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Semantic Segmentation Intended Satellite Image Enhancement Method Using Deep Auto Encoders

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ABSTRACT

Satellite imageries are at a greatest importance for land cover examining. Numerous studies have been conducted with satellite images and uses semantic segmentation techniques to extract information which has higher altitude viewpoint. The device which is taking these images must employee wireless communication links to send them to receiving ground stations. Wireless communications from a satellite are inevitably affected due to transmission errors. Evidently images which are being transmitted are distorted because of the information loss. Current semantic segmentation techniques are not made for segmenting distorted images. Traditional image enhancement methods have their own limitations when they are used for satellite images enhancement. This paper proposes an auto-encoder based image pre-enhancing method for satellite images. As a distorted satellite images dataset, images received from a real radio transmitter were used. Training process of the proposed auto-encoder was done by letting it learn to produce a proper approximation of the source image which was sent by the image transmitter. Unlike traditional image enhancing methods, the proposed method was able to provide more applicable image to a segmentation model. Results showed that by using the proposed pre-enhancing technique, segmentation results have been greatly improved. Enhancements made to the aerial images are contributed the correct assessment of land resources.

Keywords : Image Enhancement, Auto-Encoders, Semantic Segmentation, Deep Learning

심층 자동 인코더를 이용한 시맨틱 세그멘테이션용 위성 이미지 향상 방법

K. Dilusha Malintha De Silva† · 이 효 종††

요 약

위성 이미지는 토지 표면 조사에서 매우 중요하다. 따라서 위성에서 지상국으로 이미지를 전송하기 위해 다양한 방법을 사용하고 있다. 그러나 전송 시스템의 품질 저하로 인해 이미지는 왜곡에 취약하고 올바른 데이터를 제공하지 못하고 있다. 그러한 이미지의 세그먼트 결과는 토지 표면 데이터를 올바르게 분류할 수 없다. 본 논문에서는 위성영상에 대한 자동인코더 기반의 영상 전처리 방법을 제안한다. 실험결과 사전 향상 기술을 사용하여 세그멘테이션 결과도 크게 향상될 수 있음을 보여주었다. 또한 본 논문에서 적용한 항공 이미지 향상기법은 토지 자원의 정확한 평가에 이바지할 수 있음을 확인하였다.

키워드 : 이미지 향상, 자동 인코더, 시맨틱 분할, 심층학습

1. Introduction

Satellite images are being used in many studies as they provide valuable information on high altitude point of view. One of the important category is aerial imagery which clearly depicts land cover related information. Land cover and land use monitoring is essential in natural resource management [1]. They have become an increasingly important source of data for various other applications, such as urban planning, agriculture, and disaster impact assessment. Computer vision and deep learning based semantic segmentation enables accurate assessment of the natural resources and land cover types. These techniques speed up the land cover monitoring process.

Monitoring land covers can aid in assessing the impact of changes caused by human activities, climate

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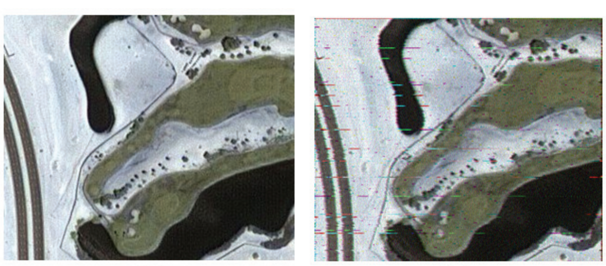
fluctuations, and natural disasters, as the land undergoes multiple transformations during a given time frame. Many practical situations where satellite images must provide their assistance strongly make use of wireless communications because the image source cannot deliver images in other ways. This activity is even eminent when it needs frequent images for necessary analysis in certain problem solving. Social economic events and natural processes leads to undergoing changes hence change detection became an active research field [2]. Proper vegetation planning requires satellite images [3] and finding good possibilities for urban planning [4] is another major activity. In order to compare the impacts of a disaster, pre-disaster and post disaster satellite images must be compared [5].

Being the image source, a satellite has to take an image and transmit it through the air by using radio waves. In the case of analog transmission, an image is converted into a set of audio tones which contain all the information about the image. Each pixel is converted to this intermediate form and these tones are frequency modulated (FM) with a carrier to transmit. During transmission, radio waves can be disturbed due to interference and attenuation which causes information loss. As a result of that, the received image is distorted and noisy because the received data do not contain 100% image information to demodulate the image. Fig. 1 (a) shows the image which was sent by the satellite and Fig. 1 (b) shows the received image.

Convolutional neural networks (CNN) embodies innate ability of feature extraction and are being used in object detection. By adding a lateral inverted set of convolutional layers at the end of such CNN, auto-encoders are made. Encoder down scales the input to features and the decoder part creates an expected



(a) (b)

Fig. 1. Original Image (a), and Received Image (b)

output. These structures can be used for image enhancement and noise reduction [6]. Deep auto-encoders have high noise reduction ability when compared to traditional image enhancement methods such as total variation minimization (TV) algorithm and non-local means (NLM) algorithm [7].

Distortions in aerial images due to wireless communication interference and attenuation can severely affect the accuracy of semantic segmentation. The current widely used segmentation models such as SegNet [8] and U-net [9] are not made for segment images with distortions and they are not able to handle these distortions, resulting in poor segmentation results. To address this issue, we propose a method that can eliminate distortions in aerial images and improve the segmentation accuracy. Our approach involves making proper approximations for distorted aerial images by using a deep auto-encoder, so they appear like the source image without distortions. We aim to emulate an analog image transmitting satellite to collect distorted images and train the proposed auto-encoder targeting source images. The enhanced images generated by the auto-encoder will be given to a segmentation model, improving the segmentation accuracy.

The proposed method has the potential to significantly improve the quality of aerial image segmentation, which can lead to more accurate analysis and decision-making in various fields. Our research will contribute to the development of more advanced image enhancing techniques, and provide practical solutions to improve the accuracy of aerial images semantic segmentation.

The main contributions from the proposed method are listed as follows.

1. We have designed an auto-encoder based satellite image enhancement method which can be easily implemented in software based radio receivers.
2. A programmable interconnection between auto-encoder and the segmentation model to pass the made approximations to the segmentation model for semantic segmentation.
3. Compatibility of the proposed auto-encoder ensures to work with current segmentation models to improve the segmentation score for a distorted image.

2. Related Work

The work process for semantic segmentations has been conducted through several phases including classical methods to deep learning based methods. Classical methods include edge-based, region-based and threshold-based methods. In edge-based methods, results rely on identifying edges by detecting local changes on an image intensity but it is not suitable for image with smooth or many edges and the process becomes harder for images containing distortions because the edges cannot be identified correctly. Region-based methods make use of a seed point to start the segmentation process and grow the region by examining the intensity of neighboring pixel to decide whether to include it to the current region. This method is computationally expensive and different seed points lead to different segmentations. Both edge-based and region-based methods can be combined to address their shortcomings made more robust segmentation methods [10,11]. Threshold-based methods are simpler and commonly used [12,13]. By calculating an optimal threshold which distinguishes between two regions while minimizing intra-class variance and maximizing inter-class variance. This method works well when an image histogram has bimodal distribution but cannot be used for images which are having unimodal intensity distribution [14-16].

The effectiveness of deep convolutional neural networks (CNN) for image classification, as demonstrated by models like VGG16 [17], is due to their convolutional layers which extract features from the image. The research, outlined in [18], shows that end-to-end training methods are capable of pixel-to-pixel semantic segmentation using fully convolutional networks (FCNs). Unlike traditional CNNs, FCNs can take an input of any size and produce a segmented output of the same size. Various pretrained deep CNN models like AlexNet [19], VGG [17], and GoogLeNet [20] have been utilized for segmentation in FCNs. Pooling indices are no longer needed with the use of deep deconvolutional neural networks [21,8]. Many segmentation techniques are inspired by auto-encoders, where inputs are encoded into a feature space that can be decoded into spatial categorization to achieve segmentation SegNet [8], which has topological similarities with VGG16, is composed of an encoder followed by a decoder network. LinkNet [22] may be better for images with distortions, as it has a mechanism to bypass spatial information directly from its corresponding encoders to decoder blocks. While each encoder can potentially result in information loss, LinkNet can preserve a significant amount of information without losing details. ParseNet is an effective, end-to-end CNN for semantic segmentation that utilizes a technique to add global context to fully convolutional neural networks [23].

The U-net [9] is a semantic segmentation model for biomedical images that builds on the architecture of the FCN [18]. Its design includes an internal concatenation operation that can be executed on systems with low computational power. The U-net architecture consists of a contracting path for context capturing and a symmetric expanding path for precise localization. Additionally, Feature pyramid networks (FPNs) have been shown to be more robust in handling image distortions due to their internal structure. FPNs have demonstrated significant improvements as a feature extractor and can be employed for both object detection and semantic segmentation tasks [24].

Semantic segmentation of the aerial images was performed with a dataset in [1] to achieve higher accuracy for each land cover type such as buildings, forests, water, roads, and others. In the case of image enhancement, an auto-encoder was trained for high resolution sonar image enhancing [6]. Sonar images contain random noise. Auto-encoder performed better than averaging filters in the noise reduction process for sonar images. Noise in Range-Doppler maps in specific radar types can be greatly reduced by using deep convolutional auto-encoders [25]. There are some traditional ways of enhancement, but the study in [25] was to find better methods.

An image enhancing method using dual auto encoders was proposed to enhance low-light images [26]. Two auto-encoders were set one after another to enhance the image. Based on retinex theory, mainly targeted to achieve two things, low-light enhancement and noise reduction, and both auto-encoders with different targeted tasks performed well.

As a preprocessing step, fingerprint samples were tested for enhancement by using auto encoders [27]. As a solution for still occurring false positives and false negatives in fingerprints recognition, the work in [27] proposed a de-convolutional auto-encoder to enhance fingerprints sample for better recognition.

3. Methodology

An image pre-enhancement method is proposed with an auto-encoder so that, the output of the auto-encoder is presented to the segmentation model to improve the segmentation accuracy.

3.1 Dataset

Satellite images of Dubai [28]. This dataset contains satellite imagery of Dubai and they are annotated with pixel-wise semantic segmentation in six classes. The classes are building, land, road, vegetation, water, and unlabeled. Images were cut into 320x256 smaller parts which made the size of the dataset is 709 images. All images were used for segmentation model training. First 120 images were used for the transmission operation which was explained below. Among 120 images, 100 images were used for auto-encoder training with the corresponding received images.

3.2 Device Setup

For data collection to train the auto-encoder, an analog satellite transmitter was emulated. Fig. 2 (a) shows the transmitter and Fig. 2 (b) shows the receiver. An image is converted to a set of audio tones and modulated with a radio carrier. Transmitter used Narrowband frequency modulation (NBFM) type and the carrier frequency was 454 MHz.

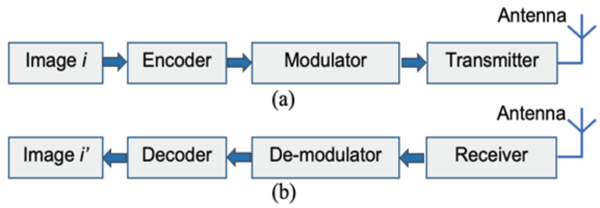


Fig. 2. Image Transmitter (a), and Image Receiver (b)

3.3 Data Collection

For each transmitted image i, the corresponding received image is i'. Since the received images are different from the original images, those pairs are kept as inputs and targets for the auto-encoder training.

3.4 Deep Learning Models

Mainly this work focuses on the auto-encoder based image enhancement. An auto-encoder is a neural network structure with convolutional layers and de-convolution layers to reconstruct an output which has the input size [6]. For the enhancement of satellite images which are intended to semantic segmentation, a new more appropriate encoder-decoder structure was built. Proposed model accepts input size of 320x256 and output size is also 320x256. Every convolutional and de-convolutional layer use rectified linear unit (ReLU) [29] activation function and have 3x3 sized 64 filters. Fig. 3 shows its structure. For semantic segmentation, pretrained U-net [9] (Structure is shown in Fig. 4) was used with Resnet18 [30] backbone (Fig. 5).

In the auto-encoder training, Adam optimizer [31] was used and the training loss is calculated by using Mean Squared Error (MSE) loss function. For MSE, number of samples is n and vector of observed values

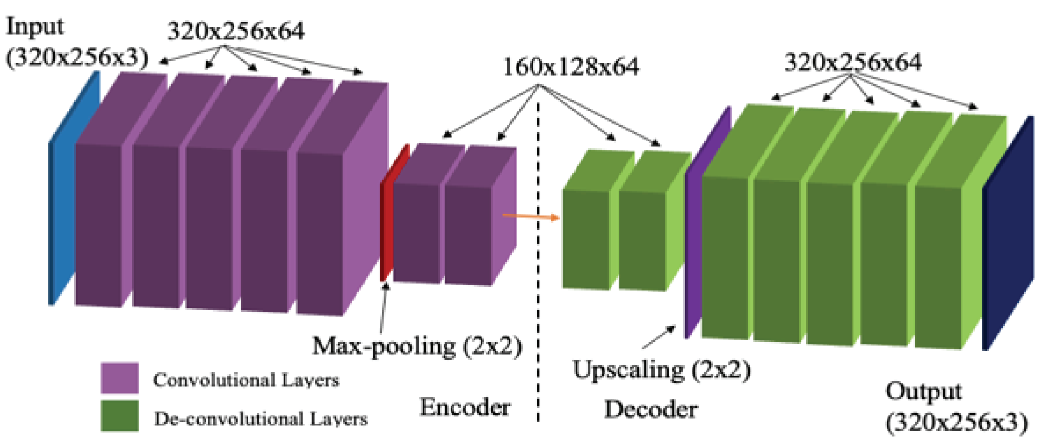


Fig. 3. Proposed Encoder-Decoder Structure

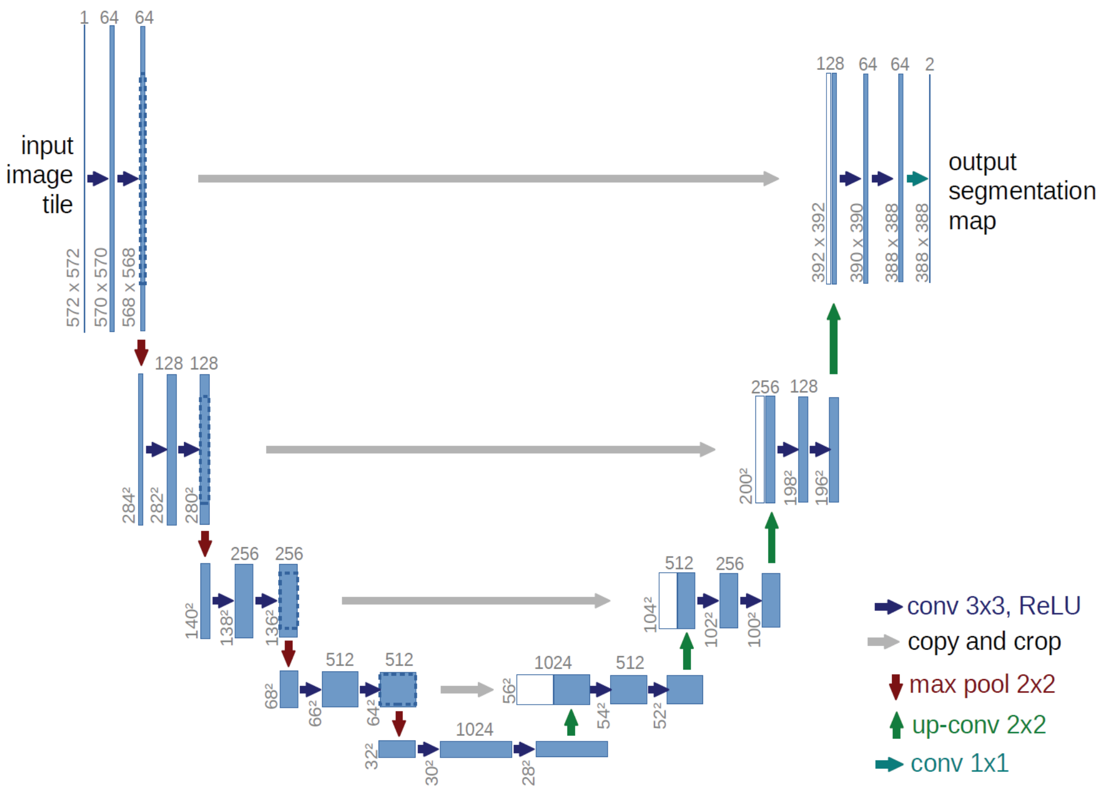


Fig. 4. U-net Architecture [9]

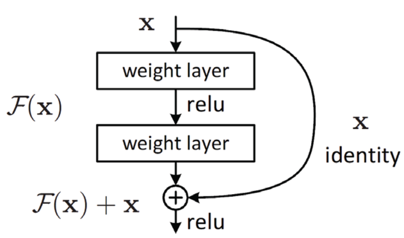


Fig. 5. Residual Block [30]

is Y and predictions are $\hat{Y}$.

$$MSE = (1/n)\sum_{i=0}^{n}(Y_i - \hat{Y}_i) \tag{1}$$

For the segmentation models, Jaccard loss function was used for training, and its definition is given below. A is the prediction set and B is the target set.

$$L(A,\ B) = 1 - (A \cap B) / (A \cup B) \tag{2}$$

As an accuracy metric for semantic segmentation results, intersection over union (IoU) score was used and following is its definition. A is the prediction set and B is the target set.

$$IoU = (A \cap B) / (A \cup B) \tag{3}$$

4. Results

Proposed deep learning model is trained by using two cores of Intel Zeon of 2.3 GHz with 13 GB RAM and NVIDEA Tesla GPU. Batch size for training is 32 and the parameters for Adam optimizer are, learning rate is 0.001, β_1 is 0.9, β_2 is 0.999. Common dimensions for an image to be transmitted by using the methods of analog image transmissions is 320x256, and this size was kept as a constant throughout the training images and testing images. For 400 epochs, the proposed auto-encoder has learned to produce noise free realistic aerial images as the loss (MSE) became 0.0011 which was shown in Fig. 6.

Five images from the testing data set were arbitrary selected which is shown in Fig. 7, and a transmission operation was performed again to receive those images.

After that the received images were semantically segmented by using the pre-trained U-net [9] with Resnet18 [30] backbone before and after enhancing by using traditional image enhancement methods such as

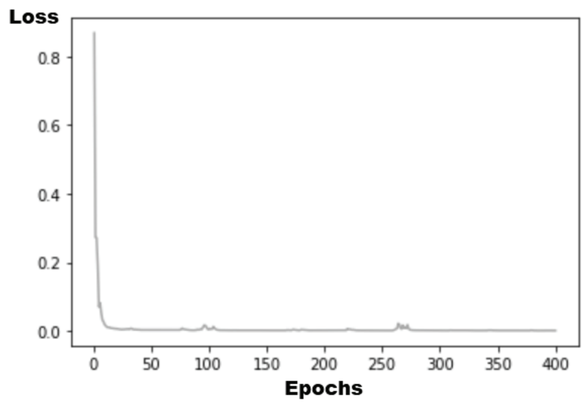


Fig. 6. Training Loss During 400 Epochs

mean filter, Gaussian filter, bilateral filter, non-local means (NLM) algorithm and total variation (TV) minimization algorithm, and the proposed auto-encoder.

Evaluation of the enhancement is done by using two metrics, Root mean squared error (RMSE) which is shown in Table 1, and Peak signal to noise ratio (PSNR) which is shown in Table 2.

For an evaluation matric for semantic segmentation, Mean intersection over union (mean IoU) score was used by setting its parameters in such a way that the number of evaluating images in a set is equal to 1, hence it gives a relative score for a single testing

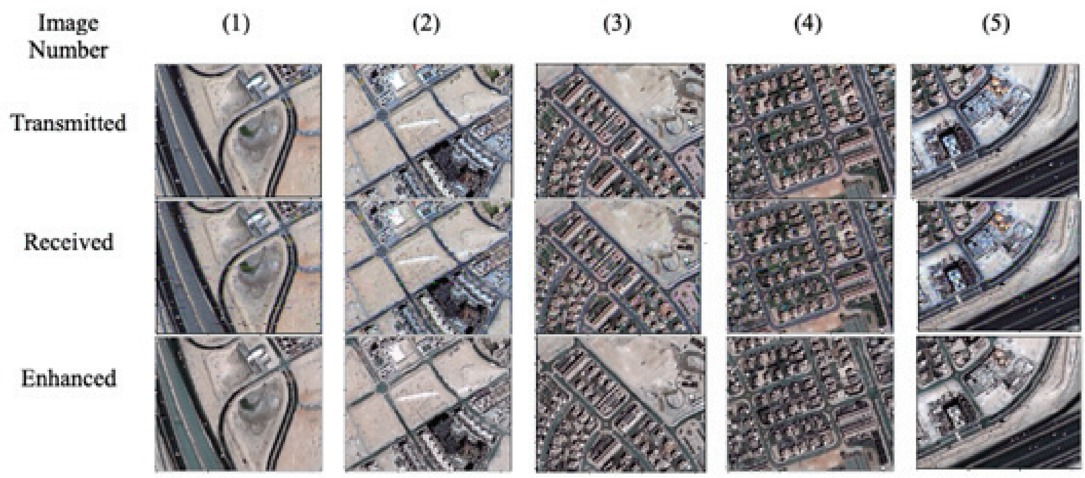


Fig. 7. Enhancement Results for Five Testing Images

Table 1. Evaluation of the Performance Using RMSE Five Testing Images

Method	(1)	(2)	(3)	(4)	(5)
Median (3x3)	0.1369	0.1526	0.1896	0.2357	0.1760
Gaussian(sigma=1)	0.1459	0.1639	0.2017	0.2499	0.1854
Bilateral	0.1499	0.1708	0.2095	0.2592	0.1924
NLM	0.1542	0.1626	0.1989	0.2439	0.1890
TV	0.1482	0.1635	0.2009	0.2531	0.1873
Proposed method	0.0809	0.0988	0.1143	0.1543	0.1149

Table 2. Evaluation of the Performance Using PSNR Five Testing Images

Method	(1)	(2)	(3)	(4)	(5)
Median (3x3)	22.16	20.29	19.53	19.34	20.24
Gaussian(sigma=1)	21.61	19.67	19.00	18.83	19.78
Bilateral	21.37	19.31	18.67	18.52	19.46
NLM	21.13	19.74	19.12	19.05	19.62
TV	21.47	19.69	19.03	18.72	19.70
Proposed method	26.73	24.06	23.93	23.02	23.94

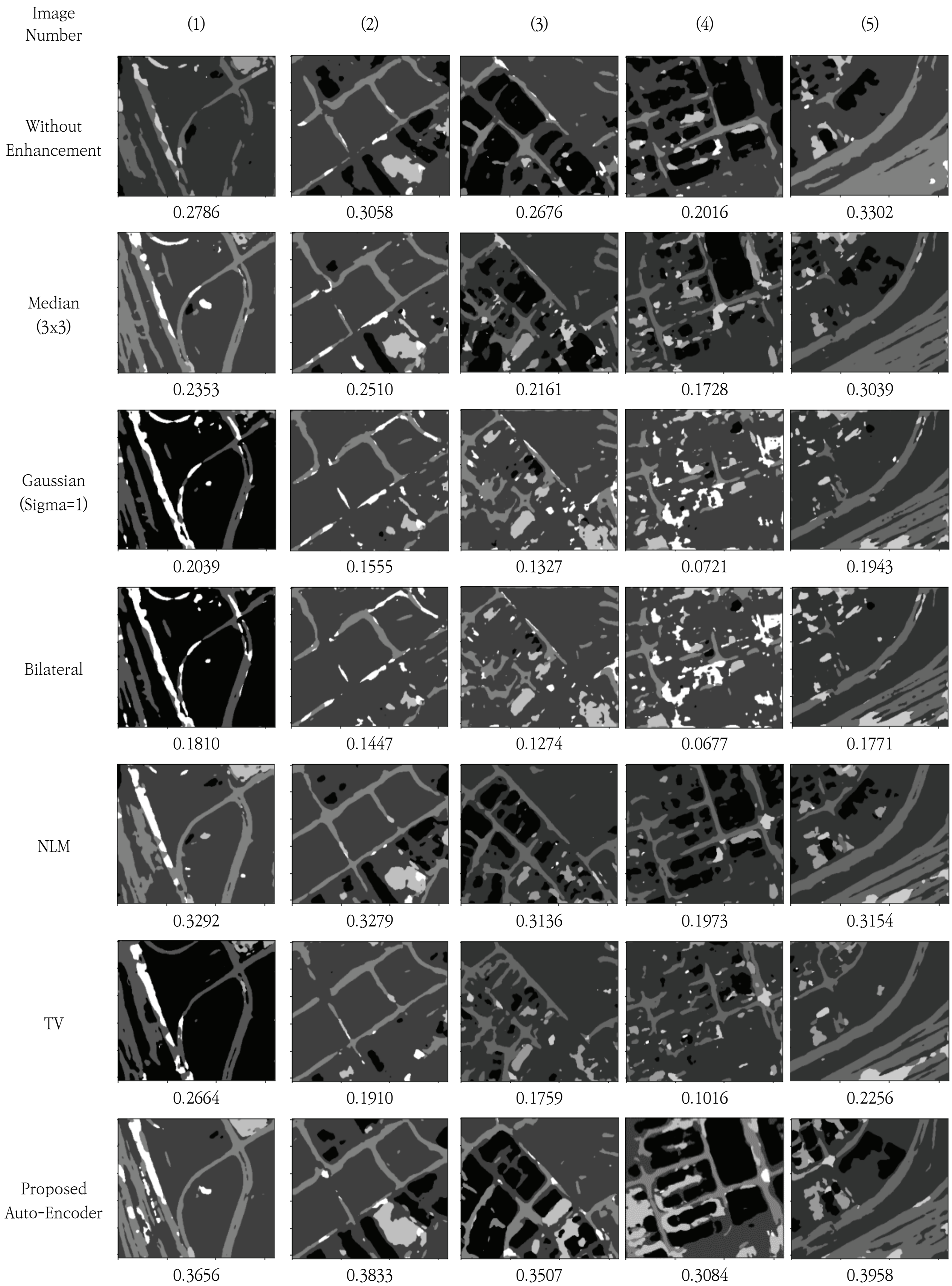


Fig. 8. Segmentation Results for Five Testing Images. Obtained IoU Scores are shown below to each result

image rather than calculating a score for a set of images. In Fig. 8, results obtained from different enhancing methods are shown. And it is clear that the proposed image enhancing auto-encoder has given the highest score rather than the traditional image enhancing methods.

5. Conclusion and Future Work

Accurate land cover identification is a crucial task that requires semantic segmentation of aerial images. Satellites mainly rely upon wireless communication links to transmit taken images to ground receiver stations. However, the inevitable issue of which images received from satellites may contain noise due to transmission errors is apparent, making them difficult to segment. To overcome this issue, this paper proposes a new auto-encoder structure which is compatible with a segmentation model to deploy an image enhancement method that enhances noisy images prior to segmentation. To test the proposed method, aerial images from an existing dataset were used to emulate the satellite image transmission process. The received noisy images were then enhanced using the proposed auto-encoder and segmented using a segmentation model. The obtained results indicate that the proposed method significantly improves the segmentation score of the enhanced images when compared with the traditional image enhancement methods. The proposed method not only enhances the segmentation performance of aerial images but also addresses the transmission errors that are inevitable in satellite imagery. Moreover, the proposed method is highly flexible and adaptable to different types of images and datasets. It can also be used as a preprocessing step in other image processing applications. Future research could investigate the integration of other deep learning techniques with the proposed method for further performance improvement and implementation in a real software based image receiver hardware for making a proper use of the power of software defined radio technology. Additionally, the proposed method will be tested on a larger and more diverse dataset to evaluate its robustness and generalization capabilities.

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