Microalgae Detection by Digital Image Processing and Artificial Intelligence

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Abstract

This article presents a technical approach to the video computer analysis, to automatically identifying the two most frequently identified microalgae in water supplies. To handle some difficulties encountered in image segmentation problem such as unclear algae boundary and noisy background, we proposed a deep learning-based method for classifiers or localizers to perform microalgae detection and counting process. The system achieves approximately 91% accuracy on Melosira and Oscillatoria detection, which around 4.82 seconds per grid. (Intel Xeon(R) CPU E5-2667 12 CPU at 2.66GHz and 32.0GB RAM, NVIDIA Quadro K5200 with 2304 CUDA cores). The system can significantly reduce 33.33 - 55.56% of the counting time when compared with the visual inspection of manual methods, and eliminate the error due to the human fatigue.

Keywords: Microalgae detection, Melosira, Oscillatoria, YOLO

1. Introduction

Nowadays, the quality of water from natural sources is de-creasing by human activities, agriculture, and industrial consumption. Piped water requires to be clean because people use this water for their consumption. Therefore, the Metropolitan Waterworks Authority monitors the water quality to detect possible pollutants and eutrophication phenomena which affect the production and quality control of piped water. Water supply production needs to screen all the algae with the conventional water filtration system. The filtration system is reducing its efficiency by approximately 30 percent [1], due to the algae clogging the sand filter. For this reason, the workers require to manage many algae and clean the filter more often.

The Metropolitan Waterworks Authority, in Thailand, has several departments responsible for inspecting and monitoring water sources and water supply canals. Furthermore, they collect water samples for quality analysis regularly over the year. Moreover, they also request cooperation from other organizations, such as the Department of Health, the Pollution Control Department, the Harbor Department, the Department of Agriculture Provincial, and the Public Health Office. To ensure, raw water used to produce the water supply has high quality and appropriate use for produce water supply with ISO 9002 quality standard of the Metropolitan Water-works Authority [2].

The microalgae problem in the water supply system is the main problem that is focused on this research. Microalgae are unicellular organisms that have various shapes, sizes, and structures. Classifying these microalgae manually may require experts and different experts have a different standard. To classify the microalgae, it has several steps for pre-paring the test slide and needs to use a counter-press to count a multiple of them according to the type of microalgae. The human visual system is fast and accurate, allowing us to perform complex tasks with little conscious thought. As being human, eye fatigue can make a mistake, but the computer does not. Therefore, it has various difficulties in the operation. It takes approximately four hours each day to finish the classification and counting process that means the Metropolitan Waterworks Authority spent a lot of time and cost on this work. Therefore, it will be better if they have an application that can detect and counting the microalgae directly.

There have been many researches proposing the algae detection and classification. For example, research proposed the technique which extracted features and segmentation in the algae images such as distance of contour points from centroid, number of edges, and the number of square pixels inside the edge [3]. Another work was presented by Sansoen Promdaen and et.al [4], 12 microalgae that most commonly found in water source of Thailand was classified by using blurry texture object with Sequential Minimal Optimization (SMO). Their result is pretty high with 97% of accuracy. Moreover, some researches aimed to classify the plankton image that casually share some characteristics with microalgae. However, the planktons were extracted the larger features [5]–[7] for satisfied result for classification. Currently, the machine learning become the useful tool for the object classification and recognition in the image processing. Many works applied the Support Vector Machine (SVM) for their plankton or microalgae classification [8]–[9]. For instance, Lili Xu and et.al. used the supervised learning with SVM classifier [9]. This approach obtains the information through a density method that could be sensitive to the microalgae size. Thus, the result of this proposed was still unfeasible. In addition, Paulo Drews-Jr and et.al [10]. pro-posed the microalgae classification using the semi-supervised and active learning based on Gaussian mixture models. Especially, deep learning is the popular and powerful for image processing which can apply for microalgae classification. Lago Correa and et.al [11]–[12] solved the problem using deep convolution neural network (CNN) for microalgae classification with their collected datasets. Although, these previous researches proposed the various techniques for algae or plankton classification, they could not apply counting microalgae practically. There was a re-search of microscopic algae detection by segmentation with Mask-RCNN, especially of diatoms [13]. This research had a drawback is that the performance of the detection step limits the performance of the segmentation.

With the above limitations, it is a drawback to keep up with work in conditions that algae grow well in the nature sources. In addition, the number of samples and analysis frequency could not be increased. This research aims to solve this problem with a deep learning technique called YOLO (You Only Look Once). It is a single neural network that predicts bounding boxes and class probabilities directly from full images in one evaluation [14]. We also created a classified dataset for training and making data weights to apply with the Window Form Application that we write for automated image processing the type of microalgae and evaluate the program accuracy in identifying algae type against the expert analysis.

2. Materials and Methods

2.1. *Microalgae*

Algae is a low-class organism with a simple structure that important in balancing nature. It is commonly found in nature, mostly in humid areas. Algae can be growth using water source from municipal, some industrial runoff and rainwater. According to Bold (1985) [15] dividing algae into 9 divisions. It can be categorized by characteristics of the cell. It could be single-celled algae (Unicellular) or multicellular algae (Multicellular). Algae is a simple plant that can range from the microalgae to macroalgae. Most microalgae growth requires light, carbon dioxide, water and a few nutrients [16].

Microalgae are unicellular organisms of various shapes, sizes, and structures. Only the most common and problematic microalgae were selected for data collection in this research. The expert at the Metropolitan Waterworks Authority provided information and labelled data on the two most common algae while we collected data, which are Melosira and Oscillatoria as shown in Fig. 1.

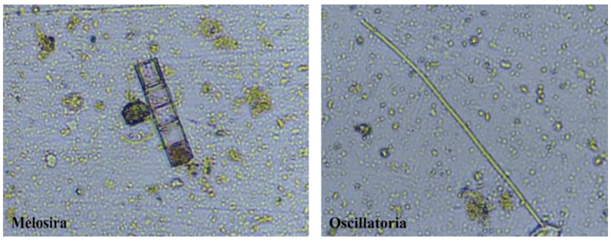

Fig. 1 Sample of Melosira and Oscillatoria.

Melosira belongs to the Division Chrysophyta, the genus Bacillariophyceae (Diatom), characterized by a round, oval, or cylindrical cell. The melosira arranged in a straight line like a chain. There are unequal dots lined up around the edge of the cell. Melosira is distinguished from Aulacoseira and other fresh-water diatoms with similar colonial growth habits by uniformly structured walls, without costae or septae, and lack of spines visible under the light microscope. The most common freshwater species that can be found in both sea and fresh water. It is generally benthic in growth habit, but it is also commonly entrained into the plankton. Some authorities consider it as indicator of organic pollution [17].

Oscillatoria is a genus of blue-green algae common in freshwater environments, including hot springs. These unbranched filamentous algae, occurring singly or in tangled mats, derives its name from its slow, rhythmic oscillating motion, which is thought to result from a secretion of mucilage that pushes the filament away from the direction of excretion [18]. Blue-green algae poisoning occurs when the algae form a scum on top of ponds or other stagnant waters. That is why this problem should be a serious concern [19].

2.2. *Methods*

This research proposes the microalgae detection on the test slide. Two main types of microalgae consist of Melosira and Oscillatoria which are very difficult to distinguish without expert skill. Classification and localization of these microalgae are extremely challenge because of complex step of preparation for microalgae sample and unclear objects on the various background in the images. This article overcomes the mentioned challenge by deep learning-based object detection technique. Therefore, this section explains the detection technique with YOLOv3, preparation of sample and system setup.

YOLO (You Only Look Once) is a real-time object detection algorithm based on the convolutional neural networks which is originally developed by Joseph Redmon et al., 2016 [14]. In additional, YOLO can detect multiple objects on a single image which the class prediction and location identification. This article applies third version of YOLO, which is faster and better than original version.

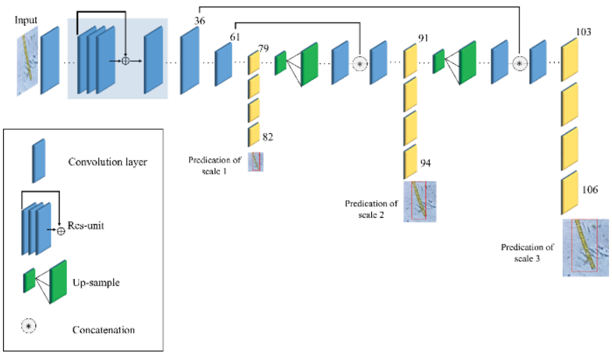

Figure 2 YOLOv3 network architecture.

The YOLOv3 network architecture is shown in the Fig. 2. This version is design with a deeper architecture of feature extraction namely Darknet-53 [14]. According to its name, there are 53 convolutional layers for this network which can detect objects on multi-scale feature maps as 79, 91 and 103 layers. Moreover, each layer followed by a batch normalization layer and Leaky ReLU activation function.

Table 1 Configurations for training model using YOLOv3.

Parameters	Configuration
Size of input image	2048 px. × 1152 px.
Number of training images	794 images for Melosira, 1159 images for Oscillatoria
Learning rate	0.001
Decay of Learning rate	0.0005
Number of epochs	4000
Batch size	64

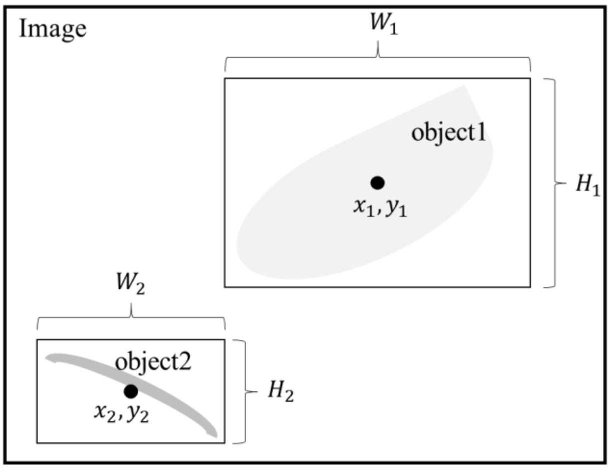

Figure 3 Bounding box for training the YOLO.

For the training process of YOLOv3, the bounding boxes of the whole object targets with their labels are required. Fig. 3 shows the bounding box and its essential parameters for training the YOLOv3. There are totally five parameters for each object including x-coordinate of center in a bounding box (x), y-coordinate of the center in a bounding box (y), width of the bounding box(W), height of the bounding box (H) and an object label, which can create the training matrix of these parameter as Eq. 1. Furthermore, training configurations are described in Table 1. This article focuses on two types of microalgae, Melosira and Oscillatoria. In order to obtain the correct microalgae images, these training images are labelled by the expert from Metropolitan Waterworks Authority.

$$Y = \begin{bmatrix} object1 & x_1 & y_1 & W_1 & H_1 \\ object2 & x_2 & y_2 & W_2 & H_2 \\ & & \vdots & & \\ objectn & x_n & y_n & W_n & H_n \end{bmatrix} \tag{1}$$

The output of YOLO will provide the five values involving the object location in the image as same as the values of training parameters. Moreover, the confidence values will return the probability (0–1) of detected object for each bounding box which zero means the lowest confidence of object prediction and one are the highest confidence of prediction.

2.3. *Preparation of Microalgae Samples*

Samples of microalgae were obtained from raw water supplies. Raw water with 50 mL., from the raw water source, were poured to the test tube. To separate the components of liquid in the test tube, a centrifuge was used for this process. The centrifuge was set as 2500 round per minute, with 20 minute of process time. The obtained liquid in the test tube would be separated into two parts, which are liquid and pel-let (microalgae) for the top and bottom parts respectively. Then, upper part of liquid was drawn off 40 mL. using pipette. The remained liquid with 10 mL., in the test tube, was brought to the Vortex mixer machine for mixing the sample of 10 second. To prepare the samples of microalgae, finally, dropping the sample from the test tube to the microscope slide. The Fig. 4 is shown the overview process of these preparation.

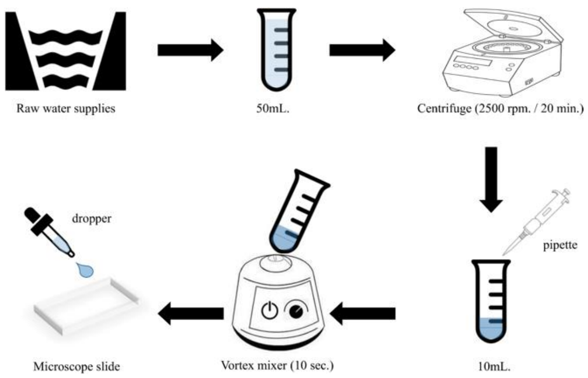

Figure 4 Steps of Microalgae samples preparation.

2.4. *Apparatus and system setup*

In order to collect the digital images of microalgae, apparatus selection and system setup are the crucial process. There are three main components consisting of light micro-scope, digital microscope and computer.

The proposed system uses the microscope which is set the 10× magnification for objective lens, because it is fit enough to observe the microalgae. Next component is the digital microscope, which is the important part for collecting the digital images from microscope. This article uses Eakins Digital Microscope which specification of this device is shown in Table 2.

Table 2 Specification of Eakins Digital Microscope.

Specifications	Configuration
Model	21MP 30MP Microscope camera
Picture pixel	38MP / 30MP / 21MP
Video size	30fps for 4K / 60fps for 1080P
CMOS Sensor	1/2.33 inch
Lens Interface	Industrial 200X, 500X, 100X

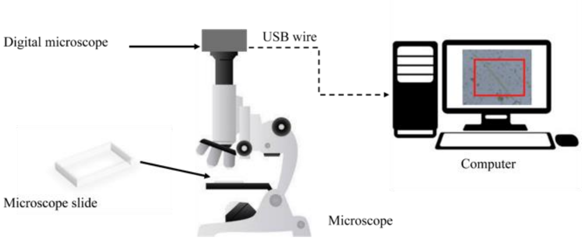

Figure 5 Image acquisition system.

The digital microscope was attached to the C-mount lens where was on the top of the microscope as shown in the Fig 5. The images with the size of 8,320 px. × 4,680 px. were acquired by saving on the micro SD card, which was built-in on the Eakins Digital Microscope. Because a large number of images were trained by using YOLOv3, the GPU on a computer was required. The specification of the computer was Intel Xeon(R) CPU E5-2667 12 CPU at 2.66GHz and 32.0GB RAM, NVIDIA Quadro K5200 with 2304 CUDA cores.

3. Experiments and Results

After training the model of YOLOv3 as explaining in previous section, the performance of detection will be measured. This article provides and develops the user-interface on Visual Studio C# that can read the images and detect the micro-algae using YOLOv3 as shown in Fig. 6–7. The tested images show the various sizes of microalgae and noisy background. The experiment tests the 23 unknown images which contains the ground truth of Melosira and Oscillatoria as 9 and 14 images, respectively. Table 3. shows the confusion matrix of microalgae detection, which can calculate necessary performance as shown in equation 2 to 8. The proposed method shows the high accuracy of detection by 0.91, and high performance of F1 score both of Melosira and Oscillatoria.

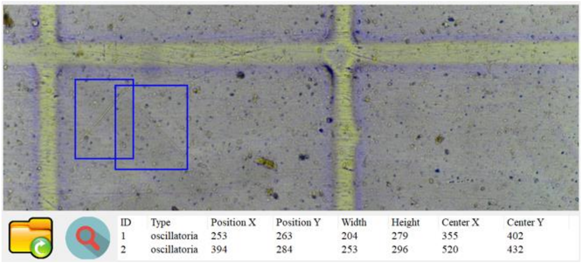

Figure 6 Detection of Oscillatoria.

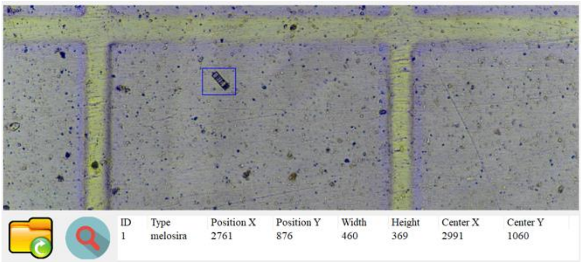

Figure 7 Detection of Melosira.

Table 3 Confusion matrix of detection.

Actual Values / Predicted Values	Melosira	Oscillatoria
Melosira	9	0
Oscillatoria	2	12

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = 0.91 \quad (2)$$

$$Precision(Melosira) = \frac{TP}{TP + FP} = 1.00 \quad (3)$$

$$Precision(Oscillatoria) = \frac{TN}{FN + TN} = 0.85 \quad (4)$$

$$Recall(Melosira) = \frac{TP}{TP + FN} = 0.82 \quad (5)$$

$$Recall(Oscillatoria) = \frac{TN}{FP + TN} = 1.00 \quad (6)$$

$$F1(Melosira) = \frac{2 \times Precision \times Recall}{Precision + Recall} = 0.90 \quad (7)$$

$$F1(Oscillatoria) = \frac{2 \times Precision \times Recall}{Precision + Recall} = 0.92 \quad (8)$$

Generally, a test slide has a thousand of grid. The expert usually takes 2-3 hours per slide for counting the microalgae. For this proposed technique, the average processing time of detection is 4.82 seconds per image (or per grid). Therefore, it will take around 1 hour and 20 minutes for counting microalgae per a test slide, which is 1.50-2.25% faster than visual inspection of an expert. The proposed system can significantly reduce 33.33-55.56% of the counting time, and eliminate the error due to the human fatigue.

4. Conclusion

This article has shown the feasibility of microalgae detection with the noisy background and various size of microalgae. Especially, Melosira and Oscillatoria are the most frequently found microalgae in water supplies that impact to the quality assessment of the water source. According to the experiment, the system can detect and count the Melosira and Oscillatoria by 91.00% accuracy and 4.82 second per grid using the YOLOv3. The system can reduce 33.33-55.56% of the counting time of microalgae compared to human counting. However, the limitations and problems for some images are still faced such as the missed detection in case of scratch on the microscope slide and lacerated microalgae.

Future work is to develop the automatic microalgae counting system with moving the stage of the microscope. Moreover, other microalgae types will be detected for this automatic counting system.

Acknowledgements

This work is supported by Metropolitan Waterworks Authority – MWA and Associate Professor Doctor Ramil Kesvarakul from King Mongkut's University of Technology North Bangkok.

References

1. Provincial Waterworks Authority with the problem of algae and drought [Online]. 2014, Website: https://www.pwa.co.th/news/view/30398.
2. Quality of raw water for provincial waterworks authority in Thailand. 2005, Website: https://www.mwa.co.th/ewt_news.php?nid=428&filename=Event.
3. P. Coltelli and et al., "Water monitoring: automated and real time identification and classification of algae using digital microscopy", Environmental Science: Processes & Impacts vol. 16, no. 11 ,pp. 2656-2665, 2014.
4. S. Promdaen, P. Wattuya and N. Sanevas, "Automated microalgae image classification", Procedia Computer Science, vol. 29, pp. 1981-1992, 2014.
5. M.A. Mosleh and et al., "A preliminary study on automated freshwater algae recognition and classification

system", BMC bioinformatics, vol. 13. no. 17, BioMed Central, 2012.
6. M.C. Benfield and et al., "RAPID: research on automated plankton identification", Oceanography, vol. 20, no.2, pp. 172-187, 2007
7. A. Verikas and et al., "An integrated approach to analysis of phytoplankton images" IEEE Journal of Oceanic Engineering, vol. 40, no.2, pp. 315-326, 2014.
8. Q. Hu and . Davis, "Accurate automatic quantification of taxa-specific plankton abundance using dual classification with correction", Marine Ecology Progress Series, vol. 306, pp. 51-61, 2006.
9. L. Xu, and et al., "Red tide algae classification using svm-snp and semi-supervised fcm.", 2010 2nd International Conference on Education Technology and Computer, vol. 1. IEEE, 2010.
10. R.G. Colares snf et al., "Microalgae classification using semi-supervised and active learning based on Gaussian mixture models", Journal of the Brazilian Computer Society, vol. 19, no.4, pp 411-422, 2013.
11. I. Correa and et al., "Deep learning for microalgae classification", 2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA). IEEE, pp. 20-25, 2017.
12. S. Lakshmi, and R. Sivakumar, "Chlorella algae image analysis using artificial neural network and deep learning", Biologically Rationalized Computing Techniques For Image Processing Applications, Springer, Cham, 2018, pp. 215-248.
13. J. Ruiz Santaquiteria, and et al., "Semantic versus instance seg-mentation in microscopic algae detection", Engineering Applications of Artificial Intelligence, vol. 87, pp. 103271, 2020.
14. J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection", Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., vol. 2016-Decem, pp. 779–788, 2016, doi: 10.1109/CVPR.2016.91.
15. H. C. Bold and M. J. Wynne, Introduction to the algae: structure and reproduction, 1978.
16. S. Zullaikah, A. T. Utomo, M. Yasmin, L. K. Ong, and Y. H. Ju, "Eco-fuel conversion technology of inedible lipid feedstocks to renew-able fuel", Adv. Eco-Fuels a Sustain. Environ., pp. 237–276, 2019, doi: 10.1016/b978-0-08-102728-8.00009-7.
17. Kociolek, J. Patrick, et al. "Centric and araphid diatoms." Freshwater Algae of North America. Academic Press, 653-708, 2015.
18. T. K. Bhutia, K. Rogers, and G. Shukla, Oscillatoria, Britannica, T. Editors of Encyclopedia. 2016, [Online]. Available: https://www.britannica.com/science/Oscillatoria.
19. W. K. Rumbeiha and D. B. Snider, "Veterinary Toxicology, in Encyclopedia of Toxicology: Third Edition", Elsevier, 2014, pp. 915–928.

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