. In recent years, on the other hand, deep neural networks have brought several breakthroughs in different tasks. To automate the diagnosis of DR and provide DR patients with suitable advice, we have produced a database of DR fundus images that have been marked with the proper treatment method provided [30], so It is possible to increase the ratio.**Multimodal Medical Image Fusion based on Deep Learning Neural Network for Clinical Treatment Analysis**, in 2018, B.Rajalingam and R.Priya, dataset was taken CT, MRI, and Positron Emission Tomography (PET), to create a weight map that incorporates pixel movement data from two or more multimodality medical images, a Siamese CN is adopted. In order to be more reliable with human visual insight, the medical image fusion process is carried out multi-scale through medical image pyramids. In addition, for the decomposed coefficients, a local comparison-based strategy is applied to adapt the fusion mode. An experimental outcome of the fusion techniques proposed provides the best fused multimodal clinical images of the highest quality, the shortest processing time and the best representation in terms of both visual quality and objective assessment criteria [31],To achieve perceptually good results, some popular techniques in medical image fusion is proposed. All these advantages the proposed method is a good choice for several applications.**Training Neural Networks to Pilot Autonomous Vehicles: Scaled Self-Driving Car,** in 2018, Recommended Citation Chang and Jason Zisheng, 8-Track dataset taken, explore the use in autonomous cars of Deep Convolutionary Neural Networks (DCNN). There are many social benefits to the successful execution of autonomous vehicles. One of the main nulls is its potential to reduce track accidents cantle [32] , Light reactions may confuse the network with incorrect angle production. Diversity and quantity of learning data may be enhanced by additional research.**A Study and Evaluation of Transform Domain based Image Fusion Techniques for Visual Sensor Networks**, in 2015, Chaahat Gupta, Variable images "Lytro" used, Evaluation of various techniques for image fusion. There are many techniques for image fusion that have been developed in several applications , By reviewing the literature review, it was found that in most of the existing works on fusion, the issue of uneven illumination was also ignored [33], So can use MATLAB tool for implementation of our proposed work. **Comparative Study on Multi-focus Image Fusion Techniques in Dynamic Scene** , in 2015, Rajvi Patel Research Scholar, Various traditional strategies of multi-focus image fusion and maybe some novel techniques of multi-focus image fusion are studied, Describes how image matting can be applied to multi-focus image fusion. We can use the Rough-Fuzzy C-Means (R-FCM) method to improve the process of fusion of multi-focus images. By implementing enhanced R-FCM method to fuse multi-focus images in the

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dynamic scene, we can extend this work [34], can extend this work by implementing enhanced R-FCM method to fused Multi-Focus images in Dynamic Scene. **Modified primitive image fusion techniques for the spatial domain**, in 2015, C. Morris, R.S, dataset taken Variable images "Lytro", Comparative analysis and adjusted spatial domain approach were provided by setting pixel contrast values Between average -minimum as well as the average-maximum fusion performance, applying a Simple max 0, mid-max 39, average 79, mid-min 118, min 158 and PCA 77 means that the mid-min and mid-max fused image provides higher information than that of the fused image provided by the simple max, average, min and PCA scheme. With the support of the metric[35], it can be checked Compare with more advanced techniques.**A Novel Architecture of Medical Image Fusion Based on YCbCr-DWT Transform,** in 2018,Behzad Nobariyan, Single-Photon Emission Computerized Tomography (SPECT) and MRI images fusion dataset, Photon PET image shows the function of the brain and SPECT Illustrates local performance of internal organs including cardiac imaging as well as brain imaging. These two images were multi-spectral and have poor spatial resolution. The MRI image displays brain tissue structure and provides no functional information. A fusion scheme should preserve the source multispectral image's spectral characteristics as well as the source panchromatic image's high spatial resolution characteristics. There are many photo fusion techniquesYet any one of them has certain limits. The studies showed YCbCr where Y is really the luma component and in which CB and CR are the blue-difference and red-difference chroma elements, retains spectrum information without distortions based on the results of fused image analysis and tables presentation, the average of the datasets is given in IHS 18.872, YCbCr 13.042, Brovey 9.626, Laplacian 9.026, Contour 8.893, DWT 6.99 For both the evaluation for fused image output by average gradient, that spectral fusion output and the total fusion based on performance on entropy and Mutual Information (MI) have the greatest value in the entire proposed process, which is optimal for these tests. [36], very small disadvantage of both the number of images.

A Novel Utilization of Image Registration Techniques to Process Mastcam Images in Mars Rover With Applications to Image Fusion, Pixel Clustering, and Anomaly Detection, in 2017, Bulent Ayhan, 500000 images in National Aeronautics and Space Administration (NASA) planetary data system database , Applied to a collection of Mastcam stereo images. And use more than 100 pairs for Mastcam images, selected from more than 500,000 images in NASA's Planetary Data System database, the outcome of the two-step alignment method showed clearly that the fused images would boost pixel clustering and identification efficiency. In particular, the application of alignment method detects registration errors at the subpixel stage comparison of averaged Gaussian Mixture Model (GMM) Clustering of findings across all Pan sharpening to various cluster validity indicators using Band-Dependent Spatial Detail (BDSD) Silhouette 0.605, pan sharpening using Partial Replacement Adaptive component substitution (PRACS), The Gap statistic is a standard method for determining the number of clusters in a set of data (Gap)2.624 the results of the fused data via BDSD and PRACS pan sharpening produce less noise [37], They are considering automating the two-step alignment method, so that several Mort am stereo images and MS image cubes could be processed. **Performance Analysis of Image Fusion Techniques to Improve Quality of Satellite Data**, in 2017, Bin Yang and Jinying Zhong, taken Lytro dataset , Presents a novel multi-focus object fusion and super-resolution approach through the CNN. The first-level network features of various source images are fused from the source images with the local clarity guidance. With the reconstruction network filters, which act as averaging filters, the final high-resolution fused image is obtained. The experimental results show that the proposed method can produce the fused images with better visual performance and computational efficiency than other state of the art works [38].

Combining Multi-Modality Medical Image Fusion Based on Hybrid Intelligence for Disease Identification, in 2018 Rajalingam, MR and SPECT Image dataset used, Combines a Discrete Cosine Harmonic Wavelet Transformation (DCHWT) with a Neural Pulse Coupled Network (PCNN) for the fusion process. Experimental results show that MRI, positron emission tomography and single photon emission computed tomography can be obtained by the proposed method. Many performance metrics are used to test hybrid fusion algorithms. The proposed experimental results indicate the superior processing efficiency in both subjective and objective evaluation criteria relative to other current techniques the performance metrics production measured results in the superior performance value in bold in each column. The graphs shown in for all the results of the proposed technique surpass the current techniques for all the performance metrics. Method metrics DCHWT AG 0.0735 PCNN AG 0.0881 [39], It is possible to suggest other types of medical or different dataset variety.**Image Style Transfer Using Convolutional Neural Networks,** in 2016, Leon A. Gays, texture recognition and artistic style classification dataset, using CNN image representations designed for object recognition that make high-level image information clear. We introduce an artistic style neural algorithm that can separate and recombine the content of natural images and their style. The algorithm allows us to create new high perceptual quality images. Which combines the quality of an arbitrary image with the presence of several famous photographers works of art Visual representations enabling the isolation of visual quality from style to some extent at least. One theory may be that the network must become invariant to all object variance which maintains object identity when learning object The main finding of such a paper is that the CNN material and design representations are well-separable. This is, Can independently modify both representations to generate new, spatially meaningful images. To illustrate this finding, Generate images from two separate source images which mix content & style representation[40], the noise is very common and seems to imitate system filters in the network. Therefore, powerful demising techniques could be built after the optimization procedure to post-process the images. **Decision level based Image Fusion using Wavelet Transform and Support Vector Machine,** Kolekar 2016, used different sets of multimodal images, the fusion methods for integrating infrared images with visible spectrum images are highly focused on monitoring and remote sensing applications Decision level-based image fusion using Shift Invariant Discrete Wavelet transform and SVM is shown here. WT shift invariance is important to ensure robust sub-band fusion. SVM is trained to select from the Shift Invariant Discrete Wavelet Transform (SIDWT) coefficients the coefficient blocks with significant features experiments for the source images shown were conducted with different block sizes. It is observed that the quality metric increments and the execution time decreases as the block size increases[41]**,** so Compare The SIDWT with other ways to find wider results .**Random forest-based scheme using feature and decision levels information for multi-focus image fusion,** in 2015, Nabeela Kausar and Abdul Majid. The generic images of ,Boat,Barbara,Elaine , Lena and Cameraman are aggregated to create a more precise fusion decisions map, respectively, with projected trees. Our proposal scheme produced a stronger-fused image than the fused image created by primary member analysis and previous Wavelet-based approaches to transform using basic descriptions on function level. Our method has, nevertheless, produced better fused images than individual Machine Learning approaches based on SVM and Probabilistic Neural Network (PNN). Various qualitative and quantitative measures are used to assess the performance of the suggested scheme the proposed scheme has significantly higher PSNR values for Cameraman and Lena pictures, respectively, of 41.39 and 42.74. Nonetheless, wavelet four-band approaches, wavelet vector, and Wavelet multi-band approaches give relatively lower PSNR values for these images. Likewise, the suggested scheme received higher MI values than wavelet's four-band methods, wavelet's vector, and multi-band vector. For same images, the proposed strategy yielded the lowest RMSE values of 2.16 and 1.79. On the other hand, recent approaches based on Wavelet Gives relatively low values of RMSE for these pictures. So far as MI is concerned, our proposed scheme have provided rather good results than previous fusion approaches[42], and we plan to expand our research to medical image fusion.

Multispectral MRI Image Fusion for Enhanced Visualization of Meningioma Brain Tumors and Edema Using Contour let Transform and Fuzzy Statistics, in 2016, Subhranil Koley, MR image dataset, proposes a multi-spectral MRI image fusion scheme to better visualizations of MeninGioma (MG) brain tumor structural and pathological data incorporating contour let transformation and fuzzy statistics, Average Jaccard score of 0.88 with standard distribution of 0.05 and mean Dice score of 0.93 with standard deviation of 0.03 was obtained. The proposed methodology is applied to five various combinations (such as T1-weighted and T2-weighted, T1 post-contrast and T2-weighted etc.) generated from four modalities of MRI images (T1-weighted, T1 post-contrast, T2-weighted, and Fluid-Attenuated Inversion Recovery (FLAIR)). This statistical research shows that the identification of a full tumor region can be accomplished from the fused images (combination T1C-T2) obtained use the technique proposed. [43], throughout terms of quantitative analysis and radiological importance, the new approach outperforms the conventional methodology and some current medical image fusion techniques. **ImageNet Classification with Deep Convolutional Neural Networks,** Krizhevsky 2012, dataset used Image Net, the neural network, with 60 million parameters and 650,000 neurons, consists of five convolutionary layers, some of which are accompanied by max-pooling layers, and three fully connected layers with a final softmax of 1000-way. We used non-saturating neurons and a very successful GPU implementation of the convolution process to make learning faster appreciably, the results. Our top-1 and top-5 error rates on this dataset are 67.4 percent and 40.9 percent, reached over the last pooling layer by the net described above but with an added, sixth convolution layer. The best results published on this dataset are 78.1% and 60.9%.23 [44], use other methods of CNN to get more extensive results. **Multi-focus image fusion based on sparse feature matrix decomposition and morphological filtering,** Li 2015 Electronic and Information Engineering, Lytro dataset taken, Based on composition of a sparse matrix function and morphological sorting, a novel multifocal object fusion me the disoriented. First, by decomposing multifocus images, the sparse feature matrices of the original multi-focus images are removed. Second, it obtains a temporary matrix through measuring the matrices sparse with a key function so that original images are extracted. Eventually, Importing the derived characteristics into the base image which again is created by weighing the imaging source, the final result of fusion is produced Our process runs its time is 4.13/89.84 = 4.60% that of Robust Principal Component Analysis (RPCA) + Energy Of Laplacian (EOL) + PCNN. All experiments are performed on an Acceptable Macronutrient Distribution Range (AMDRS) 780 desktop running Windows XP [45], The proposed method can be extended to other forms of fusion activities, such as fusion of the infrared visible image. **A Medical Image Fusion Method Based on Convolutional Neural Networks**, in 2017, Yu Liu, the dataset is pair of computed to CT and MRI, This proposes a method of clinical object fusion based on CNNs. To generate a weight map that integrates the pixel activity information from two origin images, a Siamese convolutional network is adopted in our system. In order to be more compatible with human visual experience, the fusion process is performed in a multi-scale way by object pyramids the result Method Nonsubsampled Contourlet Transform (NSCT) 15.8 – Primary Care Development Corporation (PCDC) 46.3, Simultaneous Orthogonal Matching Pursuit (SR-SOMP) 0.06 , Guided Filtering (GF) 12.1 proposed 0.08 [10], the disadvantage use a few images from the same source . **Multispectral and Hyperspectral Image Fusion Using a 3-D-Convolutional Neural Network,** Palsson 2017, the HyperSpectra

(HS) image used in the experiments is the Reflective Optics System Imaging Spectrometer (ROSIS) pavia center data set, propose a method to combine multispectral And HS images that use a 3D CNN to get a high resolution image. The HS picture is reduced in Dimensionality before fusion to reduce the processing time significantly and make the process more resilient to noise The results for the Error Relative Global Adimensionnelle De Syntheses (ERGAS) and Spectral Angle Mapper (SAM) metrics calculated methods are summarized in ERGAS Bicubic, Both the comparison models were based on the calculation of wavelet coefficients by Maximum A Posteriori (MAP), while the MAP2 method is identical to MAP1, except for the reduction in PCA dimensionality, similar to the method proposed (MAP1 2.86, MAP2 2.170, three dimensional (3D)-CNN 1.676), ERGAS Bilinear (MAP1 3.080, MAP2 2.233, 3D-CNN 3.104), ERGAS Nearest (MAP1 5.680, MAP2 5.234, 3D-CNN 5.234) Decimation provides Best outcomes for all strategies as per bicubic. System efficiency using bilinear degradations in terms of ERGAS and SAM metrics, but the proposed method and MAP2 are less affected than the MAP1 method. Finally, for MAP1 and MAP2 methods, nearest neighbor decimation reduces the performance significantly more than the proposed method when compared to the results obtained using bicubic decimation [46], The method suggested is compared to the number of methods based on MAP estimation for better result.**Multi-focus Image Fusion Based on the Improved PCNN and Guided Filter**, in 2016, ZhaobinWang, Lytro dataset used, A novel PCNN and directed filter object fusion system. PCNN is very well suited For visual perception in humans. And Guided Filter is also an edge-conserving filter proposed over the past few years. The fusion process consists of the following steps in our method: first The source images being preliminarily blended with the directed filter to compare the fusion results, three objective criteria are used. Mutual information (MI) is the first criterion. It is a metric defined between each input image and the fused image as the sum of mutual data. The second criterion is the QAB / F metric, which takes into account the sum of edge information transmitted to the fused image from the input images. This method uses a Sobel edge detector to measure in both origin and fusion images strength and orientation information at each pixel. The objective criteria for mutual knowledge (MI), QAB / F and The Structural Similarity Index (SSI) are compared Time consumptions are contrasted with all the experimental methods. On even a desktop computer fitted with an Intel Quad- Core i5 3.3 GHz CPU & 6 GB memory that run times for these methods are calculated. The findings are published in Disk Our method Clock 0.9798, Newspaper 0.1683, Cell 0.2264, Magazine 0.4890, Leopard 0.2247. It can be shown that the computational complexity of system is lower than the Q system, but algorithm needs to spend more times than other approaches, such as m-PCNN as well as the Global Financing Facility. Still have a lot of work to do to reduce the computational complexity. Firstly, our approach is applied to the GFF.This means method's computational complexity is significantly higher than that of GFF. [47]There needs to be a more time-saving preliminary fusing process. In addition, the code can also be further optimized.

A novel improved deep convolutional neural network model for medical image fusion, in 2018, Kai-jian Xia1, the CT and MR images dataset, A novel fusion scheme for muti-modal clinical objects using both multi-scale transformation functionality and a profound convolution neural network. Next, the source images are decomposed Gauss-Laplace filter and Gauussian filter into multiple sub-images in the first layer of the network. Human embryonic kidney (HeK)-based approach is then used to initialize the remaining layers of kernel convolution, construct the basic unit and then use the back propagation algorithm to test the basic unit, the approach proposed as approximately 6.62, 6.07, 5.1, 4.56, 3.74, 2.08, 1.16 and 3.14 percent. Superior to other approaches. Such findings mean that the fused images obtained by the method generated provide more details than others. The increased value of the MI and SF metric of both the fused images provided by the proposed method ensures more information preservation and increased operation and clarity in a the fused images. Superior to other approaches. Such findings mean that the fused images obtained by the method generated provide more details than others. The increased value of the MI and SF metric of both the fused images provided by the proposed method ensures more information preservation and increased operation and clarity in a the fused images. This achieves roughly 11.73, 7–11 and 4–5 percent higher SF values than the process of fusion based on Discrete Cosine Transform Wavelet Transform (DTCWT), NSCT and NonSubsampled Shearlet Transform (NSST). It also has 26.9% and 1.44–26.21% higher MI values than fusion process based on Heterogeneous Convolutional Neural Networks (HCNN) and Anatomically Constrained Neural Networks (ACNN), respectively. Therefore, Based on the quantitative & visual results review, it will be observed that perhaps the proposed fusion algorithm outperforms the others by generating fused images with good quality with much more details and edge information present throughout the source image[48], should concentrate on improving the fusion rule in order to create an efficient multi-modal fusion for images.**Image Fusion and Super-Resolution with Convolutional Neural Network,** in 2016, Jinying Zhong, the dataset used medical images, and the Near-Infrared (NIR) and Visible Light (VL) images, The suggested input images were broken down onto Undecimated Wavelet Transform (UWT) coefficients, which are enhanced with CNN resolution, and a new joint image fusion and super-resolution algorithm. Instead, with some fusion law, the coefficients are further combined. Finally, from the combined coefficients, the fused image is constructed, through CT and MRI image fusion; the proposed method can also work well and obtain appropriate and sufficient data To be treated. The first case subjective evaluation and the suggested approach is and the right to summarize the objective assessment of different methods of fusion of CT and MRI, Due to the low frequency fusion approach, the CT picture shallows the approach. The fused picture of the proposed method provides better edge and texture information than other four comparative methods.The proposed method generally performs the fusion of CT and MRI, the objective evaluation of NIR and VL image fusion in two cases and the proposed method is shown in the Super-Resolution (SR) followed by fusion NSCT 0.5058, Stationary Wavelet Transform (SWT) 0.4935, dual tree DTCWT 0.4450, Guide Filtering Fusion (GFF) 0.4673, DTCWT 0.4450, GFF 0.4673, Which endorses subjective outcomes. [49] Better fused results will be given by a more rational fusion strategy for LFC sub-images. Further study into the efficacy of both the proposed method for other similar image fusion tasks is worthwhile.

IV. Image fusion Models

There are three types of fusion image models provided in **Figure 3**

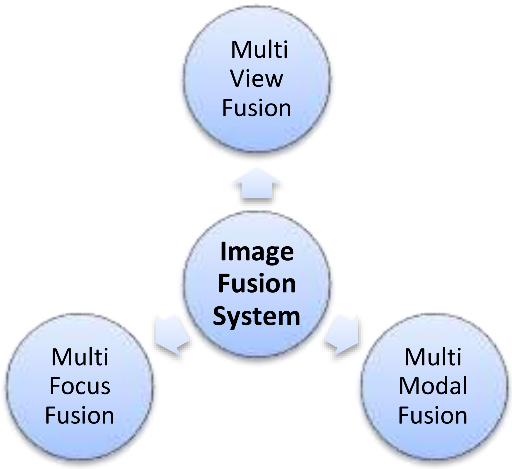

Fig.3 **Image fusion Models**

4.1 Multi View Fusions

The multi-view fusion approach has the characteristic of integrating 3D equivalent value data with corresponding samples by beginning various viewpoints within the resulting single image[50].

4.2 Multi Modal Fusions

Different models being merged and fused onto one image for multimodal image fusion [51].

4.3 Multi focus fusions

The fusion technique of multi focus objects merges and blends essential information and features for two or more images in to a single image resulting in centered image[(Huang)].This means that there is a proper focus for every function or element in the output image [52].In a situation where one site includes a variety of drugs, the camera could be dedicated one after the other to each piece of information within the image, creating a group of images[53]. Then, a picture with superior emphasis over the whole area could be created by means of image fusion.

V. Basic Image Fusion Steps

In the image fusion process there will be three essential steps that are done[54]. These steps are shown in Figure 4.

Fig 4. Basic Image Fusion Steps

5.1 Image Registration

The image logging process aligns the sequence of images to correctly overlap the related features and details[55].

5.2 Pre-Processing:

The fundamental goal of this stage in the image fusion process Will be to make images more acceptable for the fusion algorithm [56].

5.3 Post-processing:

This stage depends fundamentally on the form or classification of display used in the process of fusion. The quality of this system is a human operator's tendency [56].

VI. Image Fusion Classification

Methods of image fusion could be divided through two major domains including [57]

• Spatial Domain Fusion

• Temporal Domain Fusion

6.1 Spatial Domain Fusion Methods:

A process of Spatial Domain Fusion appears in Figure 4. Here is a brief description of each process within the system class of spatial domain fusion.

6.1.1 Brovey Transformations

The brovey transformations accomplish the task for image fusion through taking into account a chromaticity transformation factor[58]. Programs whereby images are also to be fused in to a single composite image by using various sensors to take the image sequence are regarded as the easiest and perhaps most appropriate solution.

As for a case such, three bands are limited, so Brovey Transformations (BT) aims to standardize the different spectral That is, 3- Dimensional RGB screen bands. Such a condition is another explanation why BT is the most appropriate form.

Apply the dimension of brightness and intensity to a resulting fused image using a anticipated data to multiply the result[59].

6.1.2 High-Pass Filtering (HPF)

High-resolution panchromatic images(HRPI) and low-spatial resolution multispectral Images (LRMIs) were the two key factors in the above regard, as they can be combined for acquire the HRMI factor[60], this feature is the fundamental and essential objective for high-pass filtering in a the image fusion process.Basic workflow for HPFs is acquiring high-frequency information. Such data is projected through the filtration process where the HRPI is filtered with a high pass filter. Through subtracting the Lembaga Riset Perkebunan Indonesia (LRPI) from the native HRPI, the same process can be done.The method provides the benefit of retaining the image's 3-dimensional characteristics. The explanation is that because it includes the high frequency picture dataThe spectral and spatial domain information are associated or identified in the high and low frequency data[61].

6.1.3 Principal Component Analysis (PCA)

PCA is a computational Approaching uses orthogonal-based transformations. The Orthogonal function results in a collection of the acquired linear values from conceivably related variables by transforming a group of opinions. The acquired linear values are also referred to as the main Ingredients. The proportion of all these principal components must be equal to or less than the initial Variables inside images PCA is the easiest and simplest form in the possibility of multivariate analysis [62].

6.2 Temporal Domain Fusion Methods

In the Figure 5 shows a complete and detailed Temporary Domain Fusion Process [63].

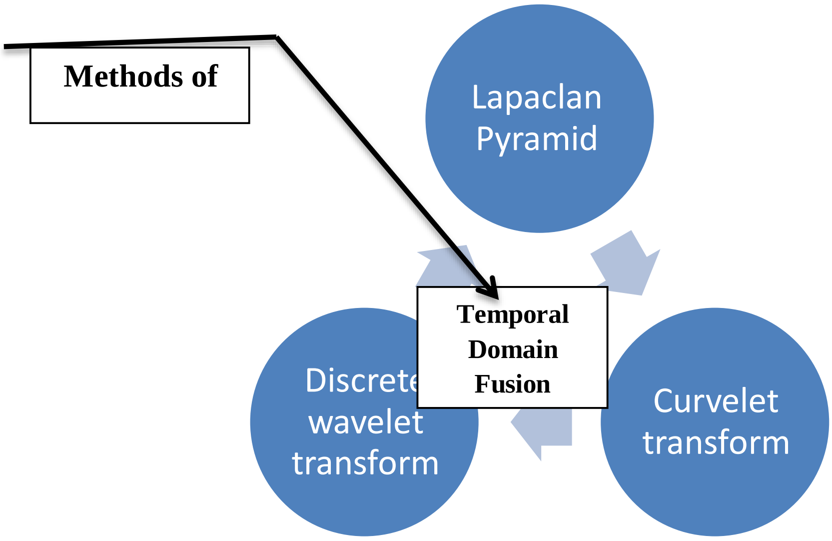

Fig 5. Temporal Domain Fusion Methods

Below is a brief description of every fusion cycle in the temporal domain method class.

6.2.1 Pyramidal Method

Under umbrella for an image-fusion temporal system,the Triangular method uses a data structure consisting of a band pass series or the original image's low pass copies. In a such a scenario, each copy presents statistics of various scales. The benefit of such an approach is that it results in a strong, smoother and more attractive and sharp contrast picture while maintaining the basic and important characteristics of an objects On one sequence of images [64].

6.2.2 Laplacian Pyramid

When talked about the pyramid of images discussed that basically consists of bands copies and low pass filters from each band presenting different image level and scale data. In a the case The Mass of a Pyramid decreased in steady phases. Another one characteristic of the pyramid is that it is the blurred copy of its previous image in a series of images. The resulting image shows the image With native image equivalent at a the lowest size. The lowest-level picture contains information of the high quality [65].

6.2.3 Discrete Wavelet Transform Method

The DWT's basic function is the discrete sampling of wavelets. The advantage this strategy provides is its propensity to favor temporal resolution handling[45]. Another significant advantage DWT provides is that together with the specifics of the frequency variable, it includes location information. DWT's technology scope is broad enough to cover areas like math, engineering, robotics, and computer science. DWT's other big application is in the field of signal processing [65].

VII. Conclusion

The aim of this survey is to collectively examine the basic image fusion process with its categorization, based on its modal systems and algorithms. The analysis showed that tremendous research has been done throughout the field of image fusion, but there's still considerable scope for new and creative research in this process. The research has shown that every algorithm has its strengths and weaknesses. An analyst can clearly observe that no technique of image fusion is superior to another; the selection and the effectiveness of a particular method depends on its implementation. According to research point of view, it can be concluded that PCA-based image fusion techniques result in a better-enhanced image without altering the spatial and spectral information of the image. The wavelet-based methods are used in applications where original values of RGB components are to be preserved are suitable. And approaches based on wavelets lead to less distortion of the image.

Eventually, documented transformations led to clearer pictures, but changed the Initial image colors by rendering dark image areas lighter and white in the resulting image region whiter

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