

Automated molting detection system for commercial soft-shell crab (*Portunus pelagicus*) production

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ABSTRACT: Cost, availability and reliability of labor are major problems in any aquaculture operation, and particularly in the soft-shell crab industry, since its success depends on the precise timing and accuracy of the workers to observe and harvest the newly molted crabs before their shells harden. To improve efficiency and reduce the dependence on human intervention, we have developed an automated molting detection system. The detection system utilizes the fact that the crab's carapace reflects infrared light (appearing as white pixels) much more strongly than the surrounding areas. By using Internet Protocol (IP) cameras, network video recorder (NVR), personal computer and newly designed image analysis software, molting can be detected by continuously measuring relative changes in white pixel area. Two-dimensional Gaussian function and Otsu's thresholding method are incorporated into the detection software. Snapshot images, date, and time of molting are recorded automatically and displayed via user interface. Test results indicated that the highest (100%) hit rate and lowest precision (13.92%) were obtained when detection threshold was 20%. Lower hit rates and higher precision were observed at higher threshold levels. The optimum threshold for detecting molting in commercial operations is discussed.

KEYWORDS: automation, molting, soft-shell crab, *Portunus pelagicus*

INTRODUCTION

Crabs, like other decapod crustaceans, need to periodically shed their old exoskeleton to increase their body size. This extraordinary and highly complex behavior is known as molting. Since a newly molted crab (i.e., soft-shell crab) has a soft exoskeleton, the entire body can be consumed with ease. Soft-shell crabs have gained popularity, especially in high gastronomy, thanks to their excellent taste, high level of protein and almost no fat, in addition to a general perception as a healthy food [1, 2].

Currently, the soft-shell crab industry depends on capturing wild crabs, mostly in the genera *Scylla* and *Callinectes*, and maintaining the animals in controlled conditions, such as in trays (*Callinectes*) [3, 4] or floating boxes (*Scylla*) [5]. In Thailand, almost all the soft-shell crab production is of mud crab in genus *Scylla*, because this species adapts relatively well to the culture environment. After stocking, crabs are observed every four hours (during both day and night) for molting status [5]. The demand for juvenile mud crabs has grown substantially in the past decade and now juveniles need to be imported from overseas.

Blue swimming crab (*Portunus pelagicus*) is also an economically important species, and it has potential to be another candidate for soft-shell crab production. However, its shell begins hardening much faster than the mud crab, thus requiring a monitoring interval of

less than 30 min (communication with blue swimming crab farmer and personal experience) and making it extremely difficult to culture with conventional methods. Since the market value of the soft-shell crab declines as the crab exoskeleton hardens, a reliable detection method and skilled labor are crucial for the success of the industry.

Image processing techniques have been widely used in many fields such as medicine [6], fingerprint identification [7], traffic control [8], insect monitoring [9, 10] and even to assess fish quality and freshness [11]. This technology performs tasks previously reliant on human inspection, and provides even more accuracy and enables continuous monitoring. In the present study, image processing software was developed and connected with IP cameras to automatically detect molting of blue swimming crab. This system minimizes labor requirements for the soft-shell crab industry, and creates a platform for future molting research.

MATERIALS AND METHODS

Blue swimming crab culture

Egg-bearing female blue swimming crabs (*Portunus pelagicus*) were purchased and cultured in 200 l plastic tanks (one individual per tank) at Klongwan Fisheries Research Station, Prachuabkirkhan Province, Thailand. Cleaned and aerated seawater (30 ppt salinity)



Fig. 1 Network diagram of molting detection system including IP camera, NVR, and personal computer. All components were connected by local-area network (LAN) cable.

was used in each tank. After 24 h, hatched eggs were transferred to 3000 l cement ponds at the density of 100 individuals/l.

During larval development from zoea stage until first crab stage (approximately 21 days), phytoplankton (*Chaetoceros* sp.) and zooplankton (*Rotifer* sp. and *Artemia* sp.) were fed to crab larvae. Small shrimp pellets (40% protein) were fed to the crabs for another 20–25 days until the average carapace width reached 1.5 cm. Then, young crabs were transferred to a 1600 m² earthen pond (1.5–1.7 m depth) at the density of 2 individuals/m² and cultured for another 90–120 days. These crabs were fed with commercial shrimp pellets (40% protein) at the rate of 5% body weight per day. Foldable traps baited with chicken were used to harvest crabs. Wild-caught crabs were also used in the experiment to compare their molting and survival rates with the cultured crabs.

Water quality analysis

Dissolved oxygen (DO) meter (YSI, Ohio, USA 550A) and pH meter (Cyber scan, Illinois, USA pH 11) were used to monitor DO (including water temperature) and pH, respectively. Alkalinity was measured by titration, while Koroleff's indophenol blue method and colorimetric method were used to measure total ammonia nitrogen (TAN) and nitrite, respectively. Water exchanges were carried out every seven days at the rate of 50% to maintain optimum water quality. All measurements were according to standard methods for the examination of water and wastewater [12].

Camera and recording system

Four IP cameras (Watashi, Bangkok, Thailand WIP086) were installed 210 cm above the raft (described below) and connected to a network video recorder (NVR: Watashi WRC170-4K) with output to a personal computer (Lenovo, Bangkok, Thailand AIO 510-221SH) (Fig. 1).

Crab boxes and floating raft

To monitor molting, modified commercially available crab boxes (19 × 26 × 9.5 cm) were used (Fig. 2).



Fig. 2 Modified crab boxes covered with nylon netting on floating raft made from PVC pipes. Each raft can hold 50 crab boxes.

Crabs were kept individually (i.e., one per box) to prevent cannibalistic behavior during molting. A nylon net cover was put on top of each box to prevent crabs from escaping. Floating rafts (200 × 140 cm) made from PVC pipes were constructed to each hold 50 boxes (Fig. 2). Each raft was anchored at a fixed position in a concrete pond (1.2 × 6.0 × 1.0 m) during the experiment. To optimize the lighting conditions for the IP cameras, the entire concrete pond was covered with black plastic sheeting.

Autonomous molting detection software

The principle of this detection system is the fact that the carapace of a crab reflects infrared light very intensely, with the carapace appearing as white pixels and the surrounding area appearing as black pixels. Therefore, by using IP cameras in the absence of external light, molting can be detected by capturing images and comparing the ratio of white pixels to total pixels in each area of interest (Fig. 3).

The imaging analysis software was designed and developed from Visual C#.net by using .Net Framework version 4.5 in combination with Emgu CV (cross-platform .Net Wrapper) to create an algorithm to analyze molting in each captured image. Once the molting is detected, the software notifies the user via user interface. Snapshot images of the molting along with time, date and location are recorded and displayed.

Architecture and design

IP cameras are connected to NVR and computer by local area network (LAN) cable. User interface of the program comprises three major components: (1) main control panel, (2) detection area identification, and (3) control panel for molting detection.

Main control panel: Camera connection, detection configuration and detection area recording are controlled by this component. Up to four cameras are able to connect with the program simultaneously by using the Internet Protocol address (IP address) of each camera. Parameter configuration can be adjusted by

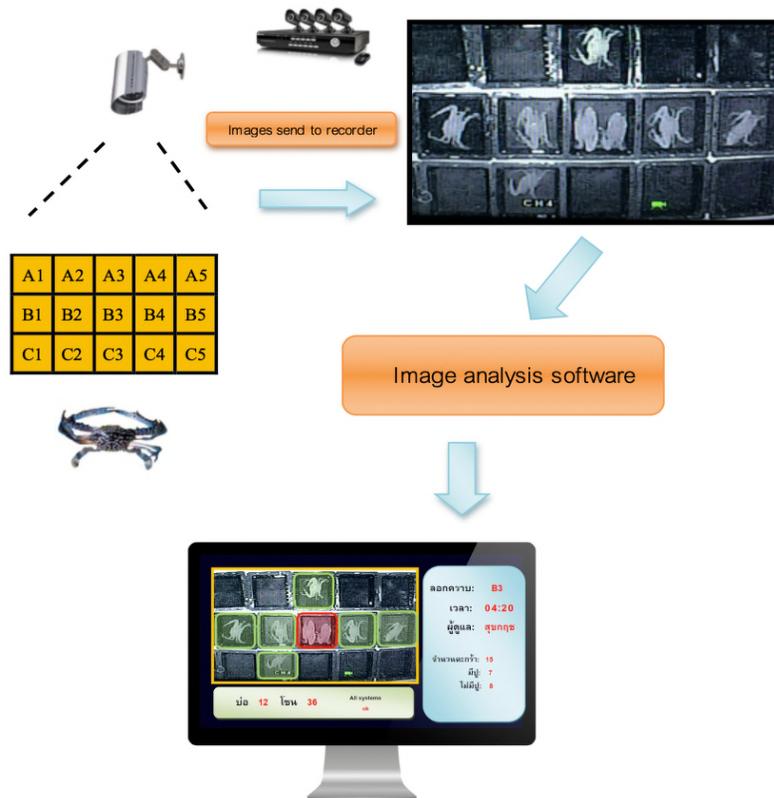


Fig. 3 System overview of the molting detection system. IP cameras acquire images of crabs from the raft and transmit them to NVR for recording. Then, image analysis software in personal computer analyzes crab images from each area of interest and displays the result via user interface.

the user to maximize the molting detection accuracy. Capture Time Interval is the duration between each picture in frames per second. Maximum Capture Time is the maximum recording duration. Minimum crab size is the least possible size (area in pixels) of each crab in the area of interest, while Beware and Molt threshold are the size values that will trigger the program to give warning and molting messages for each crab. The size of the area of interest (detection area) for each crab can also be adjusted.

Detection area identification: This component manages the areas of interest and their locations by labelling a snapshot from the IP camera with green squares. These green squares can be added, moved or removed at any point. The program only monitors the ratio of white: total pixels within each green square.

Control panel for molting detection: This component can be used to activate, pause, reset and stop the program during molt monitoring.

Camera calibration

Each camera was calibrated for perspective correction, since the curved lens of the camera has two inherent types of distortion, namely radial distortion and tan-

gential distortion. By using these equations, both types of distortion were corrected.

Radial distortion correction:

$$x_{\text{corrected}} = x(1 + k_1r^2 + k_2r^4 + k_3r^6)$$

$$y_{\text{corrected}} = y(1 + k_1r^2 + k_2r^4 + k_3r^6)$$

Tangential distortion correction:

$$x_{\text{corrected}} = x + [2p_1xy + p_2(r^2 + 2x^2)]$$

$$y_{\text{corrected}} = y + [p_1(r^2 + 2y^2) + 2p_2xy]$$

Combined radial and tangential distortion correction:

$$x_{\text{corrected}} = x + [2p_1xy + p_2(r^2 + 2x^2) + x(1 + k_1r^2 + k_2r^4 + k_3r^6)]$$

$$y_{\text{corrected}} = y + [p_1(r^2 + 2y^2) + 2p_2xy + y(1 + k_1r^2 + k_2r^4 + k_3r^6)]$$

where $r = \sqrt{x^2 + y^2}$, (x, y) is an undistorted pixel location, $(x_{\text{corrected}}, y_{\text{corrected}})$ is a corrected pixel location, and $(k_1, k_2, p_1, p_2, k_3)$ are the distortion coefficients. In this scenario, distortion coefficients were designated as $k_1 = -0.31$, $k_2 = -0.31$, $p_1 = 0$, $p_2 = 0$, and $k_3 = 0$.

Nylon net removal

To prevent crabs from escaping, nylon netting was used to cover each box. However, this interfered with the images and needed to be filtered out. Two-dimensional Gaussian function was used in this situation to filter out the net from the images.

$$f_{out}(x, y) = f_{in}(x, y) * G(x, y)$$

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where $f_{in}(x, y)$ is the input image, $f_{out}(x, y)$ is the output image, $G(x, y)$ is two-dimensional Gaussian filter, (x, y) is the image coordinate, and σ is the standard deviation.

Image thresholding

Otsu’s Thresholding method was used to detect the crab images. First, a histogram of intensity values was calculated for each crab, then optimum threshold was determined by the maximum interclass variance (σ_b^2).

Histogram calculation:

$$p(i) = \sum_{(x,y) \in f} n_i$$

where n_i is the number of pixels at intensity i and $p(i)$ is the histogram of image f .

Inter-class variance (σ_b^2) calculation:

$$\sigma_b^2(t) = \omega_0(t)\omega_1(t)[\mu_0(t) - \mu_1(t)]^2,$$

$$\omega_0(t) = \sum_{i=1}^{t-1} p(i), \quad \mu_0(t) = \frac{\sum_{i=0}^{t-1} ip(i)}{\omega_0(t)},$$

$$\omega_1(t) = \sum_{i=t}^{L-1} p(i), \quad \mu_1(t) = \frac{\sum_{i=t}^{L-1} ip(i)}{\omega_1(t)},$$

where σ_b^2 is the inter-class variance, ω_0, ω_1 are class probabilities, and μ_0, μ_1 are class means.

Any intensities under the determined threshold (t) are classified as black, whereas any intensities above this threshold are classified as white.

Molt detection

The ratio between white pixels and total pixels within each green square was continually monitored at 5-min intervals. The program uses maximum and minimum ratio recorded from the previous 5 min ($T_{n-5} \rightarrow T_n$) to determine molting. By using the following equation, when the ratio changes more than a predetermined level, the program automatically notifies its user via the program interface.

$$\text{Molt ratio (\%)} = \frac{A_{\max(T_{n-5} \rightarrow T_n)} - A_{\min(T_{n-5} \rightarrow T_n)}}{A_{\min(T_{n-5} \rightarrow T_n)}} \times 100$$

where Molt ratio is the ratio of area change, $A_{\max(T_{n-5} \rightarrow T_n)}$ is the maximum area detected during the previous 5 min, and $A_{\min(T_{n-5} \rightarrow T_n)}$ is the minimum area detected during the previous 5 min.

Statistical analysis

Results were analyzed by using Student’s t -test for unpaired samples. Differences are accepted as significant at $p < 0.05$. The program SPSS Statistics was used for calculations.

RESULTS

Molting in crab boxes

The majority of the molting events (55.9%) occurred between 00:00 and 06:00, while no molting was detected between 06:00 and 12:00. During the 30-day period, crabs from earth-pond culture (average carapace width 8.8 ± 0.7 cm, average body weight 53.2 ± 11.7 g) appeared to outperform wild-caught crabs (average body weight 66.0–83.0 g) in both molting rate and survival rate. While not statistically significant ($p = 0.131$), the molting rate of cultured crabs ($19.0 \pm 12.1\%$) was higher than that of wild crabs ($8.0 \pm 3.6\%$). However, the most striking difference was found in survival rate. Cultured crabs had much higher survival ($96.0 \pm 1.6\%$) than wild-caught crabs ($23.0 \pm 10.8\%$), and the difference was statistically significant ($p < 0.0001$).

Water quality

All water-quality parameters were within with the ranges recommended by various publications (temperature [13, 14], salinity [15], ammonia [16], nitrite [17], dissolved oxygen [18]).

Dissolved oxygen concentrations in all ponds were above 4 mg/l, while the average pH was 8.16 ± 0.01 and average temperature was 27.82 ± 0.66 °C. Average salinity (31.52 ± 0.25 ppt) and alkalinity (124.52 ± 1.48 mg/l as CaCO_3) were consistent with normal seawater, while average total ammonia and nitrite were 0.21 ± 0.04 mg/l and 0.12 ± 0.01 mg/l, respectively, and therefore not considered harmful to the experimental crabs.

Automated molting detection software

Camera calibration

The images from the IP cameras were calibrated for correct perspective, since the curved lens creates radial distortion and tangential distortion (Fig. 4). The results indicated that the best distortion coefficients were $k_1 = -0.31, k_2 = -0.31, p_1 = 0, p_2 = 0$ and $k_3 = 0$.

Nylon net removal, image thresholding and molt detection

The nylon netting in images from IP cameras was filtered out by using two-dimensional Gaussian function. Then, Otsu’s thresholding method was used to separate crabs (white pixels) from background (black pixels) (Fig. 5). The proportion of white pixel area was continuously calculated, and when the percent change in this proportion during the previous 5 min

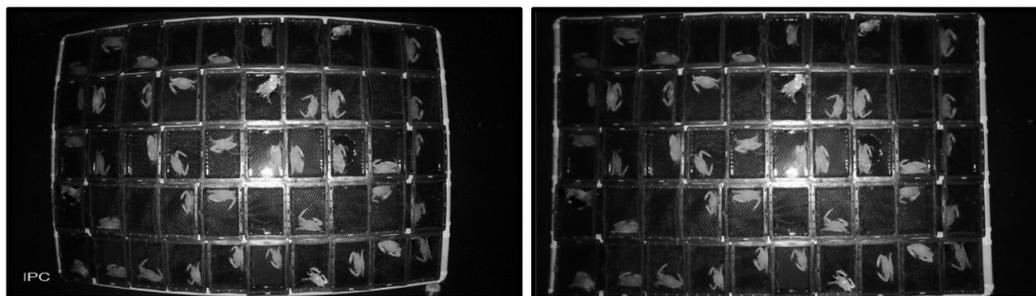


Fig. 4 Uncalibrated (left) and calibrated (right) images. Camera calibration transforms pixel point at (x, y) from distorted image to corrected pixel point at $(x_{corrected}, y_{corrected})$; thus, the distorted area on each side of the raft is corrected to a rectangular shape.

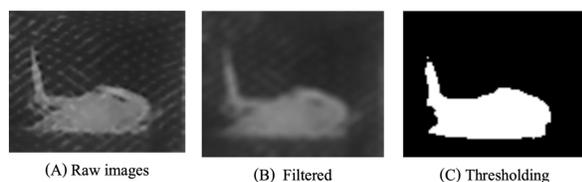


Fig. 5 2D-Gaussian filter removes high-frequency patterns such as net and Gaussian noise in the image. Otsu's thresholding method decides which pixels belong to crab area (white pixel) or background area (black pixel) by calculating the maximal inter-class variance of image intensity.

exceeded a predetermined value, the user was notified via program interface.

When molting crabs were monitored continuously for 10 min (Fig. 6), the area of white pixels continuously increased, from 15.02% in the first minute to 29.09% after 10 min. This area increase was because both new and old shells were classified by the program as white pixels. Maximum percentage change of white pixel area was 97.07% (8 min) which is more than the predetermined threshold of 50%. The program decided that molting had occurred and notified the user via the program interface.

In the case of non-molting crabs (Fig. 6), the area of white pixels fluctuated slightly (20.56%–25.81%) due to changes in crab posture. When calculated as percentage change of white pixel area over time, the maximum rate of change was 15.68%. Since the predetermined threshold was set at 50% for molting, the program did not decide that molting occurred during this 10-min test period.

Location, date, and time of molting are displayed via user interface. To prevent false positive warnings (program falsely detects molting), a snapshot image of the green square appears so that it can be verified by the user (Fig. 7). Pixel location, box number, height and width of green square (in pixels), molting status, date and time of molting are recorded in a text file.

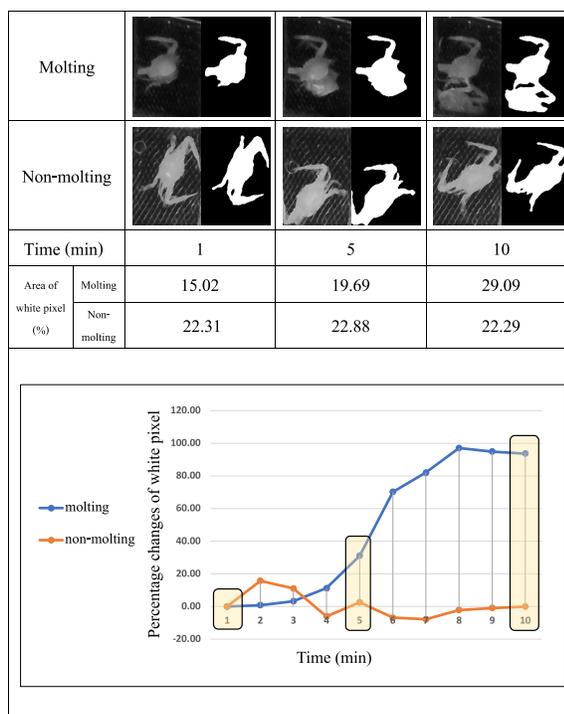


Fig. 6 Percentage change of white pixel area between molting and non-molting crabs. In non-molting crabs, the percentage change fluctuated by less than 20%, and was due to crab movements. In molting crabs, the percentage change increased every min and crossed the 50% threshold between 5–6 min, then reached almost 100% at 8 min.

Program testing

To test the accuracy of the detection program, 50 crabs were continuously monitored for 90 h. Eleven molting events from 11 crabs were detected. The detection program took a snapshot every 10 s, resulting in 31 159 images (raft images). Each image contained 50 green squares; therefore, over 1 557 950 images (green square images) were processed. Different molting

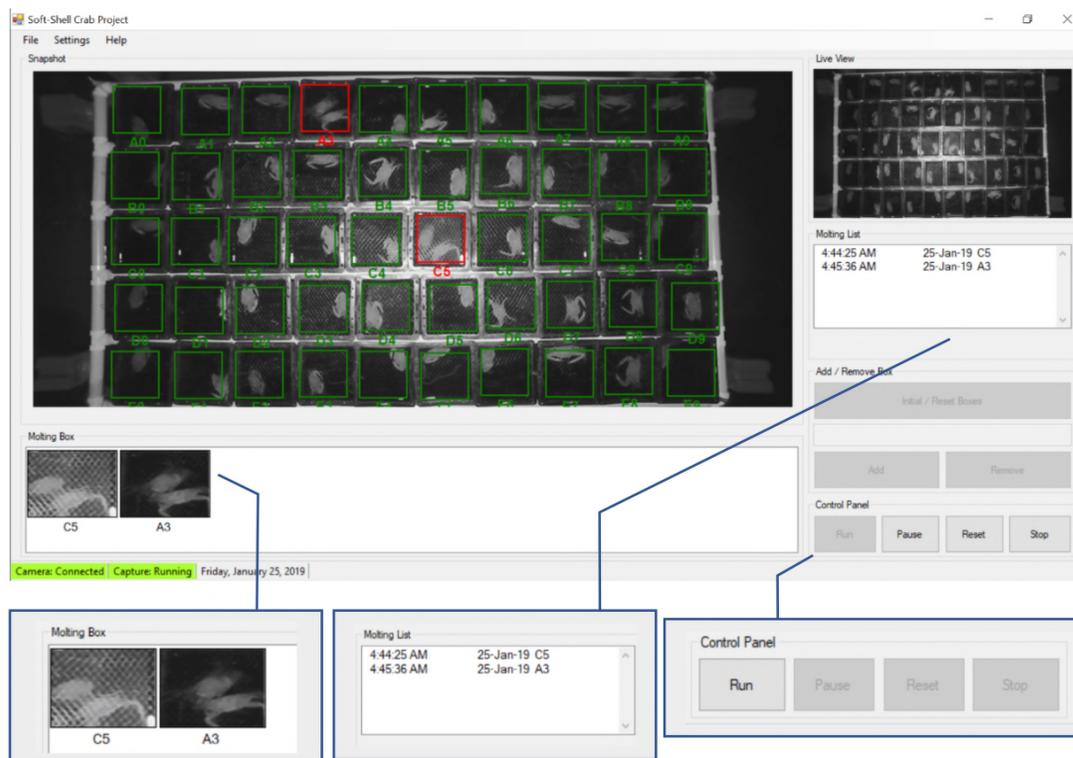


Fig. 7 User interface with molting information. When molting occurs, the green square changes to red to be easily noticed by user.

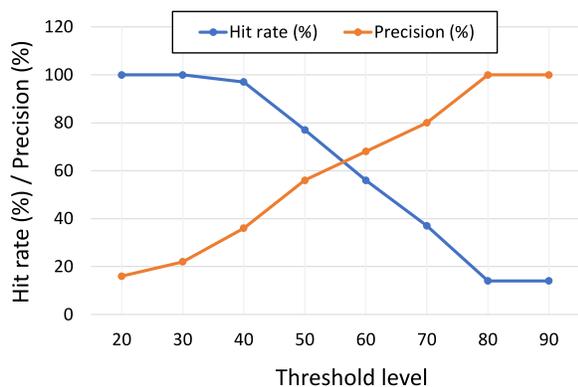


Fig. 8 Hit rate and precision of the detection program with different molting thresholds. Hit rate decreased from 100% to 9.09% while precision increased from 13.92% to 100% when threshold level increased from 20% to 90%.

thresholds (from 20% to 90%) were tested separately to observe the relationship between hit rate and threshold level (Fig. 8).

Hit rate is the accuracy of the software in detecting actual molting events without considering the false positives during the detection. Precision is the accuracy of the software in detecting actual molting events

when including false positive events. False-positive detection is when the program indicates molting but no actual molting has occurred. In our trial, at a 30% threshold, the program reported 49 molting events when, in fact, only 11 actual moltings had occurred. The other 38 detections were false positives. In this scenario, hit rate was 100%, while precision was only 22.45% (Fig. 8).

At the lowest threshold setting of 20%, hit rate was 100% while precision was only 13.92%. When threshold level increased, hit rate continued to decline in contrast to precision, which kept increasing. Hit rate and precision were equal when thresholds were 50%–60%.

DISCUSSION

The majority (80%) of the molting events occurred between 18:00 and 06:00, while only 20% were observed between 12:00 and 18:00, and none were observed from 06:00 to 12:00. This night-time molting behavior is thought to help crabs avoid predation, since the newly molted crabs are soft and defenseless. Both internal and external factors such as intensity and duration of light, temperature, salinity [19,20] and even conspecific density may influence the timing of molting. It also has been demonstrated that crabs have an ability to defer molting in some life-threatening sit-

uations, such as in the presence of a predator [21]. To reduce the risk of being preyed upon, some crab species exhibit synchronized molting behavior, in which the majority of the animals molt during the same period and in the same location. In the case of the Tanner crab (*Chionoecetes bairdi*) in Alaska, an estimated 11 500 crab exuviae were reported in an area of approximately 0.034 km² [22]. From a farm management perspective, this molting plasticity has the potential to be useful for production planning, both in labor management and in the harvesting schedule. For example, changing the lighting scheme, temperature or even the direction of water flow to avoid conspecific cues could stimulate or prolong molting, according to the farm's requirements.

Wild-caught crabs had lower molting rate and higher mortality rate than cultured crabs. This was not unexpected, since gill nets are the primary fishing gear for blue swimming crab in Thailand [23]. Trauma from gear entanglement, air/temperature exposure and mishandling during transportation [24] contribute to high mortality rates. However, to achieve commercial-scale blue swimming crab culture that is profitable, better survival rates, especially at early and late larval stages [25] and higher stocking density must be realized.

The proposed molting detection method consists of three main stages: (1) preprocessing, (2) crab detection, and (3) molting classification. The preprocessing stage prepares the images to eliminate noise. In our trial, noise was caused by low-light photography (higher ISO light sensitivity) as well as by the netting covering each box, which interfered with the crab detection system. Most noise interference was characterized as high frequency objects. Thus, a Gaussian low-pass filter [26] was used to reduce the effect of that particular noise, while maintaining relatively good crab area images. The standard deviation variable in the Gaussian filter was related to the size and frequency of the netting.

The crab detection stage is designed to detect the crab area in each green square. As the crab's carapace strongly reflects infrared light in contrast to the background, Otsu's method [27] was chosen as the most appropriate tool for this stage. Since the reflection of infrared light across the raft was non-uniform due to the location of light sources, the appropriate value of Otsu's threshold of each green square had to be adaptive. To accommodate this, Otsu's method was applied for each green square separately.

The molting classification equation was designed to calculate the rate of change in white (crab shell) area over a fixed time, in this case 5 min. Since each crab has a different size and posture, it is far more effective to define the molting classification conditions based on percentage change of each individual crab area rather than by a universal fixed constant. Snapshot

images were taken every 10 s to reduce computational workload. Since actual molting events usually took under 10 min to complete, a 5-min calculation window was deemed sufficient to detect any molting. The program's user interface was also designed to present all necessary molting information. It also provides actual molting details such as date and time, which may be valuable for future research. To the best of our knowledge, this is the first attempt to detect molting by using infrared light reflection and image processing in this manner.

The testing showed that low threshold settings (20% and 30%) had the highest hit rates (100%) but also the lowest precision (13.92% and 22.45%). This is because the low-threshold levels were extremely sensitive to any changes in crab area, resulting in 100% detection of actual molting cases. However, the majority of the detections (77.55%–86.08%) were false positives, making precision very low. At 40 and 50% thresholds, the hit rate dropped to 90.91% and 72.73%, respectively, while precision increased to 33.33% and 53.33%. At thresholds of 80–90%, it was rare for the program to detect any molting. The hit rate was very low at 9.09% while the precision was 100%, without a single case of false positive detection.

It is tempting to believe that a good detection system must have both high hit rate and high precision at the same time, but this is not always the case. In some situations such as in facial recognition, it is more important to have high precision than high hit rate to avoid the nuisance of too many false positive detections [28]. However, in the case of molting, each molt is very important because it is a source of income for the farm, while false positive detection only causes minor nuisance, and can be further improved upon in the program. In the case of a 40% threshold, the farm would lose almost 10% of the total production but have little improvement in precision. This loss would be even greater in the case of a higher threshold. For these reasons, it is recommended that the threshold for the current version of the detection program be set at 30% to provide the highest hit rate of molting and to maximize the soft-shell crab production.

Although a perfect system with 100% hit rate and precision is nearly impossible to achieve, one can still improve the system so that both values are relatively high across different thresholds. One possibility to improve both hit rate and precision is to improve lighting conditions. Most of the IP cameras have infrared array LED lights near the lens that cause water reflection in the center of images and uneven distribution of light across the raft. This reflection can interfere with the detection program because the bright white light results in a higher number of false positive/negative detections. Meanwhile, around the edge of the raft, reflection is very dim. To avoid this, the source of infrared light should be relocated from the top-center

to the top-left and top-right of the raft to avoid direct reflection and provide more even light distribution. It has also been demonstrated that the accuracy of finger vein authentication technology could be improved by adjusting the intensity of infrared light [29].

Movements of rafts due to maintenance activities such as feeding or harvesting also interfere with the detection system, causing more false positive/negative detection. Installing augmented reality markers (AR markers) to track orientation and position of the raft might resolve this issue. A similar method has been demonstrated [30] to help visually impaired persons by recognizing dynamic content and fixed positions.

Crab posture also needs to be considered in the use of this system, and as a matter for further development. Some crabs align themselves with the wall in a vertical position, which makes the detectable area much less than for a horizontal position. When a crab changes posture from vertical to horizontal, the detectable area increases, causing false positive detection. As a result, “Minimum Crab Size%” was introduced to the detection configuration so the program would ignore any area less than a predetermined level.

The conventional method of soft-shell crab (mud crab) production in Thailand is by floating crab boxes in earthen ponds, exposing crabs to both sunlight and rain. Workers physically inspect each box using a flashlight and personal expertise. The detection system introduced in this study was designed not only for blue swimming crab (which cannot be cultured by conventional methods for biological and physiological reasons) but also could be adapted to improve the conventional method for mud crab. The detection software also lays the groundwork for a novel soft-shell crab production method by incorporating image processing technologies with aquaculture. For the detection system to achieve highest effectiveness, the entire production facility should be redesigned from the ground up. Environmental control (to prevent light interference) and a monitoring system need to be factored in from the beginning. Monitoring via cameras would enable the farmer to use less space and resources by stacking crab boxes vertically, reducing both the workload and skill required to detect and collect molted crabs. This, in turn, would enable the farmer to increase not only the production output but also the quality of the soft-shell crabs. The size of the production facility is not limited by the system per se but by the availability of crab seeds and investment level. It would also require farmers with a technology- and data-driven mindset, and initial financial investment for the system.

CONCLUSION

Labor shortage and unskilled human error contribute to the significant loss of soft-shell crab production annually. To improve efficiency and reduce human

workload, an autonomous system to detect molting has been developed. We have demonstrated that the reflection of infrared light from the crab’s carapace in combination with image-analysis software can be coupled to detect molting.

The authors consider this detection program useful not only for the soft-shell crab industry, but also as a research platform for any future molting experiments. Molting frequency, date, and time, along with crab behavior could be tracked and analyzed in a real-time fashion. It is also possible to collect data from various off-site locations simultaneously via internet network, thus enabling even greater molting detection and prediction.

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