Classification of Matrices in Quadrat Images by Using Convolutional Neural Network and Gaussian Filter

Akiyuki Sakai, Shinya Nozaki, and Takashi Sakamaki

Abstract—**When matrices on images of the sea bottom is classified, it takes human cost with human visual classification. It is necessary to develop a method of an automatic classification of the matrices. In the past, we proposed a method by using Convolutional Neural Network (CNN). The classification is performed using information surrounding the attention pixel selected randomly for the classification. However, the influence of irrelevant information on surrounding the attention pixel is considered to be one of the causes of the misclassification. In this paper, we performed a method of blurring away from the attention point, and showed usefulness of the method through experiments.**

Index Terms—**Quadrat image, convolutional neural network, patch image, Gaussian filters.**

I. Introduction

In researches of coral reef ecology, we very often need to know coral types and numbers of them. In many cases of those studies, quadrat images of the sea bottom are taken by camera at first and then their matrix are classified to each pixel. However, it takes a lot of human cost because the huge number of pixels are visually classified.

In the past, we have proposed a method to classify quadrat images into 3 categories using Convolution Neural Network (CNN) to reduce human cost [1]. When we classify the matrices by CNN, some attention point to classify its matrix is randomly selected and information of pixels surrounding the attention points are used. However, when the matrix pixels surrounding the attention pixel are different from the matrix of the attention pixel, sometimes it may occur misclassification. In this paper, we propose to use Gaussian filter to appropriately reduce information surrounding the attention pixels.

II. Quadrat Method

The quadrat method is commonly used in environmental science studies [2]. In our case of study, sea bottom images of coral reefs were obtained as the example of the quadrat image shown in Fig. 1. We classified the matrix of some pixels within the frame in the image. Then, we analyzed them statistically to obtain insights to ecology and conservation. There are various types of corals depending on their appearance and shape: encrusting coral, branched coral, massive coral, foliose coral, and soft coral.

However, it takes human cost because the matrix is classified visually by human [3]. For example, if we take about 540 images per study site and plot 50 points per image, we need to classify about 27,000 points. By automating this operation, the human cost can be greatly reduced.

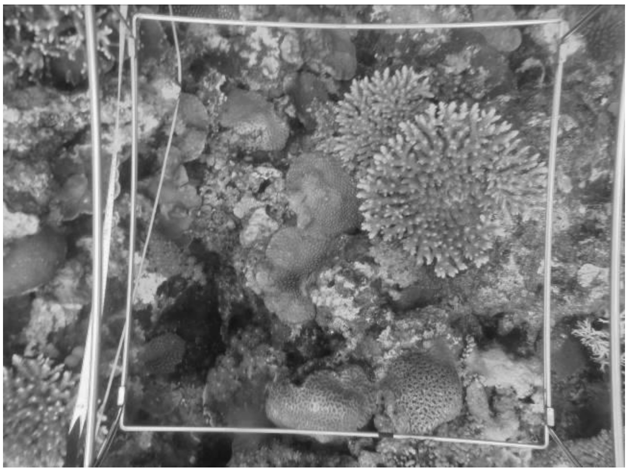

Fig. 1. Quadrat image with 50cm × 50cm frame.

III. Image Processing and CNN

A. Conventional Methods and Problems

For the automatic classification, the matrix of the attention point (pixel) is classified. However, it is impossible to classify the matrix using attention pixel only. Therefore, information on surrounding pixels is used for the classification. In our previous method, quadrat image has been cropped in the area 6.5cm × 6.5cm (Fig.2(a), (b)), and sometimes a measure or a frame appear in the edge of the area. Therefore, we classified the image into three categories: corals, rocks, and artificial materials. Artificial materials could be correctly classified with more than 90% accuracy [1].

As described above, in order to classify the matrix of attention pixel, information on surrounding pixels are required. The example is shown Fig. 3. As shown in Fig. 3 (a), if the surrounding pixel is rocks although the attention pixel is corals, it was misclassified as rocks in conventional method. On the other hand, as shown in Fig. 3 (b), if the cropped area is narrowed, we have to use the few information from the narrow area, and it may lead the misclassification. In this paper, we improve the classification method of the matrix by using the surrounding pixel efficiently [4].

Manuscript received February 10, 2020; revised June 3, 2020.

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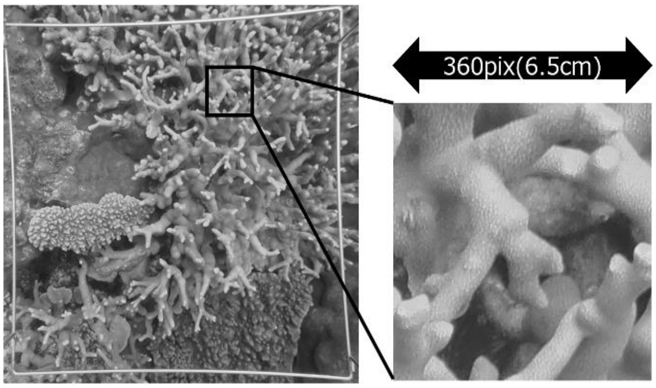
doi: 10.18178/jacn.2020.8.1.273



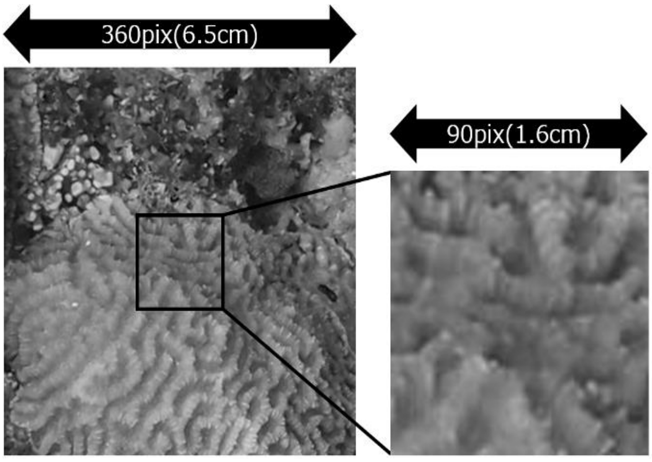
(a) (b)

Fig. 2. Cropped images from the quadrat image.
(a): Original images, (b): Cropped images

B. Proposed Method Using Gaussian Filter

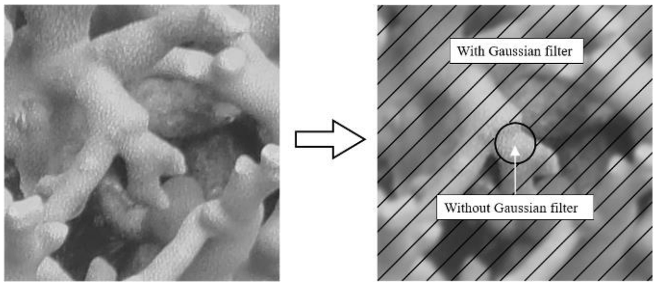
In our previous method, quadrat images have been cropped in the area 6.5cm × 6.5cm. However, the influence of irrelevant information on surrounding the attention pixel would be one of the causes of the misclassification. In contrast, as shown in Fig. 3, when the image was cropped in the smaller area like 1.6cm × 1.6cm from the cropped image stated in Fig. 2, it also leads misclassification due to few information [4]. In the proposed method, we use the Gaussian filter to distant pixels from the attention pixel expect the near of the attention pixel. The reason is that the influence of the information of distant pixel can be decreased but we can use the information appropriately.

The basic concept of the blurring process is shown in Fig. 4. At first, a circle with the 30 pixels in diameter is masked on the surrounding attention, and Gaussian filter is applied to the outside of the circle. We repeat the procedure by increasing the diameter. An example of the repeat procedure is shown in Fig. 5. The diameter of the circle is increased by constant pixel and Gaussian filter is similarly applied to processed image. By the procedure, the blur can be applied more from the center to the outside. A result of the procedure is shown in Fig. 6. In the case, number of the iteration (n) is 16. We can see that the center of the result image (Fig. 6 (b)) is clear. On the other hand, the distant pixels from the center of the image are strongly blurred by the Gaussian filters.



(a) (b)

Fig. 3. Cropped image for smaller area.
(a): Image size: 6.5cm × 6.5cm, (b): Image size: 1.6cm × 1.6cm.



(a) (b)

Fig. 4. Use of Gaussian filter in the proposed method.
(a): Original image, (b): Filtering area

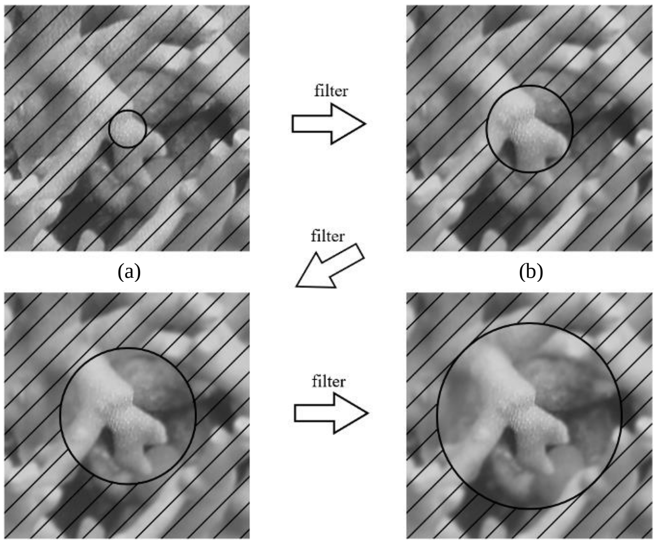
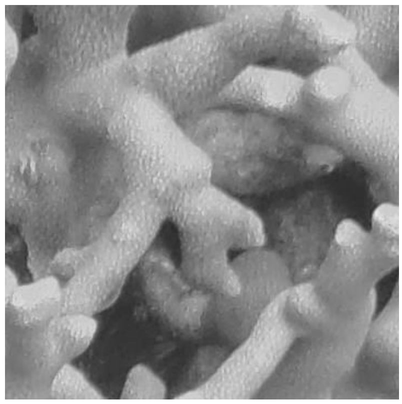


Fig. 5. Iteration of Gaussian filter.
(a): d = 30 pixels, (b): d = 70 pixels, (c): d = 110 pixels, (d): d = 150 pixels



(a)

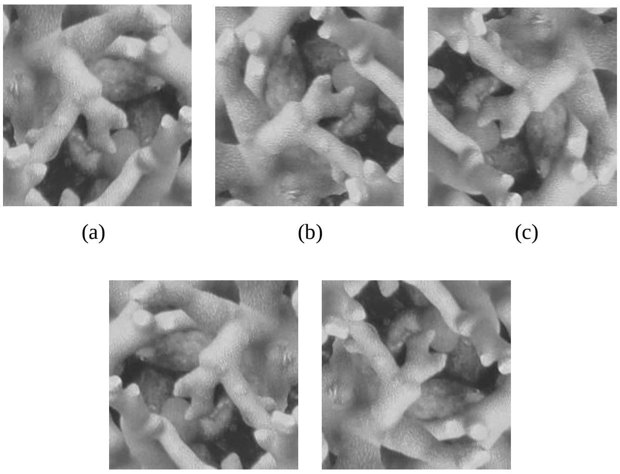
(b)

Fig. 6. Processed image by Gaussian filter.
(a): Original image, (b): n = 16

C. CNN and Dataset

To classify the matrices of the quadrat image by the proposed method. We used VGG network which is one of the CNNs [5], [6]. The network consists of 13 convolutional layers, 5 pooling layers, and 3 fully connected layers.

In this study, we used quadrat images which taken at 27 areas of Ryukyu arc. We have to set a lot of images for training and classification. In order to increase the number of images, image augmentation is performed. The image augmentation example is shown Fig. 7. The image is rotated 90 and 270 degrees (Fig. 7 (b), (c)) respectively and flipped horizontal and vertical (Fig. 7 (d), (e)) respectively. By this process, the number of images can be increased five times before the image augmentation.



(a) (b) (c)

(d) (e)

Fig. 7. Augmentation of images.
(a): Original image, (b): Rotated image (90 degree), (c): Rotated image (270 degree), (d): Horizontal flipped image, (e): Vertically flipped image

IV. Experiment

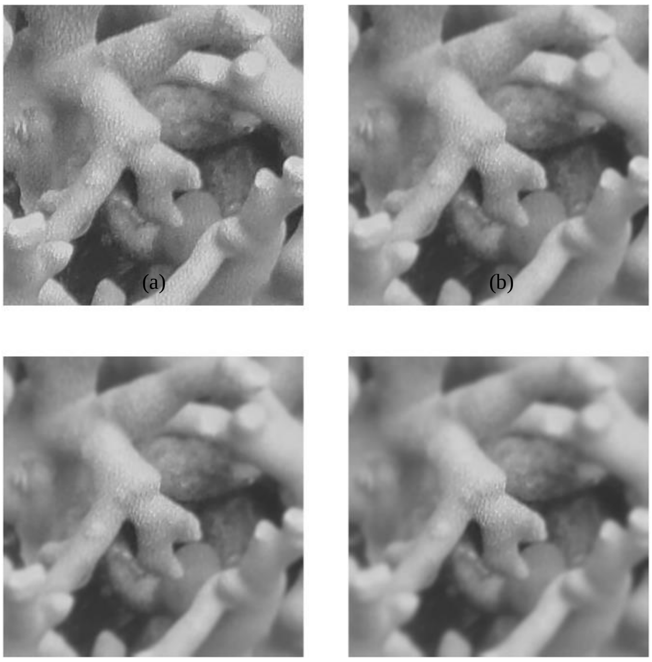
The experiment condition is shown in Table I. Quadrat images were automatically classified by the VGG, and the results were evaluated. VGG is performed using the training images described above to create a learning model. Then, similarly randomly cropped image is given to the learning model as evaluation image, and automatic classification is performed. Each 690 images of corals and rocks are increased to 3450 images by the augmentation as the training data. We also prepared 230 images of corals and rocks respectively for the evaluation of the classification.

The result of applying the Gaussian filter is shown in Fig.8. It can be seen the more the number of the iteration the Gaussian filter is applied, the stronger the distant pixels from the center of the image is blurred.

For the evaluation, cross-validation experiment was done. Training images before the augmentation is replaced with evaluation images by 230 images in each categories, and learning and automatic classification are similarly performed. We repeated the replacement by 4 times and obtained Recall, Precision, and F-measure respectively [7]. This experiment was done when Gaussian filter was not applied and Gaussian filter is used with $n = 4, 8, 16$, respectively. The experimental results are shown in Table II. We obtained Recall, Precision and F-measure by the conventional method (no filter) and the proposed methods respectively.

TABLE I: An Experiment Condition

OS	Ubuntu 18.04
GPU	GeForce RTX 2060 SUPER
NVIDIA Driver	430.50
CUDA	10.0
CuDNN	7.6.4
TensorFlow GPU	1.13.0rc0
Keras	2.3.1
Python	3.6.9



(a) (b)

(c) (d)

Fig. 8. Processed images by Gaussian filter.
(a): Original image, (b): $n = 4$, (c): $n = 8$, (d): $n = 16$

V. Discussion

From Table II, it can be seen that the results with Gaussian filter are better than the ones without Gaussian filter. In other words, blurring the distant pixels from the center of the image is effective for the automatic classification in this case. In addition, since the results of $n = 4$ and $n = 8$ is better than the one of $n = 16$.

From experimental results, although the images were misclassified when Gaussian filter was not applied, it might be correctly classified when Gaussian filter was applied, and such images had a certain tendency. The massive coral as shown in Fig. 9. It is often correctly classified when Gaussian filter is applied. When the CNN without Gaussian filter is applied, it misclassified as rock. On the other hand, it correctly classified as massive coral when the CNN is applied with Gaussian filter. It can be seen that we could appropriately use the information of pixels surrounding the attention pixel by the use of Gaussian filter.

TABLE II: EXPERIMENTAL RESULT

Image size (Gaussian filter)	6.5cm×6.5cm (no filter)		1.6cm×1.6cm (no filter)		6.5cm×6.5cm (n = 4)		6.5cm×6.5cm (n = 8)		6.5cm×6.5cm (n = 16)	
Category	Corals	Rocks	Corals	Rocks	Corals	Rocks	Corals	Rocks	Corals	Rocks
Recall	0.64	0.61	0.71	0.62	0.64	0.81	0.66	0.80	0.58	0.82
Precision	0.63	0.64	0.65	0.70	0.79	0.70	0.82	0.71	0.76	0.67
F-measure	0.62	0.61	0.67	0.64	0.70	0.74	0.71	0.73	0.65	0.73

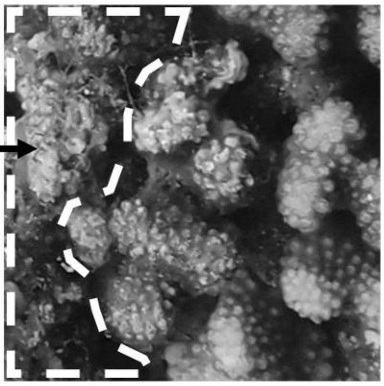


Fig. 9. An image successfully classified with the proposed method.

On the other hand, a result which is misclassified by the proposed method is shown in Fig. 10. It may be due to a loss of edge information of the massive coral appearing above area in the image.

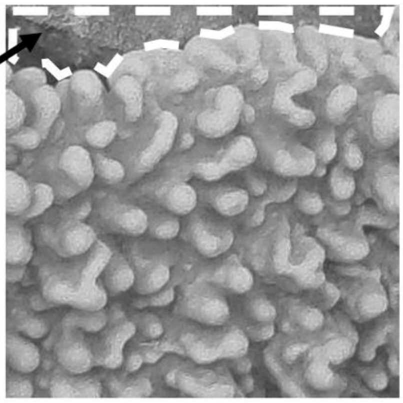


Fig. 10. An image unsuccessfully classified with the proposed method.

VI. CONCLUSION

In this paper, we classified automatically quadrat images into two categories: corals and rocks using CNN to automatize classification of matrices by quadrat method. And we also compared the classification results when Gaussian filter was applied to the images of the dataset. As a result, the proposed method performed approximately 0.7 of F-measure.

In the future, we will improve the classification accuracy by adjusting the approach to apply Gaussian filter, and will compare the proposed method with other learning methods.

CONFLICT OF INTEREST

The author declares no conflict of interest.

REFERENCES

[1] S. Nozaki, M. Suzuyama, and T. Sakamaki, "An evaluation of classification of Quadrat images into 3 categories using deep learning," *National Convention Record I.E.E. Japan*, p. 57, 2019.

[2] S. Eda, S. Nozaki, and T. Sakamaki, in *Proc. 2015 Conference of IEEJ in Okinawa*, OKI-2015-38, 2015.

[3] O. Beijbom *et al.*, "Towards automated annotation of benthic survey images: Variability of human experts and operational modes of automation," *PLoS One*, vol. 10, no. 7, pp. 1-22, 2015.

[4] A. Sakai, S. Nozaki, and Sakamaki, "Recognition of matrices of sea bottom by using deep learning," in *Proc. 2019 Conf. of IEEJ in Okinawa*, 2019, pp. 128-130.

[5] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *ICLR*, 2015.

[6] A. Watanabe and A. Sakurai, "Classification of flower images using a convolutional neural network," *Information Processing Society of Japan*, pp. 197-198, 2016.

[7] J. Ohno, S. Shirakawa, K. Ohara, and T. Toyota, "Subjective contour extraction using deep learning," *The Japanese Society for Artificial Intelligence*, 2016.

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