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Original Article

Image recognition method using Local Binary Pattern and the Random forest classifier to count post larvae shrimp

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ABSTRACT

Thailand is one of the world's largest shrimp producers. However, Thailand's fishery industry, which includes the shrimp industry, is still using human labor intensively. The culture process starts with getting shrimp that are at the early "post-larvae" stage from a supplier and growing them in a closed environment. One of the most basic tasks, counting the number of larvae, is tedious labor-intensive work. To increase the effectiveness of this traditional task, the use of image recognition techniques for larvae counting was investigated through the evaluation of two feature extraction methods: Local Binary Pattern (LBP) and Red, Green, Blue (RGB) feature extraction, with an ensemble tree classifier, Random Forest (RF). Assessing the results with K-fold cross validation (k = 5) showed the LBP method was 98.50% accurate. This research had a relatively large root mean square error (RMSE) of 14.43 due to the overlapping of shrimp. This method has the potential to help with this basic and essential task and increase the efficiency of the shrimp farming process.

Introduction

Thailand is one of the world's largest producers of farmed shrimp, having produced 314,018 t in 2016 (Food and Agriculture Organization of the United Nations, 2016). Shrimp farming has become an economically significant industry for Thailand, so the effective management of this industry is important. One major factor for shrimp farming management is maintaining a proper stocking density. Overstocking results in various problems such as increased rates of disease (Holmström et al., 2003). One of the key methods for controlling shrimp diseases is to maintain water quality by controlling the number of shrimp per area, with the recommended density being 50,000–100,000 shrimps per 1600 m^2 (Department of Fisheries, 2016).

The importance of maintaining proper population densities makes counting the shrimp a crucial task. However, the current counting method is time-consuming and frequently leads to human error. In practice, most counting techniques involve manual work whereby the post larvae shrimp are captured and hand-counted. The limitations of manual counting has interested researchers in developing counting techniques based on computer technology. One study by Panmanee and Taparhudee (2012) proposed automated fish counting image processing and reported that the errors within frames increased with the number of fish with 0.8% error, with the error mainly due to overlapping of the fish fry. More previous studies are provided in the next section. The current research developed shrimp counting software for automatic shrimp counting that can be utilized for both future farming use and for marine science research. By accurately estimating the total number of the post larvae shrimp population in a sample location by applying various image recognition techniques to still images, the number of shrimp can be used to estimate the number of shrimp per unit volume and to regulate the shrimp density to prevent diseases. The main contribution of this paper was to apply image recognition techniques for shrimp population counting and to develop techniques that may eventually help shrimp farmers to work more efficiently.

Materials and methods

Previous studies on possible ways of counting fish fry such as Zheng and Zhang (2010) explored new methods of fish counting,

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Table 1
Photo setting parameters.

Item	Setting
Object distance	50 cm
Image dimension (pixels)	4032 × 3024
F stop	f 3.5
Exposure time (s)	1/60
ISO speed	ISO 800
Shutter	1/50

using digital pictures, fuzzy theory and Artificial Neural Networks. That research examined overlapping fish in congested situations as well as different sizes of fish. Another study of counting and measuring fish by Westling et al. (2014) had three modules (identification, tracking and measuring), which were the main parts of their suggested framework. They also added two steps in case there were insufficient data. A study that showed a simple method to count and track underwater fish from videos provided additional knowledge about fish behavior (Sharif et al., 2015), by applying a new technique for background subtraction using the Hungarian algorithm and a Kalman filter. A study that explored an algorithm for skeleton reconstruction (Boonchuaychu et al., 2015) to identify and isolate individual objects in a cluster of overlapping objects used information on edges and statistical geometric measures. Another study (Toh et al., 2009) reported how an automatically feeder fish count method could use image processing. An automated fish fry counting system proposed by Labuguen et al. (2012) presented an immediate counting answer. The proposed counting process was made simpler and faster by using computer vision and image processing. In that system, a photo of fish fry in a specially designed container undergoes binarization and edge detection. For every image frame, the total fish count is the sum of the area inside every contour. Then the average number of fish for every frame was summed. The first prototype of the Aquatic Tool Kit (ATK) with the aim of counting and measuring the total number of fish larvae through image processing techniques was presented by Loh et al. (2011). The software-based larvae detection system provided improved reliability, efficiency and accuracy when estimating the total number of fish as well. Detection and tracking can be integrated for use in detecting and counting fish (Fier et al., 2014). The approach consisted of three consecutive modules: preprocessing, detection and tracking. Three research studies (Cadieux et al., 2000; Morais et al., 2005; Fabic et al., 2013) have shown image processing techniques can be applied to detect and count the number of fish. These various studies attempted to eliminate the need for the time-consuming counting of fish using human labor. An efficient method of fish counting would enable many marine scientists to accelerate their tasks. A statistical method of texture analysis was proposed by He and Wang (1990) by first using the concept of texture unit and then texture spectrum described the distribution of all the texture units within the image. The results showed the potential usefulness of the proposed method in texture analysis. A new study (Liu et al., 2016) reported that the Local Binary Pattern (LBP) method had been successfully applied to many diverse problems. A large number of LBP variants have been developed to improve its robustness, discriminative power and applicability. Random Forests (Breiman, 2001) are an effective tool in prediction. Based on the Law of Large Numbers, they do not overfit. Applying the right kind of randomness makes them accurate classifiers and regressors. Furthermore, the framework in terms of strength of the individual predictors and their correlations provides insight into the ability of the random forest to predict. Another study (Ristin, 2016) examined how two variants of Random Forests (Nearest Class Mean Forests and Support Vector Machine Forests) performed in large-scale, multiclass image classification.

The present study developed a method for counting a post larvae shrimp population. The main contribution of this method is automated counting of the post larvae through image recognition methods. Manual counting is a difficult process for humans to perform manually; therefore, to overcome this problem, machine vision software was employed.

The experiments started at a shrimp farm at the Faculty of Science and Fisheries Technology, Rajamangala University of Technology Srivijaya, Trang, Thailand. Photographs were taken of post larvae shrimp from the suppliers and studied using the computer laboratory facilities at the Department of Engineered Technology, Faculty of Engineering and Technology, Rajamangala University of Technology Srivijaya, Trang, Thailand.

The proposed image recognition techniques for larvae counting involved the comparison of two features of extraction methods: local binary pattern (LBP) and RGB feature, with an ensemble tree classifier, Random Forest (RF; Pedregosa et al., 2011). Finally, it was found that LBP is more accurate and stabilized than RGB starting at a radius of 3 pixels and half-window-size of 3 pixels.

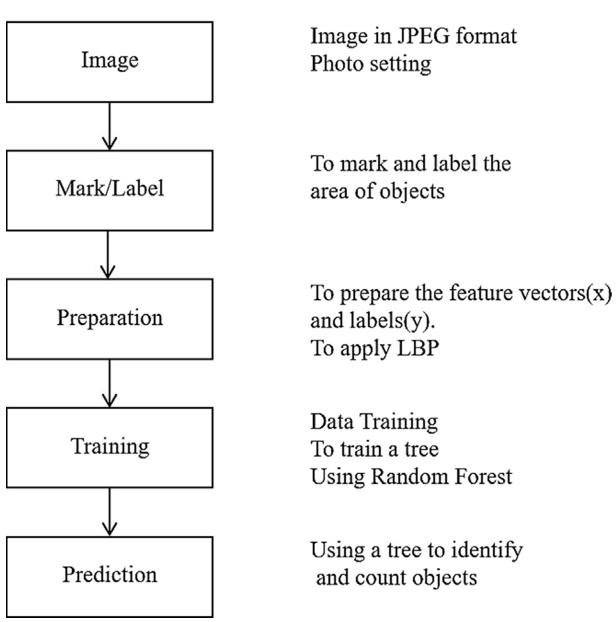

Fig. 1. Image recognition method for counting post larvae of shrimp.

Fig. 2. Original photograph of post larvae shrimp.

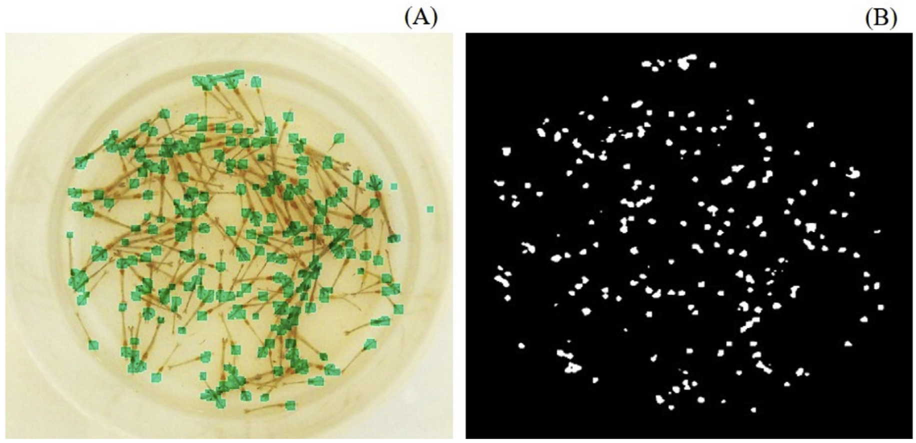

Fig. 3. Images in Red, Green, Blue extraction: (A) prediction; (B) count of post larvae shrimp. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

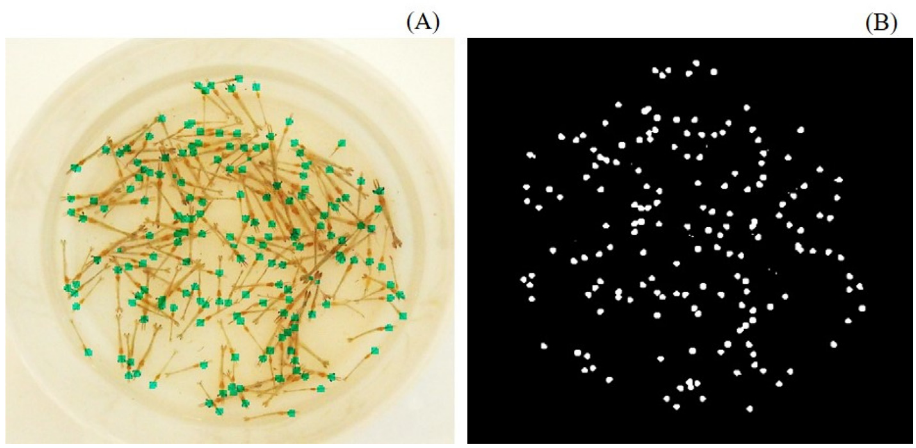

Fig. 4. Images in Local Binary Pattern extraction: (A) prediction; (B) count of post larvae shrimp.

The result from this experiment showed that this technique was acceptable with 98.5% accuracy. The software can predict new untrained pictures of post larvae shrimp using the photo settings shown in Table 1. This method needs further development to produce a web-based or mobile phone application for Thai farmers. Cv2 (Laganière, 2014) and NumPy (Oliphant, 2006) were used for the computing program development.

The following steps were used in conducting the experiment.

1. Prepare sample by pouring shrimp larvae into a 100 cm^3 water container with background.

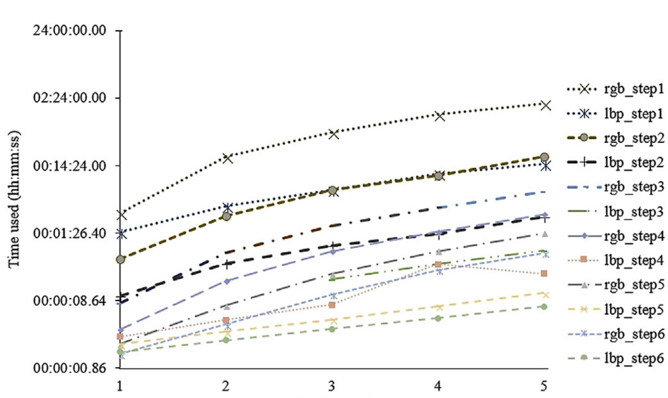

Fig. 5. Comparison of time used for feature extraction.

2. Capture the image as shown in Table 1.
3. Collect all images in the working directory (dataset).
4. Extract features and count the number of shrimps.
5. Record the number of shrimps from each preparation for future analytics.

General view of the methodology

The software used was designed to mark and identify the post larvae shrimp. A combination of photo setting and machine vision software was used to process the images obtained, as shown in Fig. 1.

First, pictures were produced to serve as datasets. An example of a dataset picture is shown in Fig. 2, and the photo setting is shown in Table 1.

Next, images were extracted and processed using the software from the beginning of experiment to compare the two features extractions (RGB and LBP and ensemble tree decision, RF). Later LBP feature extraction and RF were used as classifiers.

Preliminary

The RGB feature extraction is shown in Fig. 3. The program displays some areas with counting result errors. In these areas, the program prediction displays two types of errors. It shows shrimp in areas that do not contain shrimp and fails to show shrimp in cases of overlap. These errors can make the total count inaccurate.

LBP feature extraction is shown in Fig. 4.

The two image recognition methods (RGB and LBP) were compared with manual counting for time used and accuracy as shown in Figs. 5–7. The radius settings of RGB and five half-window-size settings of LBP were used in the comparisons.

Fig. 5 shows that RGB feature extraction required more time than LBP. For LBP, the tests showed that higher half-window sizes resulted in higher accuracy but required more time (Fig. 6).

Fig. 7 shows that LBP was more accurate and stabilized than RGB starting at hwz = 3. Fig. 7 shows that a value of hwz = 3 produced the most accurate prediction of the number of shrimp. After this preliminary testing to identify the optimal method and

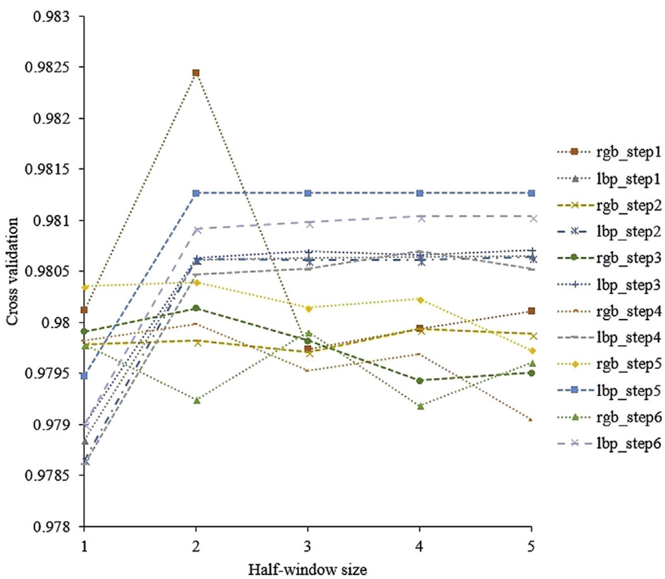

Fig. 6. Comparison of cross validation for feature extractions using Local Binary Pattern and Red, Green, Blue extraction methods (lbp and rgb, respectively, in legend entries). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

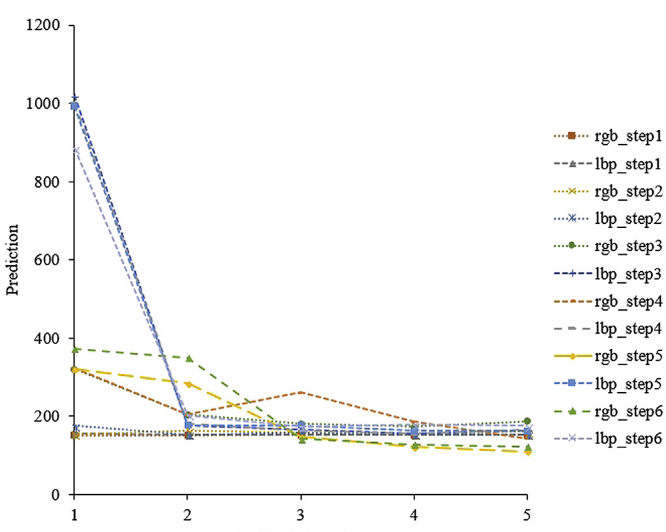

Fig. 7. Comparison of accuracy prediction and stabilization of Local Binary Pattern and Red, Green, Blue extraction methods (lbp and rgb, respectively, in legend entries). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

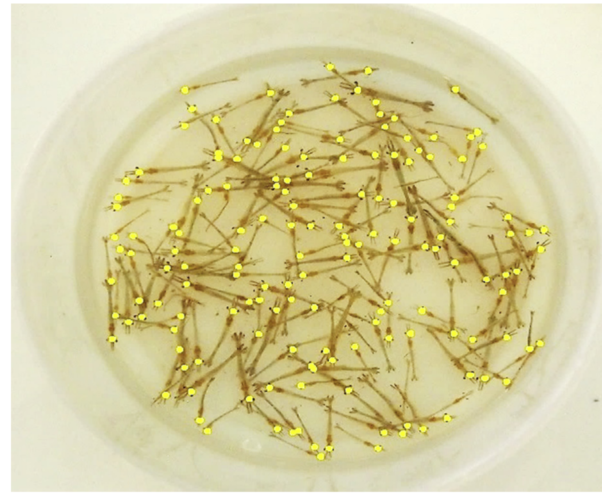

Fig. 8. Display of marked shrimp for prediction.

half-window size parameter, LBP was used for feature exaction with a value of hwz = 3.

Shrimp post larvae recognition process and prediction

The following steps were used.

Step 1: image

Read all images as program dataset. All photos have the same setting, as shown in the previous section.

Step 2: mark/label

Objects in the entire area of a dataset photo are identified and marked by experts. Cv2 (Laganière, 2014) and NumPy (Oliphant, 2006) were used to develop this program. Experts were able to mark, unmark and save their latest versions of dataset pictures. In addition, experts marked and counted the shrimp population in the original picture.

Step 3: preparation of feature vectors (x) and labels (y)

The raw image and label were converted to two sets of features (vectors x and y) for training in the next step. There were two experiments, with one for LBP and the other for RGB. The LBP feature vector was computed by comparing neighboring pixels in a radius and then transforming to binary encoding before aggregation to make a histogram of the pattern. The RGB feature vector was computed from the three channels of color at the considered pixels.

Step 4: train/combine

Images were divided into two parts, with the first part for training and the second for evaluation. An Extra-tree classifier was used to learn the image pattern and the model was then saved to a decision tree before being combined into a forest of trees.

Step 5: prediction

The second parts of the dataset were the used for model evaluation by identifying and counting the objects by forest. In this process, a Gaussian filter was used to interpolate the noisy

Fig. 9. Local Binary Pattern prediction (A) and count (B) of post larvae shrimp, showing agreement between the two methods.

```
[Parallel(n_jobs=-1)]: Done   4 out of   4 | elapsed: 19.9min finished
[Parallel(n_jobs=4)]: Done   4 out of   4 | elapsed:    2.5s finished
[Parallel(n_jobs=-1)]: Done   4 out of   4 | elapsed: 19.9min finished
[Parallel(n_jobs=4)]: Done   4 out of   4 | elapsed:    2.3s finished
[Parallel(n_jobs=-1)]: Done   4 out of   4 | elapsed: 72.2min finished
[Parallel(n_jobs=4)]: Done   4 out of   4 | elapsed:    2.8s finished
[Parallel(n_jobs=-1)]: Done   4 out of   4 | elapsed: 38.1min finished
[Parallel(n_jobs=4)]: Done   4 out of   4 | elapsed:    2.5s finished
[Parallel(n_jobs=-1)]: Done   4 out of   4 | elapsed: 18.3min finished
[Parallel(n_jobs=4)]: Done   4 out of   4 | elapsed:    2.6s finished
[ 0.98347143  0.98171179  0.98675894  0.98547199  0.98784291]
--Extra Tree: 0.985051411572
```

Fig. 10. K-fold cross validation (k = 5).

Table 2
Counting comparison of a dataset.

Dataset count								
#1–35			#36–70			#71–100		
#	Predict	Manual	#	Predict	Manual	#	Predict	Manual
1	178	170	36	157	170	71	141	150
2	171	165	37	168	190	72	150	165
3	178	160	38	164	187	73	166	175
4	173	161	39	162	185	74	169	175
5	166	152	40	168	180	75	68	74
6	146	156	41	172	192	76	150	165
7	136	152	42	175	198	77	178	175
8	146	157	43	155	175	78	68	74
9	178	198	44	163	180	79	167	175
10	171	196	45	167	184	80	168	175
11	179	192	46	158	175	81	164	175
12	150	182	47	173	186	82	171	175
13	153	183	48	167	174	83	178	180
14	156	185	49	172	183	84	162	165
15	147	166	50	164	178	85	155	165
16	144	162	51	178	180	86	141	145
17	141	158	52	162	175	87	132	145
18	171	192	53	178	180	88	153	160
19	177	195	54	171	180	89	154	160
20	173	200	55	173	175	90	161	165
21	145	169	56	66	74	91	173	175
22	147	172	57	147	150	92	172	175
23	146	172	58	177	180	93	160	165
24	155	183	59	120	140	94	68	74
25	141	162	60	137	140	95	160	175
26	132	140	61	156	165	96	70	74
27	178	182	62	163	165	97	144	150
28	171	176	63	169	170	98	166	180
29	178	180	64	172	175	99	172	175
30	177	175	65	173	180	100	71	74
31	120	155	66	64	74			
32	137	165	67	173	175			
33	159	170	68	177	180			
34	141	145	69	165	165			
35	142	160	70	69	74			

segmented image before applying a threshold to separate the object from the foreground and then using blob detection to count the number of objects.

The above process produced the dataset shown in Fig. 8, consisting of a picture with markings. The new pictures of post larvae shrimp can be used for counting by applying the Tree developed from the training data. Finally, the program displays the number counted, as shown in Fig. 9.

Ethics statements

This study was approved by the Ethics Committee of Rajamangala University of Technology Srivijaya (Approval no. IAC 02-11-61).

Results and discussion

This experiment used RF and the dataset size was 100 pictures with the transformation of the features around every pixel into a feature vector resulting in 30,051,600 records (100 pics × (300516L, 39L) = 30,051,600 records). The trained model or forest was evaluated using K-fold cross validation (k = 5), where 80% of the records were processed in the training and the other 20% were used for evaluation. This experiment achieved a score of 98.50% accuracy using the LBP method and hwz = 3, as shown in Fig. 10.

The root mean square error (14.43) from Table 2 was relatively large and error was mainly due to the overlapping of shrimps. In addition, increasing the number of datasets could improve the accuracy as suggested by other studies (Shotton et al., 2011) and (Limprasert, 2015).

Conflict of interest

The authors declare that there are no conflicts of interest.

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References

Boonchuaychu, T., Wattuya, P., Taparhudee, W., 2015. A skeleton reconstruction algorithm for identifying individual fish fry in a population image. In: Proceedings of 2015 IEEE International Conference on Imaging Systems and Techniques (IST). Macau, China, pp. 1–6.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.

Cadieux, S., Michaud, F., Lalonde, F., 2000. Intelligent system for automated fish sorting and counting. In: Proceedings of 2000 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2000. (IROS 2000).Takamatsu, Japan, pp. 1279–1284.

Department of Fisheries, 2016. The recommended density of shrimp per area (in Thai). http://ag-ebook.lib.ku.ac.th/ebooks/2016/20160076/files/assets/basic-html/page-15.html#. (Accessed 26 July 2017).

Fabic, J.N., Turla, I.E., Capacillo, J.A., David, L.T., Naval, P.C., 2013. Fish population estimation and species classification from underwater video sequences using blob counting and shape analysis. In: Proceedings of 2013 IEEE International on Underwater Technology Symposium (UT). Tokyo, Japan, pp. 1–6.

Fier, R., Albu, A.B., Hoeberechts, M., 2014. Automatic fish counting system for noisy deep-sea videos. In: Proceedings of 2014 Oceans - St. John's. 14–19 September 2014, St. John's, NL, Canada, pp. 1–6.

Food and Agriculture Organization of the United Nations, 2016. FAO 2016 Year Book, Fishery and Aquaculture Statistics, AQUACULTURE PRODUCTION. http://www.fao.org/fishery/static/Yearbook/YB2016_USBcard/root/aquaculture/b45.pdf. (Accessed 13 May 2018).

He, D.-C., Wang, L., 1990. Texture unit, texture spectrum and texture analysis. IEEE Trans. Geosci. Rem. Sens. 28, 509–512.

Holmström, K., Gräslund, S., Wahlström, A., 2003. Antibiotic use in shrimp farming and implications for environmental impacts and human health. J. Food Sci. 38, 255–266.

Labuguen, R.T., Volante, E.J.P., Causo, A., et al., 2012. Automated fish fry counting and schooling behavior analysis using computer vision. In: Proceedings of 2012 IEEE 8th International Colloquium on Signal Processing and its Applications (CSPA). Malacca, Malaysia, pp. 255–260.

Laganière, R., 2014. Open CV Computer Vision Application Programming Cookbook, second ed. Packt Publishing Ltd., Birmingham, UK.

Limprasert, W., 2015. Parallel random forest with IPython cluster. In: Proceeding of International Computer Science and Engineering Conference (ICSEC). Chiang Mai, Thailand, pp. 1–6.

Liu, L., Lao, S., Fieguth, P.W., Guo, Y., Wang, X., Pietikäinen, M., 2016. Median robust extended local binary pattern for texture classification. IEEE Trans. Image Process. 25, 1368–1381.

Loh, B.C.S., Raman, V., Then, P.H.H., 2011. First prototype of Aquatic Tool Kit: towards low-cost intelligent larval fish counting in hatcheries. In: Proceeding of 2011 IEEE Ninth International Conference on Dependable, Autonomic and Secure Computing (DASC). Sydney, NSW, Australia, pp. 192–195.

Morais, E.F., Campos, M.F.M., Padua, F.L.C., Carceroni, R.L., 2005. Particle filter-based predictive tracking for robust fish counting. In: Proceedings of XVIII Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI'05). Rio Grande do Norte, Brazil, pp. 367–374.

Oliphant, T.E., 2006. Guide to NumPy. http://web.mit.edu/dvp/Public/numpybook.pdf. (Accessed 8 July 2017).

Panmanee, P., Taparhudee, W., 2012. Counting fish fry using digital image processing. In: Proceeding of the 50th Kasetsart University Annual Conference. Bangkok, Thailand, pp. 368–374 (in Thai).

Pedregosa, F., Varoquaux, G., Gramfort, A., et al., 2011. Scikit-learn: machine learning in Python. J. Mach. Learn. Res. 12, 2825–2830.

Ristin, M., 2016. Incremental learning of random forests for large-scale image classification. IEEE T. Pattern Anal. 38, 490–503.

Sharif, M.H., Galip, F., Guler, A., Uyaver, S., 2015. A simple approach to count and track underwater fishes from videos. In: Proceedings of 2015 18th International Conference on Computer and Information Technology (ICCIT). Dhaka, Bangladesh, pp. 347–352.

Shotton, J., Fitzgibbon, A., Cook, M., et al., 2011. Real-time human pose recognition in parts from single depth. In: Proceedings of 2011 IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2011). Colorado, USA, pp. 1297–1304.

Toh, Y.H., Ng, T.M., Liew, B.K., 2009. Automated fish counting using image processing. In: Proceedings of International Conference on Computational Intelligence and Software Engineering, 2009. CiSE 2009, Wuhan, China, pp. 1–5.

Westling, F., Sun, C., Wang, D., 2014. A modular learning approach for fish counting and measurement using stereo baited remote underwater video. In: Proceedings of 2014 International Conference on Digital Image Computing: Techniques and Applications (DICTA). Sydney, NSW, Australia, pp. 1–7.

Zheng, X., Zhang, Y., 2010. A fish population counting method using fuzzy artificial neural network. In: Proceedings of 2010 IEEE International Conference on Progress in Informatics and Computing (PIC). Shanghai, China, pp. 225–228.