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SEGMENTATION AND FUSION OF MULTISPECTRAL REMOTE SENSING IMAGES USING MATHEMATICAL MORPHOLOGICAL OPERATIONS

R.Narthana Devi
Dhanalakshmi Srinivasan College of Engineering, Coimbatore, Tamil Nadu, INDIA
narthana.ramachandran@gmail.com

D.Indhu
Dhanalakshmi Srinivasan College of Engineering, Coimbatore, Tamil Nadu, INDIA

T.Joby Titus
Dhanalakshmi Srinivasan College of Engineering, Coimbatore, Tamil Nadu, INDIA

Nitin Jain
Babu Banarasi Das University, Lucknow (U.P.) India

ABSTRACT
The work introduces a new hybrid image enhancement approach driven by dominant brightness level analysis. This approach, based on the adaptive intensity transfer function and discrete wavelet transformation, can enhance simultaneously the overall contrast and the sharpness of an image. The approach also increases the visibility of specified portions or aspects of the image whilst better maintaining image gray color values. The proposed method can effectively enhance any low-contrast images acquired by a satellite camera and are also suitable for other various imaging devices. The multispectral edges were first obtained from the edge-preserved smoothed image and the initial seeds were automatically generated through the local variation characteristics of the multispectral edge. Experimental results show that the proposed algorithm enhances the overall contrast and visibility of local details better than existing techniques.

1. INTRODUCTION
The global and local methods are the two kinds of contrast enhancement techniques. Global method is a useful operation in digital image processing, because that its efficiency and low computation load. The objective of this work is to improve contrast for remote sensing images using dominant brightness level and adaptive intensity transformation. Incapability of revealing the local variation of details of an image is the drawback of a global operator. On the contrary, the advantage of a local operator is its capability of revealing the detail information of an image. There is a growing need for technologies that will enable automatic feature extraction and classification for urban applications owing to the constantly increasing public availability of high-resolution satellite data sets [1]. In extracting and classification of major object feature information from high-resolution satellite imagery, it is very difficult to obtain satisfactory results using pixel-based classification methods, which only utilize spectral information. The main reasons for this are that they have considerable difficulties dealing with the abundant information of high-resolution satellite data, they produce

inconsistent salt- and-pepper classification map, and they are not capable of extracting objects of interest [2]. The spatial domain of a processed image is used in both cases. Cluster-based segmentation algorithms use an iterative moving method that attempts to search for a cluster configuration to separate distinct structures in the spectral feature domain. The clustering technique does not consider spatial information. Edge-based segmentation has not been very successful because of its poor performance in the detection of textured objects [3]. Although several methods based on conventional region growing or watershed transformation are able to successfully segment satellite images in some cases, there are some drawbacks to using these two methods for segmenting high resolution multi-spectral satellite images [4].

Some of other techniques are also widely used to enhance the gradient amount, such as frequency domain, fuzzy systems. Nevertheless, it is worth to try to combine the local and global approach. That would overcome the shortcomings of each other. In order to improve this problem, the proposed algorithm is created.

2. BACKGROUND WORK

The application of this methodology to a popular remote sensing application called pan sharpening, which consists in the fusion of a low resolution multispectral image and a high-resolution panchromatic image. Hence design a complete pan sharpening scheme based on the use of morphological half gradient operators and demonstrate the suitability of this algorithm through the comparison with the state-of-the-art approaches. In satellite images, the lower spatial resolution multispectral images are fused with higher spatial resolution panchromatic images Using Morphological Operator. With the development of geospatial information technology, semantic segmentation of remote-sensing images has become a research hotspot. It has broad application prospects, such as land management, disaster prediction, and urban planning. Unlike image classification, the goal of semantic segmentation is to generate category labels for each pixel in the image. In recent years, the popularization and application of deep learning has greatly promoted the development of computer vision. As one of the main tasks of computer vision, semantic segmentation has also made great progress. Fully Convolution Network (FCN) is a classic work that adopts deep learning methods to perform semantic segmentation. It is transformed from the classification network and achieves end-to-end training. However, the feature map size is continuously reduced in feature extraction, resulting in the loss of image content and spatial location information, which weakens the convolution network's representational ability. The pyramid scene parsing network (PSP Net), which utilizes global average pooling with different pool kernels to reduce context loss between different subregions. Deeplab family, applies the spatial pyramid pooling (SPP) and the atrous SPP (ASPP) to integrate different scales of context information. Besides, FCN adopts a deconvolution layer to directly upsample the deep features to the original image size, which makes the segmentation result blurred and causes the networkto be insensitive to the details. Hence, a U-shaped encoder–decoder network- UNet. The encoder is responsible for converting the image contents into compact representations. The decoder hierarchically concatenates high-level feature maps with low resolution and low-level feature maps with high resolution, which helps network generate the semantic prediction. The decoder utilizes the pooling index calculated by the corresponding encoding layer to perform upsampling operations. An encoder adds a well-designed decoder to get more accurate segmentation results. Although the above methods are widely applied in natural image semantic segmentation, they are not suitable for remote-sensing images. This is because high-resolution remote-sensing images have unique attributes, such as complex scenes, dense small objects, class imbalances, overlapping objects, intraclass similarity, and interclass heterogeneity, which increase the difficulty of feature learning In recent years, some researchers have focused on the semantic segmentation of remote-sensing images. The features learned by the convolutional neural network (CNN) with additional hand-crafted features and added a post processing block to smooth the labeling results. This method improves labeling accuracy while increasing the training cost, and cannot perform end-to-end training.

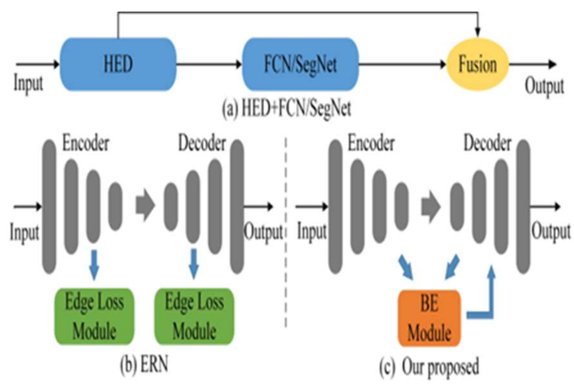

Fig1: Illustration of Different Architecture

Normally, in remote sensing a scene is represented by pixel-based features. It is possible to reduce data redundancy by a segment-feature extraction process, where the segment-features, rather than the pixel-features, are used for multispectral scene representation and classification. Object-based algorithms partition the observation space into a set of disjoint segments (called objects). Then, pixels belonging to each segment are represented by segment features.

3. NETWORK ARCHITECTURE

The computation complexity is associated with the number of model parameters and the feature map resolution. Due to limited computing resources, cut the original image into small-size patches for model training and testing. To maintain the original image size and reduce computing consumption, we accept the idea of cascaded image input Considering that remote-sensing images contain dense objects, it is not tolerable to use 1/4-size original image as input Therefore, MFFANet employs the DP structure. the architecture of the network.

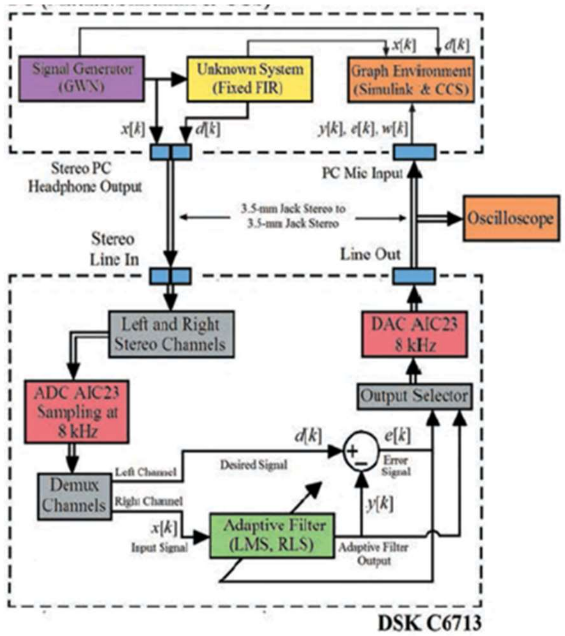

Fig2: MAR Module

In PSPNet effectively extracts global context information by average-pooling layers with different pooling kernels. The MAR module that considers both global and local features. The pooling strategy is to utilize average-pooling layers with the large kernel to retain global information and utilize max-pooling layers with the small kernel to highlight detailed texture features. Besides, The attention mechanism to establish the dependence relationship between channels, which is expressed by the channel attention tensor.

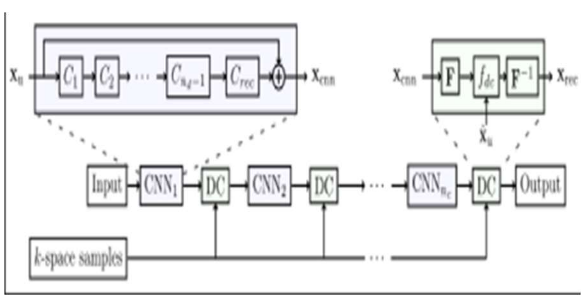

Fig3: MFF Module

In general, low-level features have rich spatial information but lack semantic information, while high-level features work in the opposite. UNet merges high- and low-level features through concatenating and gradually restores image resolution through upsampling. However, the types of information encoded by these two features are different, and the simple concatenation operation does not produce interaction within the features. To enhance the correlation and integration

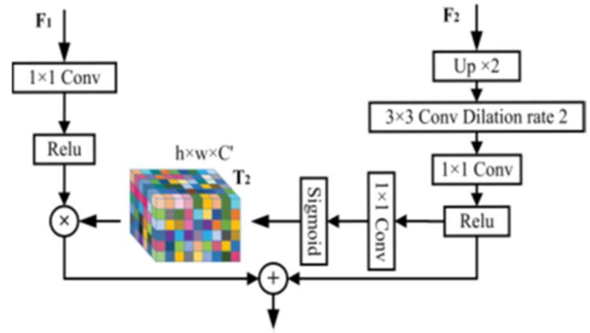

Fig4: BE Module

For remote-sensing images, the segmentation error is mainly caused by the overlaps and the indistinct boundary. Some works solve this problem by extracting boundary information, but cannot perform end-to-end training, and the boundary.

The components of the BE module. It integrates feature maps with rich information from the encoder and decoder and uses boundary labels as a learning guide. Despite its simple structure, it can still learn boundary features Then fuse the learned boundary features and semantic features. Finally, the fused features are sent to the decoder to obtain the semantic prediction. Moderate Resolution Imaging Spectrometer (MODIS) instrument is another satellite based instrument that continuously collects data over the Earth's surface. MODIS collects spectral information at several spatial resolutions including 250m, 500m and 1000m. You will be working with the 500 m spatial resolution MODIS data in this class.

4. EXISTING TECHNIQUE

Existing method of uses Histogram equalization and Adaptive Histogram equalization methods. Histogram based contrast enhancement methods cannot preserve edge details and exhibit saturation artifacts in low- and high-intensity regions. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal. In order to evaluate the performance of the proposed method, the results obtained using the proposed method were compared with the results obtained using the conventional region growing, the toboggan watershed algorithm and the mean shift algorithm. The conventional region growing algorithm is composed of simple row-wise scanning for seed selection and region growing process. This method use the Euclidean distance as the region growing criteria, which decides whether or not the pixel under current observation should be added into the region. A merging parameter of 155 and 150 for the QuickBird and GeoEye-1 images was respectively selected. Toboggan-based watershed segmentation is an edge-based segmentation algorithm not having a tuning parameter, which segments image pixels by finding a downstream path from each pixel of the gradient magnitude image to a local minimum of topographic surface

5. PROPOSED TECHNIQUE

Proposed method analyses the brightness level analysis and wavelet transform that enhances low contrast regions. The proposed algorithm can effectively enhance the overall quality and visibility of local details better. The proposed method uses Discrete wavelet transformation, Dominant brightness level analysis and adaptive intensity transfer function. We tested our method using two high-resolution satellite images of dense urban areas. To test the effectiveness of the proposed algorithm, it was compared with other established algorithms, and the obtained results for both satellite images, in general, were visually satisfactory and quantitatively somewhat superior to other methods in discriminating buildings and roads from other objects. These experimental results showed that our proposed method is promising for high-resolution satellite image segmentation. The image segmentation of remote sensing image is shown in fig 5&6.

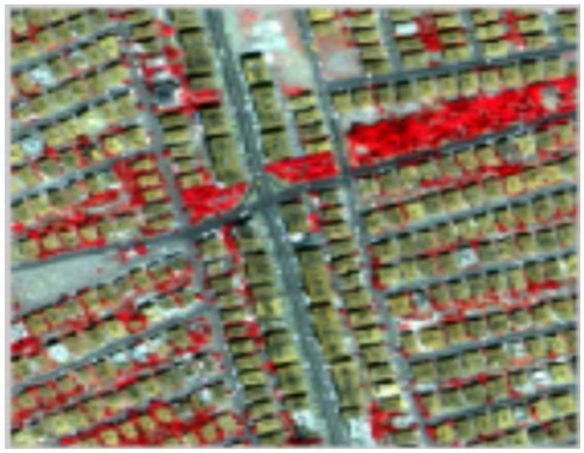

Fig5: Input Multispectral images

Also, the data are often highly correlated between spectral band, resulting in inefficient analysis. Furthermore, image-derived features, such as measures of spatial structure, may provide more useful information for classification. Thus, it is prudent to consider various pre-classification transformations to extract the greatest amount of information from the original image. In supervised classification, the analyst's role is to specify in advance the multispectral reflectance or, in the case of the thermal infrared band, emittance values typical of each land use or land cover class.

Fig6: Input Image to RGB Conversion

Fig7: Input image to PAN image

The proposed method of image segmentation using mathematical morphological operation can be extended to applications such as medical image processing, object tracking, speech recognition. Remote-sensor systems are designed within often competing constraints, among the most important being the trade-off between GIFOV and signal-to-noise ratio. Since multi spectral, and to a greater extent hyperspectral, sensors have reduced spectral bandwidths compared to panchromatic sensors, they typically have a larger IFOV in order to collect more photons and maintain image SNR.

6. CONCLUSION

The application of nonlinear image decomposition schemes based on morphological operators to data fusion, and in particular to the problem of pansharpening. Although the properties of morphology-based methods are widely exploited for applications as segmentation and denoising, only a limited number of data fusion approaches have taken advantage by their ability in dealing with shapes. The effective application of MM to pansharpening requires the choice of a suitable spatial detail extraction operator that we designed as the difference of the two half-gradients. We evidenced that it allows to highlight all the spatial changes of the input image, preserving the dynamics of the signal variation and a local zero mean value, as required by pansharpening applications. A comprehensive fusion architecture, encompassing the choice of the MRA implementation options and of the detail injection method, was here proposed and evaluated. Four data sets acquired by four different sensors were used for the algorithm assessment, using both the reduced and full resolution quality evaluation protocols.

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