Interdisciplinary
Research Review
Volume 14, Number 5, Pages 13 – 17

Detection of shrimp feed with computer vision

Nitthita Chirdchoo[1,*] and Weerasak Cheunta[2]

[1] **Department of Electrical Engineering, Nakhon Pathom Rajabhat University, Nakhon Pathom 73000, Thailand.**
[2] **Department of Industrial Computer Technology, Nakhon Pathom Rajabhat University, Nakhon Pathom 73000, Thailand.**

Abstract

In smart shrimp farming system development, while many works have been focusing on developing an effective water quality monitoring system, little attention has been paid on an automated feeding system. Ideally, an efficient feeding system should not only be able to feed automatically, but also should be able to determine and adjust the suitable amount of food at each feed. This is to save the cost from overfeeding and labor usage, as well as to achieve high shrimp growth rate. This paper proposed a simple and low-cost shrimp food pellet detection algorithm that utilized the technique of 2D-histogram and color space analysis to detect the amount of unconsumed feed left on the feeding tray. The result provided useful information on how to adjust the amount of food in the next feed. The algorithm was developed using color segmentation on three different color spaces: HSL, LAB, and YCrCb. Experimental results confirmed that the proposed algorithm can effectively determine the amount of food pellets on the feeding tray.

Keywords: Shrimp food detection, shrimp farming, feeding tray, aquaculture

Article history: Received 17 May 2019, Accepted 18 October 2019

1. Introduction

With an increasing demand for aquaculture products, together with the extreme climate change and natural resource deterioration, aquatic farming technology that can introduce efficiency and productivity is currently in high demand. Smart and precision aquaculture is a promising solution as it can provide efficient resource usage and management, leading to higher quality aquaculture products at a lower cost and less labor usage. Among all aquaculture products, farmed shrimp is strongly demanded in the global market. As a result, various smart shrimp farming systems have recently been proposed and deployed around the world. Since water quality is one of the most critical factors in determining the health of the shrimps, many works such as in [1–4] focus on developing a smart and efficient water quality monitoring and controlling system. Little work has been done in the area of intelligent feeding system. Efficient feeding is an essential part of the smart farming system. According to the study in [6], it is shown that higher feeding frequency results in a better growth rate for white leg shrimps. Unfortunately, manual feeding at high frequency is not feasible without an automatic feeding system.

Commercial automatic feeders that are currently and widely used in shrimp farms can only dispense a pre-determined specific portion of food. The determination of the amount of each feed is still performed manually by checking the amount of leftovers on the feeding tray. Accordingly, the amount of food in the next feed can be adjusted. To prevent overfeeding as well as underfeeding, feeding tray must be manually examined frequently. To reduce the time and labor usage in checking the feeding tray, an automated system should be developed. Recently, the work in [5] proposes a smart underwater surveillance system for shrimp farming that not only monitors water quality but is also able to provide underwater observation and smart feeding control, using AI (Artificial Intelligence) technologies. However, little detail has been provided on the development of smart feeding unit. In this work, we attempted to detect the amount of unconsumed food that remains on the feeding tray by using the color segmentation technique. Specifically, five different color spaces (RGB, HSL, HSV, LAB, and YCrCb) were studied and evaluated. The detection algorithm was later developed based on the three color spaces (HSL, LAB, and YCrCb).

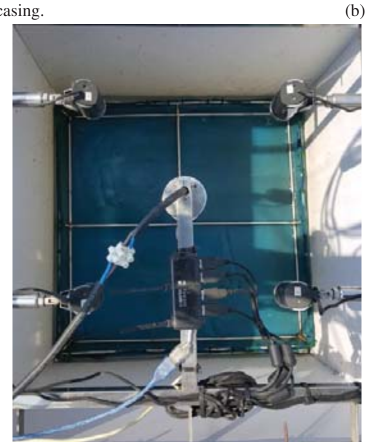
The remainder of this paper is organized as follows. Section 2 describes the design of an automated feeding system and proposes the shrimp food pellet detec-

*Corresponding author; email:nitthita@webmail.npru.ac.th

DOI: 10.14456/jtir.2019.43

(a) The proposed system without casing.

(b) The proposed system with casing.



(c) A top view of the feeding tray equipped with four digital cameras for image acquisition.

Figure 1: The proposed shrimp feed detection system.

tion algorithm. Next, section 3 shows and discuss the experiment setup and results. We then conclude our work in section 4.

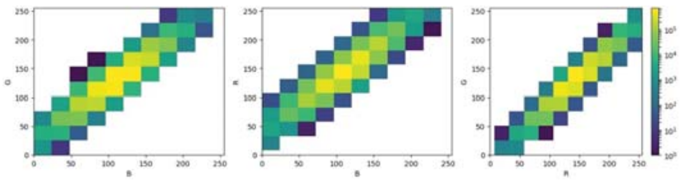
2. Proposed Design

2.1. Hardware design

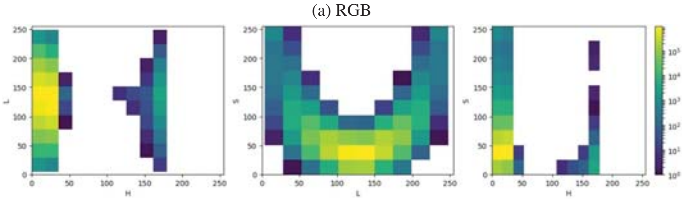
The amount of food consumed by shrimps was usually determined manually by using the amount of leftover food on the feeding tray. Specifically, the feeding tray was left underwater before the feed. After the feed, the feeding tray was checked periodically; approximately at every hour. Based on the obtained information on leftovers, the adjustment to increase/decrease the amount of feed could then be determined. The proposed system, as shown in Fig. 1, imitated the manual use of a feeding tray. In details, the feeding tray used in this system is a blue-color net with a square shape and steel framing. The dimension of the feeding tray was 63 cm × 63 cm. There was a motor that controls the position of the feeding tray. The feeding tray could be moved up above the pond so that images of the feeding tray can be taken. Once the images had been acquired, the feeding tray could then be placed back into the pond for the next cycle. In order to reduce glare and noise caused by water reflection, as well as to ensure suitable brightness of the taken images, a case was installed with a 9W white-light LED bulb for lighting propose (as shown in Fig. 1(b)). Moreover, the feeding tray was divided into four-grid regions, each of which had a low-cost 2M pixel digital camera (OKER model: 177) installed, as shown in Fig. 1(c). During the image capturing process, the feeding tray was placed at approximately 45 cm away from the cameras. A Raspberry-Pi 3 Model B+ was used as a controller.

2.2. Shrimp food detection algorithm

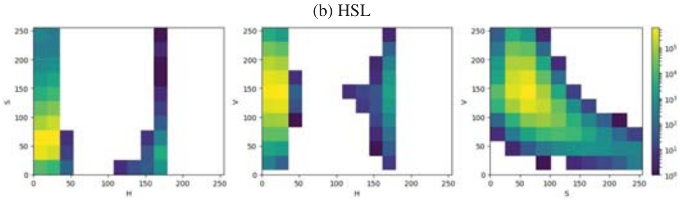
After acquiring the image of the feeding tray, the amount of leftovers on the feeding tray was determined by first identifying each of the image pixels whether it was a food pixel or a non-food pixel. Next, the total number of food pixel was converted to the amount of leftovers. In this study, a pixel color was



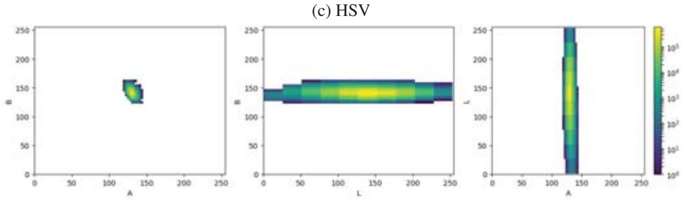
(a) RGB



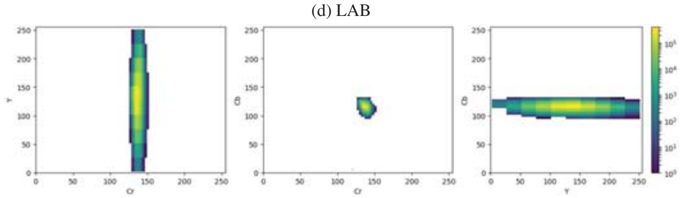
(b) HSL



(c) HSV



(d) LAB



(e) YCrCb

Figure 2: 2D-density plots showing the relationship of each component in RGB, HSL, HSV, LAB and YCrCb color spaces.

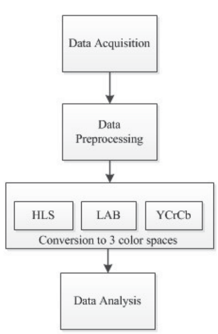


Figure 3: Processes in detecting the amount of food on the feeding tray.

used as a parameter to identify a food pixel using a technique of image segmentation on different color spaces. This was simply a technique of segmenting of an object from an image based on color. In order to develop the detection algorithm, five different color spaces were studied and evaluated on soaked shrimp food samples. These included RGB (Red, Green, Blue), HSL (Hue, Saturation, Lightness), HSV (Hue, Saturation, Value), LAB (Lightness, Red/Green value, Blue/Yellow value), and YCrCb (Luminance or Luma component obtained from RGB after gamma correction, R-Y, B-Y). Shrimp pellets samples, that were soaked in the water for the duration of 30, 60, 120, 180, 240 minutes, were examined in this work. All the food images wereacquired under the controlled environment using the hardware designed discussed in Section 2.1. A total of 300 images (60 images from each of the different soaking durations) of food pallet were used in determining the proper thresholds on each of the interesting color spaces. Fig. 2 shows the density distribution of food pixels color component in each of the color spaces.

Fig. 2(a) shows the pixel color distribution in RGB color space. Notably, all components (R, G and B) took a value between 0-255, indicating that any sin-

Table 1. Components from different color spaces used for detecting a shrimp food pixel.

Color space	The component in the color space used	Range
RBG	-	-
HLS	(H) Hue	$0 \le H \le 60$ or $109 \le H \le 180$
HSV	-	
LAB	(A) Red/Green, (B) Blue/Yellow	$110 \le A \le 148$ and $120 \le B \le 170$
YCrCb	(Cr) R-Y, (Cb) B-Y	$118 \le Cr \le 150$ and $90 \le Cb \le 135$

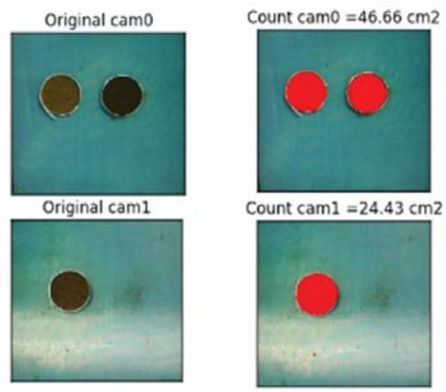


Figure 4: Detecting the amount of food pellets on the feeding tray in a laboratory.

gle component in RGB color space alone could not be easily used in identifying the food pixel. However, there were strong linear relationships between R and G, R and B and G and B components. Meaning that, any two components could simultaneously be used to identify a food pixel but the calculation would be more complex than using just a single component. Since a Raspberry Pi contained limited available computation resources, keeping the detection algorithm simple was also one of the main priorities. As a result, RGB was considered unsuitable color space for the task. For HSL color space shown in Fig. 2(b), only Hue component could be used in detecting the food pixel. The range of Hue that was used in the detection algorithm is $0 \le H \le 60$ or $109 \le H \le 180$. Similarly to the HSL, HSV shown in Fig. 2(c) indicates that only Hue component can be used in the detection algorithm. Because Hue was accounted for HLS color space, all components from HSV were not used in the detection algorithm. LAB and YCrCb color spaces, shown in Fig. 2(d) and (e), show much more compact density plots than the previously discussed color spaces, especially on the component A and B for LAB, and component Cr and Cb for YCrCb. The compact density plot was highly preferred when determining the detection algorithm. These two color spaces could certainly be used in the detection algorithm in the following ranges $110 \le A \le 148$, $120 \le B \le 170$, $118 \le Cr \le 150$, $90 \le Cb \le 135$. Table 1 summarizes all the components from different color spaces and their ranges used to form the threshold that identifies a food pixel. Eq. (1) is the proposed threshold for food pixel recognition.

$$\begin{aligned} &((0 \le H \le 60) \text{ or } (109 \le \mathrm{H} \le 180)) \text{ and} \\ &(110 \le A \le 148) \text{ and } (120 \le \mathrm{B} \le 170) \text{ and} \\ &(118 \le Cr \le 150) \text{ and } (90 \le \mathrm{Cb} \le 135) \end{aligned} \quad (1)$$

3. Experimental Setup and Results

According to Fig. 3, there are four steps involving in detecting the amount of leftovers on the feeding tray. The first step, data acquisition, was to collect four 377×377 pixel image data, each of which corresponded to each of the grid regions on the feeding tray. These image data were then preprocessed by removing the steel frame part in the image. This was to reduce the false detection caused by a rusty and muddy part that might have similar characteristics to that of a food pixel. In the third step, each image data was converted into three different color spaces: HSL, LAB, and YCrCb. Each pixel would then be determined whether it is a food pixel or non-food pixel, using Eq. (1). Finally, all the food pixels were combined and converted into the total leftovers on the feeding tray.

Fig. 4 shows some of the results obtained in the laboratory. The two images on the left are the images of shrimp food samples that was soaked in water for 30, 60, and 120 minutes. Each of which was arranged in

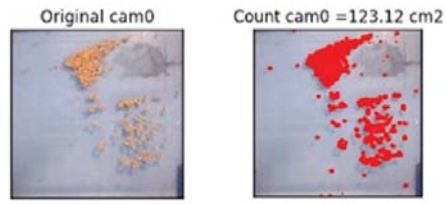


Figure 5: Food detection obtained from the field experiment.

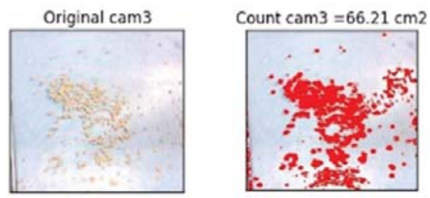


Figure 6: False-positive detections caused by the rusty part of the steel frame.

a circular-shape container with a radius of 2.7 cm, resulting in the total area of 45.8 cm^2 and 22.9 cm^2 of food, respectively. The images on the right shows that our proposed algorithm could detect the food with the total area of 46.66 cm^2 and 24.43 cm^2, respectively. Fig. 5 shows the result obtained from the experiment site after the system had been deployed and used continuously for ten days. It was evident that even with the stain and the shadow of shrimp pellets, our detection algorithm could differentiate between food and non-food pixel effectively. However, it is worth mentioning that if there was any pixel with similar color distributions to the food pellets (e.g., stain or a rusty part of the steel frame of the feeding tray), the number of false-positive detection would increase, as can be seen in Fig. 6.

4. Conclusions

We proposed the automatic shrimp food detection system which can be integrated with a shrimp smart farm system. The information about the amount of leftovers on the feeding tray was used to determine the adjustment of the amount of the next feed. Five different color spaces (RGB, HSL, HSV, LAB, and YCrCb) were examined using color segmentation technique. The proposed shrimp food detection algorithm was then developed by on three different color spaces: HSL, LAB, and YCrCb. The results of experiments both in the lab and on the field reveal that food pixel could be recognized effectively using the proposed algorithm. However, the error increased when there was a presence of objects that had similar color and lightness distribution to the shrimp food pellets.

For the future work, the size, shape and food pellet texture should also be taken into account as parameters to develop a more accurate detection algorithm. Furthermore, various techniques in machine learning are also interesting and worth exploring.

References

[1] M. Elvayandri, S. Edwin, I. H. Farkhad, Human machine interface on e-shrimp as smart control system for whiteleg shrimp pond, in: IEEE 2017 International Symposium on Electronics and Smart Devices, 2017, pp. 24–29.

[2] C. Nitthita, S. Kanittha, Design and development of a sensor mote for precision aquaculture, in: ITC-CSCC, 2018.

[3] C. Nitthita, C. Weerasak, Development of a shrimp farm management system using precision aquaculture technology, in: NCITE, 2018.

[4] J. Muhammad, Development of intensive shrimp farming, Litopenaeus Vannamei in land-based ponds: Production and management, Journal of Physics: Conference Series (2018) 1–6.

[5] H. Ing-Jer, H. Chin-Chang, K. Shiann-Rong, C. Yun-Nan, H. Kuan-Yu, T. Chang-Ru, F. Kai-Lin, The prototype of a smart underwater surveillance system for shrimp farming, in: IEEE ICAM, 2018, pp. 177–180.

[6] A. Mazdak, R. Alireza, S. B. Siamak, M. Milad, Effects of feeding frequency on growth, feed conversion ratio, survival rate technology and water quality of white leg shrimp, International Journal of Fisheries and Aquatic Studies 4 (2016) 293-297.