THE FUSION OF MICROWAVE AND OPTICAL REMOTE SENSING DATA BY DISCRETE WAVELET APPROACH

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Abstract: **The merging of images obtained by satellites through remote sensing has evolved into an established protocol. In popular parlance such blending is known as image fusion. This is done chiefly because it gives myriad advantages. Image fusion comes in extremely useful in the observation, study and analysis of diverse fields, including environment, agriculture and other related areas. In essence, what happens in image fusion is that the needed data or information is gleaned from numerous images. These images then are coalesced to form fewer pictures. The ideal, of course, is the blending of them into a lone picture. This is highly sought-after because the image thus intermingled is said to contain all relevant data and, moreover, is more suitable and error-free than an image secured from one single source. Needless to say, it also incorporates all the information that is needed. Besides this, there are other benefits. For one, it curtails the volume of data. For another, it produces images that are pertinent and apt. The chief objective of this paper is to shed light on the fusion between the capabilities of optical and microwave satellite images and to improve the visible quality of Landsat image.**

Keywords: Image Fusion; Remote Sensing; Satellite Images; Wavelet Transforms; Image Processing; Landsat; Sentinel; PSNR; Estimated Parameters; Quality

I. INTRODUCTION

Remote sensing has revolutionized the way humans gather information. In remote sensing information about an item is culled out of interpretation and analysis done at great distance away from the item. This is because the sensors recording the information are far removed from the item and do not have any truck with the item being recorded. Remote detecting, basically, is used to look at our planet and for the purpose of studying it. Remote detecting acquires information relating to the world's surface structure and its various features by collecting and interpreting spectral calculations executed from far afar[1]. This is what remote sensing is chiefly about. The earth emanates dissipated/reflected or self-created electromagnetic energy in differing wavelengths bands, which help facilitate their recordings. Remotely sensed information is provided in spatial, temporal, spatial and radiometric modes. The information gathered through remote sensing usually comes in the form of images[2].

In remote sensing electromagnetic radiation serves as a conduit for transmitting information. The information relayed by the remote sensing apparatus invariably comes in the form of images. [3] Any area that is being observed has resolution, which corresponds to the information secured[4]. The images are dependent on the sensors being used, which are equipped with diverse resolutions. Also, pixels can be seen in different, scattered portions of electromagnetic spectrum[5]. That's why, images that are remotely gathered display varying resolutions of the spectral, spatial and temporal types.

Since the information gleaned from remote sensing is in the form of images, the information may not always be clear or appropriate. This has given rise to the solution of image fusion.

In essence, image fusion is a method of amalgamating several images that are secured into a single unifying picture. [6] This unified picture tends to carry improved or better delineation of the recorded scene than any lone input picture[5]. Image fusion mainly serves two main purposes. Firstly, to curtail the volume of data[7]. And secondly, to create images out of the fusion of two or multiple images that are more suitable and discernable by humans. [8]Electromagnetic radiation in the microwave wavelength region is used in remote sensing to provide useful information about the Earth's atmosphere, land and ocean (SAR, RADAR, ERS-1,JERS-1)[9][10]. Optical remote sensing makes use of visible, near infrared and short-wave infrared sensors to form images of the earth's surface by detecting the solar radiation reflected from targets on the ground (MSS, HS, TM, LANDSAT, PAN) [11].

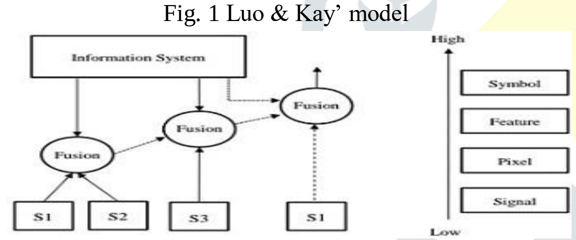
This paper comprises five sections. The current literature about methods of image fusion is reviewed in brief in Section II. Section III delineates the methodology. Section IV displays the result parameters and Section V, the conclusion.

The radars excel in disseminating all kinds of information. [12] For instance, sensors that deal in data fusion offer complementary information for the targets' behaviour analysis. In this environment, each sensor offers surveillance and makes independent measurements and reports it to the sensor's central processing node. The central process node of each sensor measures the parameters (target signature and target state parameter) and processes the decision and reports it to the fusion node. [13] In the fusion node, the 'Multi-sensory Fusion Radar' and infrared camera are employed as the data collective sensors.

II. LITERATURE REVIEW

Various researchers have been working on different data and image fusion methods. This paper takes note of some of the findings of a few of these efforts. The study of F. Chen et al. [14] advanced an improved merging technique incorporating use of a wavelet decomposition which secures detailed information of PAN images. The research of M. Ghahremani et al. [15] suggested both CS and MRA methods could be modelled through an injection scheme. Most of the methods relying on Multi-Resolution analysis take recourse to a variety of transform**.** Meanwhile, S. A.Valizadeh et al. [16] have suggested an image fusion effort based on an ICA and curvelet transform, as well as using a blending of curvelet transform and IHS. J. Rashidi et al. [17]. talk about the combined measures approach which serves as an efficient tool at the time of decision making in order to create a high yielding model of Multi-sensor image fusion. To pull out spatial details, various transforms are utilized in MRA, as pointed out by M. Choi et al. in their work[18]. The transforms they mention include, contourlet, curvelet, Laplacian to Pyramid, decimated as well as undecimated wavelet transforms. It is also worth considering the study of J. Atli Benediktsson et al. [19]. Their work focuses on hybrid classification approaches relying on harmonious discoveries culled from diverse sources. Meanwhile, Y. Luo et al. [20] have created a method incorporating additive wavelet decomposition and PCA transformation. And X. Bai et al. [21] have advanced a feature fusion method incorporating Softmax regression.

Fig. 1 Luo & Kay' model



Luo and Kay [22] suggested multi-sensor unification and made a differentiation between multi-sensor integration and fusion. According to them, multi-sensor integration refers to employing several sensors to beget different aspects of information for one task, and data fusion can be at any step in the integration which combines data. The Luo and Kay's architecture for data integration and fusion is shown in Figure 1-5. The data driven from sensors are fused in different levels and the formation of data is represented from raw data to higher level representation.

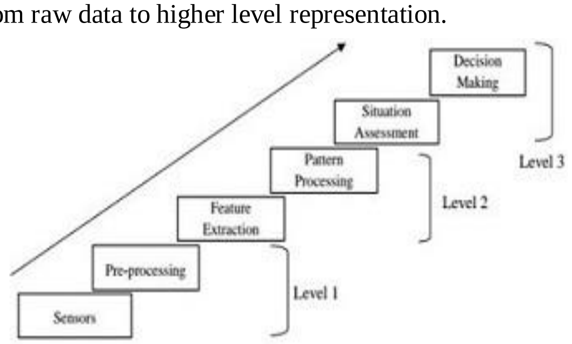


Fig. 2 Waterfall model

Harris[23] introduced a hierarchical fusion model known as waterfall model. This model is based on three levels: first level deals with the raw data pre-processing. The second level is feature level which deals with feature related processing which consists of feature extraction and pattern recognition. Finally, the third level is integration of beliefs [24].

There are many definitions of data fusion that exists in the literature. According to Abidi and Gonzalez [25], "Data fusion deals with the synergistic combination of information made available by various knowledge sources such as sensors, in order to provide better understanding of a given science." Hall [26] describes "Muti-sesor data fusion seeks to combine data from multiple sensors to perform interferences that may not be possible from single sensor up." According to DSTO [27], "Data fusion is a multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation and combination of data and information from single and multiple sources."

A. Data Fusion

As opposed to data derived from one solitary source, merged multi-sensory information presents significant benefits. The main benefit of using fusion is that it gives a unifying combined outcome that carries as comprehensible and dependable data as possible. Merging diverse data sources together also yields the benefit of the data being better represented. There are diverse disciplines that offer approaches to coalesce or merge data. Among these are pattern recognition, statistics, artificial intelligence, information, digital signal processing and other, as shown in Figure 3.

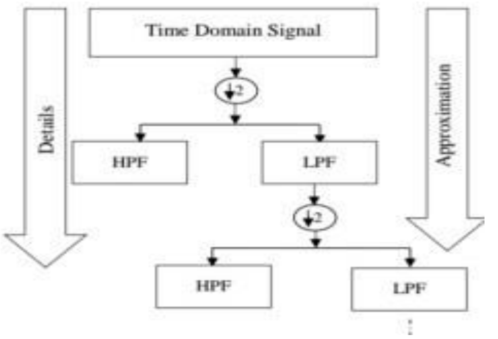
There are numerous fields using applications that integrate multi-sensory fusion. For instance, the armed forces and some other areas. Battlefield surveillance, control for autonomous vehicles, remote sensing, target recognition etc. are some of armed-forces applications that incorporate multi-sensory fusion. While, medical applications, robotics, condition-based maintenance of complex equipment, monitoring of engineering processes etc. form some of the non-armed forces applications.

B. Fusion hierarchy

The fusion fraternity normally acknowledges a fusion hierarchy of two levels. This hierarchy encompasses the metamorphosis of raw, initial data like sensor signals to a concept, symbol, information or decision, which is data in abbreviated form. Figure 5-3 here displays a hierarchy composed of three levels:

Fig. 4 Fusion category

- Fusion at raw data level: When several sensors are zeroing in on the same spot i.e. physical location or phenomenon and their raw data is merged together. This, however, is only possible if the different sensor measures are in in sync. The data merger of pixels of images taken by optical sensors could be treated as raw data or fusion at pixel level.



- Fusion at feature level: This means different sensors cull out features but their measures are not in sync. Features are merged into complex feature vectors, which stand for the multi-modal features of real physical location or phonemenon[28][29].
- Fusion at decision level: This involves using and integrating different sensors' inferences so as to beget a final merged decision. The classical and Bayesian inference or voting methods best exemplifies the decision level techniques[30][31].

III. Methodology

The Landsat and sentinel images are perused. Then it is inquired from the input user whether any of the image is tilted. An input of 0/1 is to be equivalent to a normal/rotated image. The fusion norm is executed if both images are non-tilted. In the event of one of the images being rotated, to amend the rotation a separate function is employed.

A. Discrete Wavelet Transform (DWT) Approach

Discrete Wavelet Transform (DWT), in its simplest meaning implies any wavelet transform that employs a prudent and careful approach in its sampling of wavelets. Hence, the name. In executing the transform, DWT relies on

$$CWT_x^{\varphi} = \frac{1}{\sqrt{|s|}} \int x(t)\varphi^*_{\tau,s}(t)\, dt$$

carefully selected group of translations and scales of wavelets, adhering to some laid down parameters. For instance, DWT delivers acoustic features of birds' calls or sounds through a group of coefficients. DWT breaks down the signal for depiction in terms of frequency and time, investing the signal with manifold resolution. In this

$$\varphi_{\tau,s} = \frac{1}{\sqrt{s}}\, \varphi\left(\frac{t-\tau}{s}\right)$$

application, it is this resolution that renders the wavelet better than STFT. The continuous wavelet transform relies on the interrelationship of the signal's time domain factor with a group of basis wavelet functions, as:

where the………. becomes the group of wavelet basis functions termed as a wavelet family, which, in turn, is secured by shift i.e. translation and scale i. e. dilation of

$$c_{\varphi} = \left\{2\pi \int_{-\infty}^{+\infty} \frac{|\hat{\varphi}\,(\varepsilon)|^{\,2}}{|\varepsilon|}\right\}^{\frac{1}{2}} < \infty$$

"mother wavelet", as:

where the … and……..become translation and scale parameters respectively and ( ) represents the "mother wavelet." The signal's varied features are culled out by

$$\varphi_{\tau,s} = s_0^{\frac{-j}{2}}\varphi(s_0{}^{j}t - k\tau_0)$$

shifting and scaling of the 'mother wavelet.' To build the signal back again, the 'mother wavelet' is presumed to gratify the admissibility condition, as:

whereˆ( ) becomes the Fourier transform of ( ).

As mentioned earlier, in DWT the parameters of rendering the wavelets discrete in terms of translations and scales are laid down. Thus, the DWT is defined, as:

where and become discrete scale and translation functions respectively. DWT interprets the signal using filters equipped with different cut-off frequencies at different scales. Thus, it an offer different resolution by breaking down the signal into estimated and detail information. This it does by employing low-pass and high-pass filters followed by scaling by sub-sampling, as:

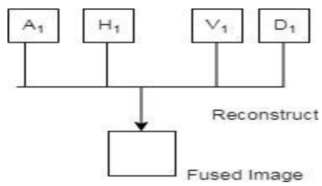
where to n and… represent the number of samples in the signal. The procedure of breaking down of a signal employing the high pass and low pass filters is shown in Figure 10.

Fig. 10 Signal decomposition by DWT

The signal's features are chosen, as the wavelet gives coefficients. These display the likeness at any scale of the signal to the wavelet. Features are categorized in four norms: minimum, maximum, standard deviation and mean showing detail coefficients in each sub-category. With different levels of break downs dependent on the different files of wave, Daubechies-2 (db2) model wavelet is employed. Based on the kind of data the data were prepared separately, owing to the plethora of sensory technology. To prepare the raw data different algorithms and methods were used. Based on the culling out of features of the calls and their categorization, preparation of acoustic data was executed. To pull out the features varied techniques were employed. The important features were culled out through the use of coefficients of discrete wavelet transform, Fourier transform and Mel frequency cepstrum.

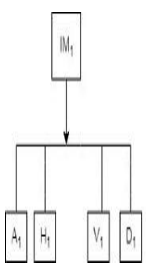
The approximation coefficients of IM1 and IM2 are average. For remaining components (horizontal, vertical, and diagonal coefficients), the coefficient having maximum value is considered.

Fig. 11



AR = (A1+A2)/2
HR, VR, DR, = Max (H1,H2),Max (V1,V2), Max (D1,D2).

An inverse wavelet is applied to the coefficients to reconstruct the merged image.



For colour fusion, all these components are to be independently processed and then displayed concisely. The angle and direction of the tilted image is to be displayed. Parameters such as correlation between first image and fused image, Correlation between second and fused image, SNR between first and fused image, SNR between second and fused image are to be evaluated. The main objective of this proposed work is to improve the visible quality of Landsat image. Thus, it could be seen from SNR between first image and fused image.

B. Flow Chart

Table 1 Observation Table

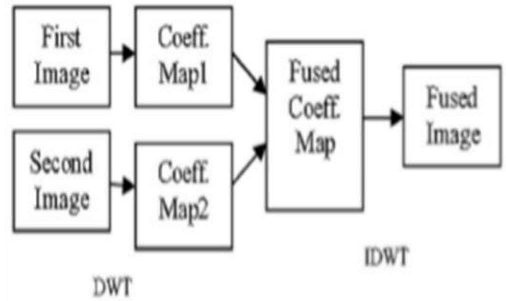


Fig 4. Image fusion process using DWT[1]

Mother Wavelets	Correlation		Signal to Noise Ratio	
	1st img fused img	2nd img & fused img	1st img fused img	2nd img & fused img
"db"	0.167092	0.661901	19.94 db	14.70 db
"sym"	0.167092	0.661901	19.94 db	14.70 db
"coif"	0.179875	0.667282	19.71 db	14.67 db
" haar"	0.167092	0.661901	19.94 db	14.70 db
"dmey"	0.172782	0.674662	19.09 db	15.33 db

When we compare results of these output images, it is found that when Mother Wavelet Discrete Approximation of Meyer Wavelet i.e. "dmey" is applied with the Discrete Wavelet Transform Method, better results of SNR 15.33db are obtained.

IV. RESULT PARAMETERS

The image merging process enjoins certain general requirements. Firstly, it needs to safeguard all pertinent and useful pattern information from the source images. Secondly, at the same time, it should not inject artifacts that might interfere in later interpretations. The performance measures employed in this paper offer some quantitative comparison between varied fusion schemes, mainly aimed at evaluating the definition of an image[8].

Peak Signal to Noise Ratio (PSNR)

PSNR represents the ratio between the signal's maximum possible power and the power of corrupting noise that affects the exactness of its representation [8][15]. The PSNR measure is given by:-

$$PSNR(dB) = 20log\frac{255\sqrt{3MN}}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(B'(i,j)-B(i,j))^2}}$$

Where, B - the perfect image, φ - 'the fused image to be assessed, i – pixel row index, j – Pixel column index, M, N- No. of row and column.

V. CONCLUSION

The data fusion of acoustics, IR, and radar possessing sensors of different types gives a disparate fusion. Therefore, to link the targets, it required efforts for merging the features from different disparate sensors. The data alignment comprises spatial and temporal alignment. It is executed to beget a common reference in dimensions of either time or space. The framework of data fusion of acoustics, IR, and radar is well constructed and executed. Still, more concern needs to be focused on the type variant data merging, particularly if there is an increase in the number of each kind of sensor.

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