フロック撮影画像の畳み込みニューラルネットワークによる最適凝集条件決定手法

Polyaluminum chloride dosage optimization by using convolutional neural network for floc images

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1. Introduction

Coagulation is an indispensable unit process for treating the turbidity and color of the surface water in more than half of the water purification plants in Japan. Because the coagulation efficiency influences the subsequent flocculation and sand filtration processes, its optimization is essential for the management of the entire water treatment systems.

Coagulation is governed by the pH and coagulant dosage. In practice, jar tests are usually conducted to determine the optimum coagulant dosages; but, the decreasing number of professional engineers and experienced operators in the water treatment plant have caused some utilities to face difficulties in controlling coagulation process using conventional jar tests.

Coagulation is expressed by complex chemical reactions resulting in nonlinear behavior, and obtaining reliable tools for coagulant dosage optimization is challenging. Several studies have been conducted studies using linear-numerical equations and artificial neural networks (ANNs) to predict optimum coagulation conditions. But, the long-term applications of ANNs-based model to an unprecedented situation or a different water basin often fails because ANNs are usually developed without a physical understanding of coagulation-flocculation process. The current climate changes cause sudden and extreme increases in feed water turbidity. Such unprecedented situations often render conventional numerical models to be obsolete.

The primary equation of flocculation is governed by Stokes equation, where the floc settling velocity is a function of the size and density of floc; here the density of floc is correlated to its fractal dimension. The state of coagulation can be assessed by extracting certain physical properties from floc images because all the parameters related to floc precipitation can be obtained based on its physical properties. If novel tools that possess the visual extraction are developed, coagulation performance can be immediately assessed using floc images, optimal conditions could be created and maintained.

Convolutional Neural Network (CNN) is a well-known deep learning architecture inspired by the natural visual perception mechanism of the living creatures. CNN has been successfully implemented in the broad of computer vision area for decades, because of their ability to recognize visual patterns from pixel images. CNN have been successfully implemented in computer vision field and applied to image classification, and object detection tasks. But, CNN implementation in water treatment field have never been done.

Herein, CNN was applied to establish a new approach for optimizing the coagulant dosages. Feeding floc images into a CNN-based model may enable it to immediately assess the state of coagulation. First, applicability of CNN was assessed using floc images of artificial surface water. Next, CNN was challenged using floc images of natural surface water. CNN-based models were enhanced to increase its performance. Finally, the potential of CNN for controlling the coagulation in comprehensive situation was assessed according to one model, which incorporated the results from jar tests obtained using different water basin samples.

2. Materials and methods

2.1 Data preparation

Artificial surface water

Five types of artificial surface water with variable turbidity levels were prepared by mixing humic acid with tap water. The Suwanee River humic acid standard III and kaolin were used as substitutes for any dissolved organic matter and suspended particles, respectively. The characteristics of artificial water are presented in Table 1.

Table 1. Artificial water characteristic

Variety	Raw water characteristic	
	Turbidity (NTU)	UV-254 nm (cm^{-1})
1	10	0.02
2	50	0.02
3	100	0.02
4	500	0.02
5	1000	0.02

Natural surface water

Natural water samples were obtained from Yoshimi Water Purification Plant, whose intake is the Ara River. Sampling were conducted twice per week from December 2018 to September 2019. Typical seasonal changes were observed with respect to the water quality. Further, the turbidity and temperature gradually increased from winter season to summer season. From December 2018 to April 2019, turbidity and temperature were very low with an average value of 3.24 NTU and 9.9°C, respectively. From May 2019 to September 2019, turbidity and temperature were 25.4 NTU and 20.5°C in average, respectively. Extremely high turbidity (1425 NTU) triggered by Hagibis typhoon also included in dataset.

Jar test

Jar test were conducted using a water cohesion tester. Commercial PAC (basicity: 54.5%) was used as the coagulant. The usage of 5 mL (2.96 mg Al/L) or 15 mL (8.88 mg Al/L) were tested for artificial surface water. For natural surface water, four variations of coagulant dosages were tested: 4x, 2x, 1x and 0.5x of empirically determined ideal dosage. With respect to the practical condition, the rotating speed of the paddle was set to be 150 rpm for the initial 2 min (rapid mixing), 30 rpm for the subsequent 10 min (slow mixing), and 0 rpm for the final 10 min (settling). After the settling, supernatant was taken at 6 cm below from the water surface. The floc formation was continuously recorded using a 4K video camera. At the end of the tests, supernatants were characterized by their turbidity.

Recording conditions

4K digital camera set on handmade aluminum frame was used for the recordings. The frame was strictly adjusted to ensure a particular region could be captured by the camera. The white balance was set to automatic, the focal distance was set at F8, the frame rate was set to 30 frames per second (fps), and the ISO sensitivity was set to 1000. The camera was manually focused on a scale placed beside a beaker.

Figure 1. Example of floc images

Each recording was twenty-two minutes long and comprised of 39,600 images, more than 1 million images were obtained from 30 trials of artificial surface water and 515 trials of natural surface water. Further, a 300 × 300-pixel portion was clipped from the upper right part of each image. This part was selected to avoid any light reflection and beaker margins, as shown in Figure 1

Data classification

The results of trials were classified into four categories according to the turbidity of supernatants. The boundary of each category was decided based on a consultation conducted with an operator working at the Yoshimi Purification Plant. Specifically, a sample with turbidity less than 0.1 NTU was regarded as “Class 1A”, which is equivalent to the drinking water standard in Japan but generates a considerable amount of sludge. “Class 2A” denoted samples having a turbidity of 0.1-0.5 NTU, which is sufficient for sand filtration but generates more sludges when compared with that generated by “Class 3A”, denoting samples having a turbidity of 0.5-1.0 NTU. These levels allow sand filtration and minimize the production of sludge. Further, “Class 4A” denoted samples having a turbidity of greater than 1.0 NTU, exceeding the allowable level. The optimum coagulant dosage was represented as “Class 3A”.

For natural surface water, all the jar tests could not achieve a level of turbidity less than 0.1 NTU even when a considerable amount of coagulant was added. Therefore, the data obtained using natural water were classified into three groups: 0.1-0.5 NTU (class 1B), 0.5-1.0 NTU (class 2B), and more than 1.0 NTU (class 3B).

Lengths of the jar test recordings

Models were constructed corresponding to the lengths of the video recordings of the jar tests. Short recordings resulted in quick assessments, and optimum recording length was determined based on the accuracy of the models.

For artificial waters, six models were constructed. For Models 1 and 2, the images obtained from the initial 1600 s and 1200 s of the recordings were used, respectively, including those during rapid mixing, slow mixing and settling. For model 3, the images including those obtained during rapid mixing, slow mixing and beginning of settling within 800 s, whereas for Models 4 and Models 5 the images, including those obtained from rapid and slow mixing from initial 400 s and 200 s, whereas the images denoting only rapid mixing from the initial 100 s were used for Model 6.

For natural surface water, eight models were constructed for every 100 s duration of the video recordings of the jar tests. For model 1, the images from 100-200 s of the recordings were used, including those during raid mixing. For model 2 to model 6, the images every 100 s from 200-700 s were used, including those in slow mixing, whereas model 7 and model 8, images every 100 s from 700-900 s were used, including those in settling.

2.1 CNN based-model

CNN architecture

Initially, the database was fed into a CNN-based model having AlexNet architecture[1], which is organized into eight learning layers. Subsequently, ResNet-50 architecture[2] were applied in case of natural surface water. ResNet-50 architecture having deeper layers, which is organized into fifty learning layers.

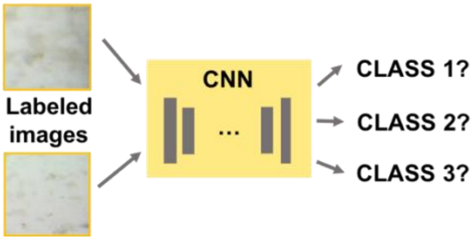

Figure 2. CNN model input and output

The activation function used to construct the neural network was rectified linear unit (ReLu), and the weight of the network was optimized using Adam Optimizer. The entire datasets were divided into (1) training data used to adjust CNN weight (68%), (2) validation data used to minimize overfitting (12%), (3) test data used to provide unbiased CNN performance dealing with new dataset (20%). The CNN models constructed with floc images as input and turbidity classification as output (Figure 2). All models were trained until 50 epochs (training cycle).

Data augmentation (Gaussian blur)

Gaussian blur used as gradient filter in CNN model enhancement, it gives effect to reduce the amount of noise and remove speckles within the image.

3. Result and Discussion

The CNN models were initially constructed using artificial surface water. The validation accuracy of each model shown in Figure 3. All the models exceeded 96% and maximum validation accuracy of 99.8% was achieved within 100 s, which required only the images of rapid mixing. This result implies that the rapid mixing images were sufficient for obtaining a reliable model, and the optimum coagulation conditions was already determined by the end of rapid mixing.

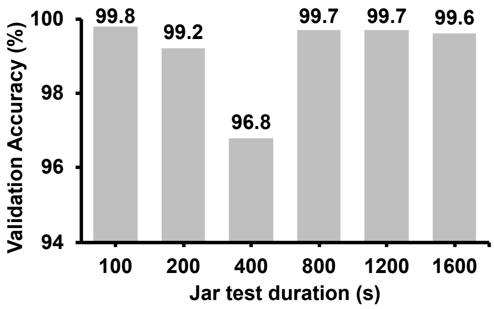

Figure 3. CNN with artificial surface water

Further, CNN was challenged using floc images of natural surface water with low temperature (4.9°C – 14.5°C). The validation accuracy of all constructed models was lower compared to CNN model built by artificial surface water (Figure 4), longer time (400-500 s) was required to achieve maximum accuracy.

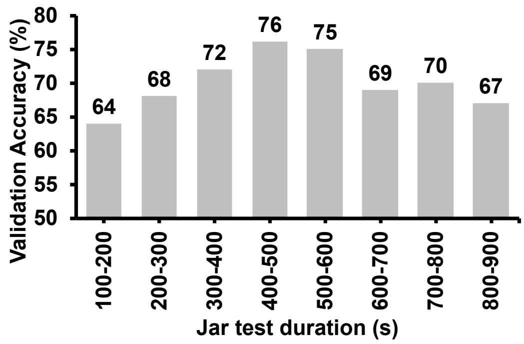

Figure 4. CNN with natural surface water (low temperature)

Performance comparison of CNN architecture

The possible factor causing lower versatility was the diversity of floc image patterns. The images taken under low feed water turbidity shows loose and unclear which seemed vague. The floc density is strongly influenced by water turbidity and unclear loose floc is formed when the water turbidity is low enough.

Initial approach to increase the accuracy were usage of different CNN architecture of ResNet-50, which has deeper layer compared to AlexNet. Deeper layer enables the extraction of intermediate features of floc between the raw images data and the classification. As illustrated in Figure 5, changes in architecture increased accuracy by less than 1%.

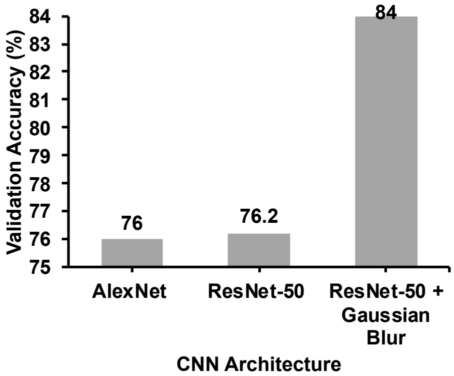

Figure 5. Performance comparison between three different methods

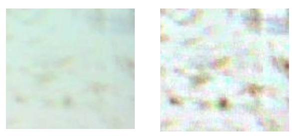

Figure 6. Floc images before (left) and after (right) Gaussian Blur

Next approach is enhancing the images character by data augmentation called Gaussian blur. Gaussian blur was used in reducing the noise in images[3] and demonstrated their effectiveness in the field of medicine. The filter was applied before inputting ResNet-50. Figure 6 illustrated that Gaussian filter made floc images more clear even for the low turbidity condition. CNN model constructed by the combination of ResNet-50 and Gaussian blur successfully increased validation accuracy of around 10% (shown in Figure 5). The result implies that application of image filter was a reliable method to increase the model robustness, especially when the captured floc was vague. Still, there is a possibility that other data augmentation methods may have better performance.

Temperature effect in coagulation process

Another possible factor influencing the constructing models was the water temperature. Previous studies that investigated key factors influencing the coagulation denoted the importance of water temperature on the floc formation because temperature affects chemical reaction rate and floc settling velocity. The experiments using artificial surface water carried out under constant room temperature (approximately 25°C), whereas that using natural surface water was fluctuated as shown in Figure 7. Temperature differences might cause a difference in floc formation speed and provide a distinction at optimum recording length between low temperature and high temperature.

Data taken using natural surface water were divided to three categories. For "category 1" including those with temperature lower than 10°C, "category 2" denoted samples having temperature 10-20°C, whereas "category 3" including those with temperature higher than 20°C. The validation accuracy of each model was shown in Figure 8. The maximum accuracy in every temperature category was achieved within 4-6 minutes of recording length.

The final model was constructed with 4-6 minutes of natural surface water floc images. All of images data was pre-processed by Gaussian blur filter before trained upon ResNet-50 architecture. The final model was tested on the data from Yoshimi Water Purification Plant (December 2018-September 2019 data) and the accuracy achieves was 80%, while when the final model tested on the data from different water basin which is Okubo Water Purification Plant (November 2019 data) the accuracy achieves was 71.6%. The result implies that further enhancement is required to increase the prediction accuracy.

Additionally, public safety is the major priority in constructing CNN model for water treatment field. In that regards, a parameter called safety level (α) was introduced, as shown in Equation (1a), where A is true prediction and B is class 3B predicted as class 2B. This parameter involved the condition were coagulant dosage is not enough to treat feed water into allowable level. The maximum value as the final goal is 100%. Implementing the safety level (α) into the final CNN model resulting in 94.2% on Yoshimi Water Purification Plant data, this implies that more enhancement is required. The safety level (α) of final model on Okubo Water Purification Plant data was 100%, but it is worth noting that the data tested was limited on November 2019 data, therefore more tests are required.

$$\alpha(safety) = \frac{\Sigma A}{\Sigma A+B} \times 100 \qquad (1a)$$

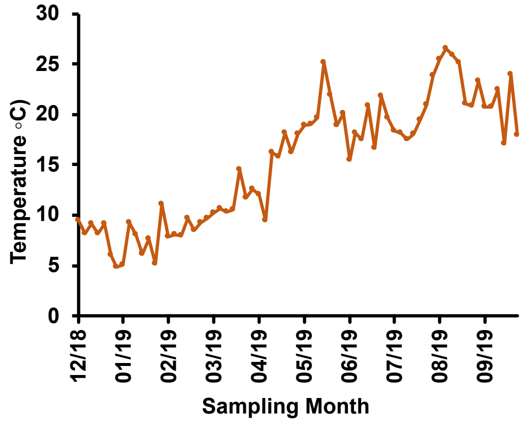

Figure 7. Natural surface water temperature

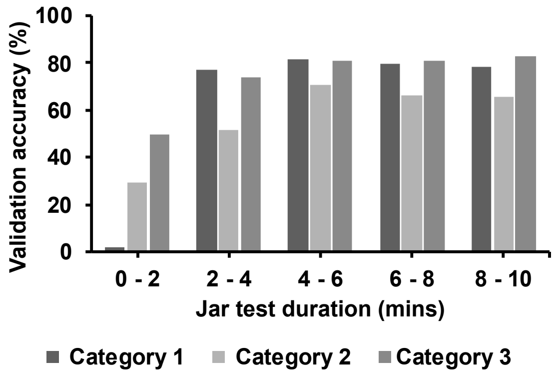

Figure 8. Validation accuracy of natural surface water in different temperature

4. Conclusion

CNN was implemented for artificial water and natural water floc images. The final CNN-based model was implemented upon Gaussian blur and ResNet-50, with 4-6 minutes jar test length considered as optimum to judge coagulation performance on natural surface water. Therefore, more enhancement and tests are required to construct more robust and viable model.

References

1) Krizhevsky, A., Sutskever, I. and E. Hinton, G., 25th International Conference on Neural Information Processing Systems, ImageNet Classification with Deep Convolutional Neural Networks, 25, 1097-1105, 2012.

2) Sivchenko, N., Kvaal, K., Ratnaweera, H. and Tsang, Y, F., Cogent Engineering, Evaluation of image texture recognition techniques in application to wastewater coagulation, 3 (1), 1-20, 2017.

3) Gedraite, E.S. and Hadad, M., International Symposium ELMAR-2011 Proceedings, Investigation on the effect of a Gaussian Blur in image filtering and segmentation, 53, 393-396, 2011.