Ship detection from X-band SAR images Using Multi-level Multi-scale Feature Pyramid Network

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ABSTRACT: Ship detection is one of the essential technique for marine monitoring. Moreover, ship detection using SAR images is necessary to detect ships irrelevant to climate condition and data acquisition time. In SAR images, ships are usually occupy very small portion, so that detecting ships in SAR image is not simple. There are various SAR ship detection studies using deep learning and many of them achieved encouraging results. However, those studies mainly consider its model architecture and didn't give much attention to input SAR images itself. In this study, we will extract features from multi-level multi-scale feature pyramid network and consider SAR images' conditions which can affect detecting performance such as speckle noise and wave texture etc. This study will contribute for detecting ships with various sizes in SAR images more accurately and improve SAR images' usage in ship detection field.

1. INSTRUCTION

Lots of researches for ship detection have been performed in remote sensing field. When use of synthetic aperture radar (SAR) image, we have benefit that can shoot ships regardless of season, weather and time. Many early ship detection researches with SAR used constant false alarm rate (CFAR) algorithm based on the feature that ships have higher values than its around water (Ai et al., 2010; Gao, 2010). However, complicated backgrounds can cause false alarm and it consume much time, so that it's hard to near real-time process. In recent years, ship detection researches applying deep learning have been performed due to the advancement of deep learning technique. These researches mainly focused on deep learning architecture rather than pre-processing of SAR images.
Although they result good detection performance, we need to consider about SAR images itself which are used for training. Since there are many noise factors that disturb identifying ships such as speckle noise, glittering sea surface, it could help to train deep learning model if we use SAR images after mitigate those noise factors. Therefore, in this study, we will mitigate noise in SAR images and use it as input of deep learning model in order to improve the detection performance.

2. METHODOLOGY

2.1 Dataset

To construct our SAR image dataset, we acquired 8 images of TerraSAR-X and 26 images of COSMO-SkyMed. Both sensors have about 2m resolution both in ground range and azimuth directions, so that it is easy to identify ships.

Table 1. SAR image dataset parameters

Sensor	Place	Polarization	Mode	Resolution (m)	# of images
COSMO-Skymed	Songdo, Gyeongju	HH	Stripmap	3	26
TerraSAR-X	Songdo, Kerch strait	HH,HV	Stripmap	3	8

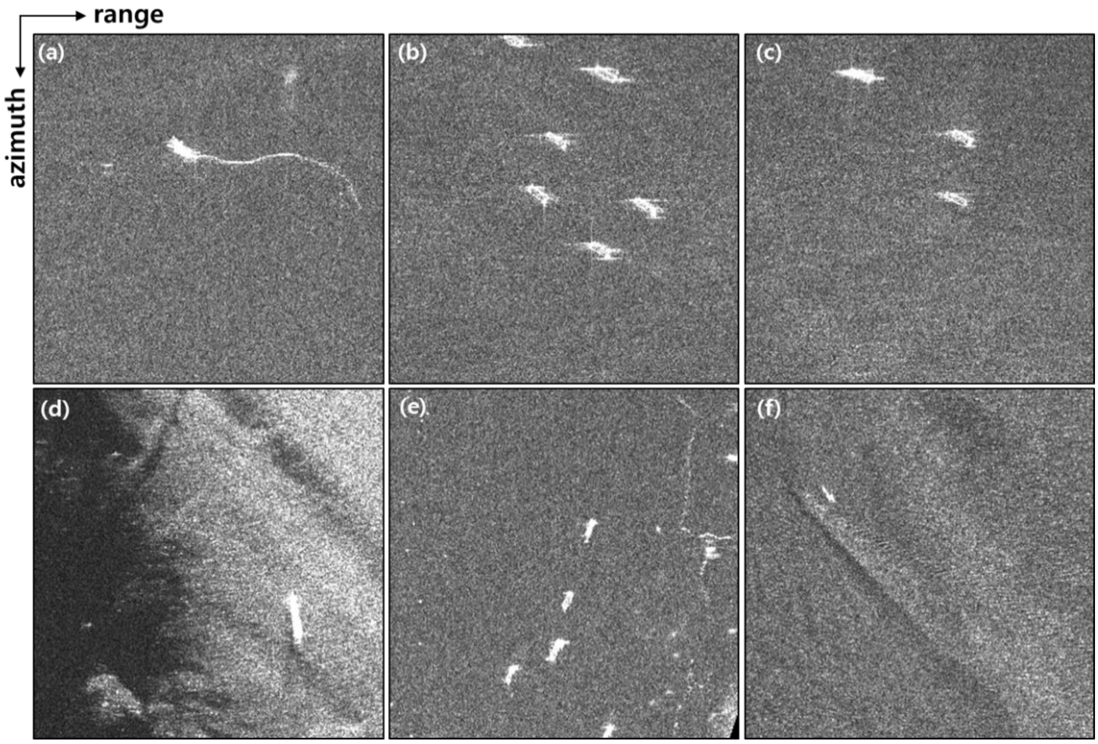

Figure 1. Multi-looking images acquired by (a-c) COSMO-SkyMed and (e-f) TerraSAR-X sensors.

Figure 1 is SAR intensity images. Ships usually have very high value compared with surrounding sea because of the double reflection (Hwang et al., 2018), so it is easy to distinguish the ships from the sea.

2.2 Method

Since this study have aimed to how to improve ship detection results by pre-processing of SAR images, we focused how to highlight ships even in the bright sea surface as shown in Figure 1 (c). We propose our pre-process method to contrast ships with the sea surface in Figure 2.

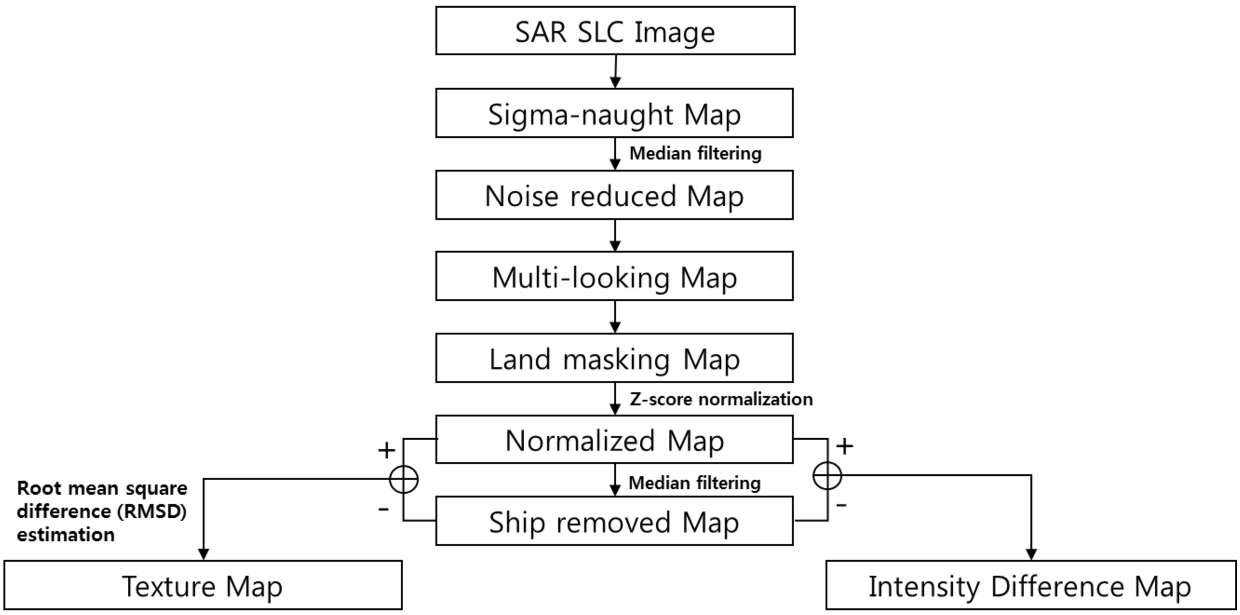

Figure 2. Flowchart of the pre-process method

Proposed method generates two type of images from a given image. Since pixel values in SAR have very wide range, we applied logarithm scaling to SAR SLC image. To reduce the speckle noise in SAR images, we performed median filtering and multi-looking process. However, large size of filter and multi-looking can reduce the size of ships and even remove the ships (Qiu et al., 2004; Hwang et al., 2018), so we used 3 x 3 median filter and 2 x 2 multi-looking. Furthermore, multi-looking is necessary to reduce whole processing time.

Since bridge, islands and land area are not our interest target and some of those looks similar to ships, so they can be detected as a ship. Therefore, it is important to mask out them (Greidanus et al., 2004; Leng et al., 2016). After normalizing, we made base map using 31 x 31 median filter. From normalized map and ship removed base map, we calculated texture map and intensity difference map. Texture map is desired to reduce noises and improve ship pixel values. Intensity Difference map is for making big difference between ships and sea surface. Figure 2 shows SAR SLC image and our two type of input images.

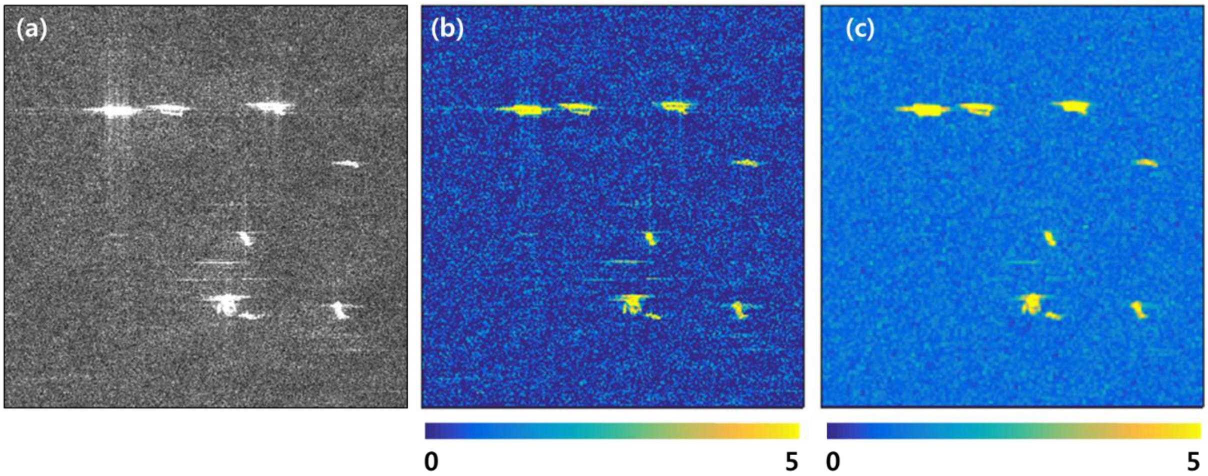

Figure 2. (a) SAR SLC image (b) Intensity difference map (c) Texture map. (b) and (c) are our proposed input images.

We cut intensity maps and texture maps into 320 x 320 images to use them as input images of deep learning model. All images were cut so that they overlap 20% each other to enlarge the amount of sub-images. We created total 1179 images from 34 SAR images and make train set with 1075 images and test set with 104 images. Figure 1 and Figure 2 images are all cut images.

2.3 M2Det

M2Det is a single shot object detection model based on multi-level feature pyramid network (MLFPN) (Zhao et al., 2019). M2Det extract the features of input images from backbone and the MLFPN. It can extract more complex feature from MLFPN so that it can discriminate different objects which have same size each other. In this study, we only consider whether the object is ship or not. However, in next study, the discriminating power of M2Det would be helpful to distinguish which object is what ship among similar size of ships. The model structure is in the figure 3.

We use DenseNet (Densely connected Convolutional Networks) as our backbone network (Huang et al., 2017). DenseNet consist of four dense blocks. DenseNet has benefit that can alleviate the vanishing-gradient problem and reduce overfitting on tasks with smaller training set sizes (Huang et al., 2017). Since we don't have many images to use training set, those features of DenseNet are very useful to us. Before use DenseNet as a backbone, we change the structure of DenseNet. When M2Det get feature from Backbone, the default feature size is 40 x 40, however, DenseNet have 5 pooling layer so that the output feature size becomes 1/32 of its original size. Because our input size is 320 x 320, it will be the size of 10 x 10. To match the feature size to 40 x 40, we used only the first three dense block layers and size up the feature size from 20 x 20 to 40 x 40 using nearest interpolation.

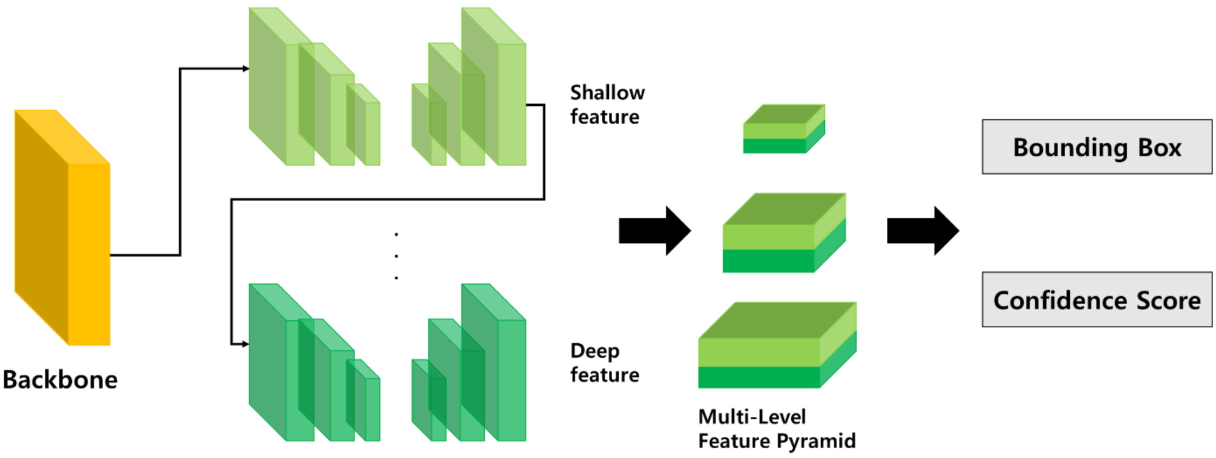

Figure 3. M2Det architecture.

3. RESULT AND CONCLUSION

We trained our train set images for 600 epochs and the results are shown in figure 4. The detailed detection result is on the table 2. Our detection recall is 93% and precision is 96%.

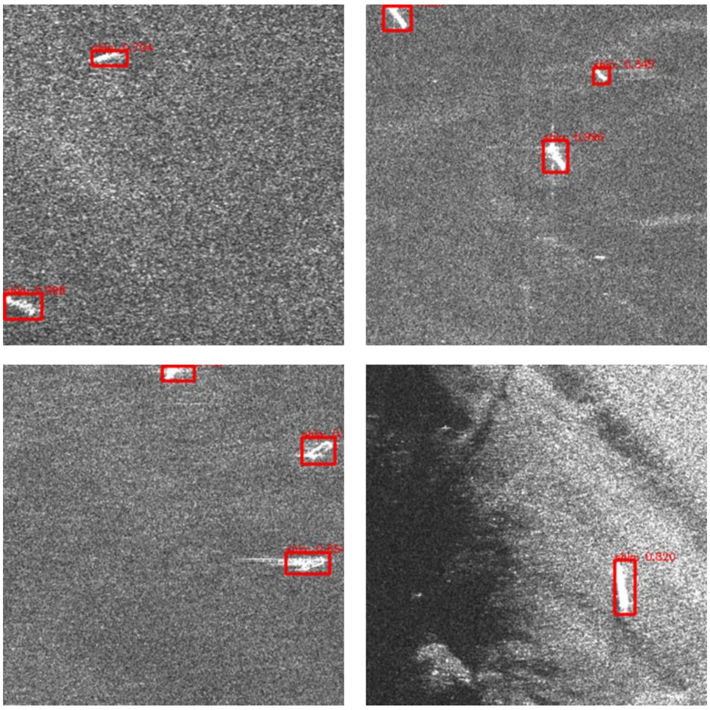

Figure 4. Ship detection results.

Table 2. Detailed result of ship detection. N_g : number of ground truth, N_{TP} : number of true positive, N_{FP} : number of false positive, N_{FN} : number of false negative

Sensor	N_g	N_{TP}	N_{FP}	N_{FN}	Recall(%)	Precision(%)
COSMO-Skymed TerraSAR-X	242	217	9	16	93	96

In this study, we have proposed a pre-process method of SAR images for ship detection. We will experiment ship detection with SAR images without any pre-process and compare its detection result with this pre-processed result. This study will be helpful to enhance the result of ship detection with SAR images without any change of detection architecture.

4. ACKNOWLEDGEMENT

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5. REFERENCES

Ai, J., Qi, X., Yu, W., Deng, Y., Liu, F. and Shi, L., 2010. A new CFAR ship detection algorithm based on 2-D joint log-normal distribution in SAR images. IEEE Geoscience and Remote Sensing Letters, 7 (4), pp.806-810.

Crisp, D.J., 2004. The state-of-the-art in ship detection in synthetic aperture radar imagery (No. DSTO-RR-0272). Info Sciences Lab, Defence Science And Technology Organisation Salisbury, Australia.

Qiu, F., Berglund, J., Jensen, J.R., Thakkar, P. and Ren, D., 2004. Speckle noise reduction in SAR imagery using a local adaptive median filter. GIScience & Remote Sensing, 41(3), pp.244-266.

Gao, G., 2010. A parzen-window-kernel-based CFAR algorithm for ship detection in SAR images. IEEE Geoscience and Remote Sensing Letters, 8 (3), pp.557-561.

Hwang, J.I. and Jung, H.S., 2018. Automatic ship detection using the artificial neural network and support vector machine from X-band SAR satellite images. Remote Sensing, 10(11), p.1799.

Greidanus, H., Clayton, P., Indregard, M., Staples, G., Suzuki, N., Vachoir, P., Wackerman, C., Tennvassas, T., Mallorquí, J., Kourti, N. and Ringrose, R., 2004. Benchmarking operational SAR ship detection. In IGARSS 2004. 2004 IEEE International Geoscience and Remote Sensing Symposium, 6, pp. 4215-4218. IEEE.

Huang, G., Liu, Z., Van Der Maaten, L. and Weinberger, K.Q., 2017. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4700-4708.

Hwang, J.I. and Jung, H.S., 2018. Automatic ship detection using the artificial neural network and support vector machine from X-band SAR satellite images. Remote Sensing, 10(11), p.1799.

Leng, X., Ji, K., Zhou, S., Xing, X. and Zou, H., 2016. An adaptive ship detection scheme for spaceborne SAR imagery. Sensors, 16(9), p.1345.

Zhao, Q., Sheng, T., Wang, Y., Tang, Z., Chen, Y., Cai, L. and Ling, H., 2019. M2det: A single-shot object detector based on multi-level feature pyramid network. In Proceedings of the AAAI Conference on Artificial Intelligence, 33, pp. 9259-9266.