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Behavioral Discrimination in Chicken Flocks: A Camera-Based Movement Analysis for Distinguishing Normal and Scared Behaviors

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Abstract

Assessing chicken behavior in coops is crucial for high-quality meat production and stress prevention. This paper introduces an innovative system for evaluating behavior in chicken flocks by integrating collective area and its rate of change, surpassing traditional metrics like individual chicken distance walked, velocity, and acceleration. The novelty lies in simultaneously using multiple methods, providing a nuanced understanding of chicken responses and enhancing precision in behavior discrimination. The proposed system utilizes camera-based movement analysis, employing procedural image processing and data association for early detection and intervention in closed cage systems. This cost-effective solution is accessible to local farmers, contributing to improved poultry farming practices. The hardware setup includes a camera with a 470 nm bandpass lens, yielding computable results suitable for procedural system processes, especially in streamlining thresholding image processing.

A. Introduction

Evaluating the behavior of chickens within their enclosures is crucial for poultry farmers, as it ensures the production of high-quality meat and mitigates the risk of sudden mortality due to stress-induced reactions. This evaluation provides valuable insights for farmers to proactively address potential causes of frightened behavior [1]-[11]. Various factors can trigger such behavior, with some studies underscoring the impact of abrupt shifts in the social hierarchy within the chicken flock, manifested through behaviors like frenzied running or chasing [11]. Accordingly, a system utilizing camera-based movement analysis can be developed to quantify and monitor these movements for effective early detection and intervention.

In less economically developed countries, constructing a system of this nature can be financially burdensome. Existing research has explored the measurement of chicken movement through neural networks and machine vision, but these methods come with high computational costs, making them less practical [1]-[7]. Our proposed system offers a more cost-effective alternative, making it accessible to local farmers. This system incorporates a procedural image processing technique and data association, ensuring its functionality within a closed cage system.

Our proposed system comprises a hardware camera equipped with a 470 nm bandpass lens, chosen for its ability to facilitate image processing with satisfactory outcomes. This selection is based on numerous prior studies indicating that the 470 nm bandpass lens yields the most discriminative values in chicken feather hyperspectral responses [8], [12], [19]. While it may not match the precision of convolutional neural networks and their derivatives when well-trained, this hardware setup provides computable results suitable for the procedural system process, particularly in simplifying thresholding image processing.

Within our proposed procedural approach, we introduce an additional dimension to behavior discrimination by incorporating the collective area of the chicken flock and the rate of change in that area as key measurements. This approach goes beyond traditional metrics such as the distance walked, velocity, and acceleration of individual chickens [9]-[17]. Our innovation lies in the comprehensive utilization of these parameters, providing a more nuanced understanding of chicken responses and enhancing the precision of our measurements. While some existing research has explored similar avenues, our novelty lies in integrating multiple methods simultaneously, elevating the sophistication and comprehensiveness of our behavior discrimination approach.

In summary, this paper endeavors to introduce an innovative system that integrates procedural image processing using a camera with a 470 nm bandpass filter. The system incorporates two distinct measurements: collective chicken flock area and individual metrics such as distance traveled, velocity, and acceleration for each chicken. This comprehensive approach aims to advance our understanding of chicken behavior by correlating data measurements with their behavioral responses. Furthermore, our research aims to pave the way for the development of an affordable system capable of obtaining essential data within the confines of a closed chicken enclosure, offering a practical and cost-effective solution for behavioral analysis in such settings.

B. Research Method

1. Chickens

Chicken movements were documented through discreetly recorded videos over a span of three days, with each video lasting 8 minutes and captured at half-hour intervals. Within the enclosure, 3-5 White Leghorn chickens, bred in Indonesia specifically as broilers, were observed in each video session. The study involved conducting two types of tests: the initial test focused on recording videos of chickens exhibiting their typical, undisturbed movements, while the second test involved capturing video data of chickens that were intentionally disturbed by isolating one of them. Subsequently, an analysis was performed on the behavioral patterns of the remaining chickens within the observation area.

2. Enclosure

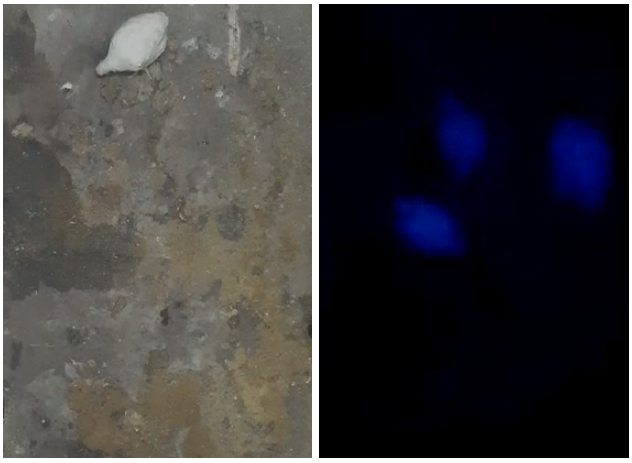
To achieve accurate tracking of individual chickens, we establish a dedicated chicken enclosure setup designed to minimize undesired interference from light intensity. It is crucial to guarantee that only the internal lamp functions as the primary light source for the camera, thereby enhancing the quality and uniformity of the captured footage. The controlled environment of the chicken coop reduces external variables that could impact the tracking process, including variations in lighting conditions or disruptions from nearby objects. By maintaining a standardized setting, researchers can acquire precise and dependable data on the area of chicken flock, rate change of area, velocity, acceleration, and position of each chicken within the enclosure.

(a) (b) (c)

Figure 1. (a) Species of the chicken in this research (white leghorn) (b) Prototype Enclosure Design (c) Prototype Enclosure Realization (photo taken from platform)

3. Camera Equipment

The camera utilized in the chicken enclosure was the Raspberry Pi Noir. It was selected for its capability to capture video spanning from visible to near-infrared wavelengths. A 470 nm bandpass filter from Midopt was affixed in front of the lens. Positioned at the center of the chicken enclosure at a height of approximately 200 cm, the camera was connected to a Raspberry Pi 4, which facilitated video acquisition through a timed mechanism. Remote access to the video footage was made possible via sftp protocols, ensuring a non-disruptive process throughout the acquisition phase.



(a) (b)

Figure 2. (a) Result photo taken from normal camera (b) Result photo taken from pi noir camera with 470 nm bandpass filter

4. Image Processing

In this study, the video obtained from the module in the enclosure was transferred and processed through a straightforward three-step procedure. Initially, the RGB values were reduced to only blue channel and stored in grayscale format. Subsequently, thresholding was applied, followed by contour analysis. These three steps were selected because they proved to be quicker in computation compared to incorporating a raw convolutional neural network.

In this research, the thresholding technique employed was the Otsu thresholding method. This method was selected for its adaptive capacity to alter the threshold of the grayscale, dynamically generating black and white video as input for contour analysis [20]. In this process, the method took the images of one frame into a histogram and divided the histogram based on minimizing intra-class intensity variance or, equivalently, maximizing inter-class variance. The equation to compute Otsu thresholding method can be seen in the equation (1)-(5).

$$\omega_1(T) = \sum_{i=0}^{T} \frac{I_i}{N} \tag{1}$$

$$\omega_2(T) = \sum_{i=T+1}^{L} \frac{I_i}{N} \tag{2}$$

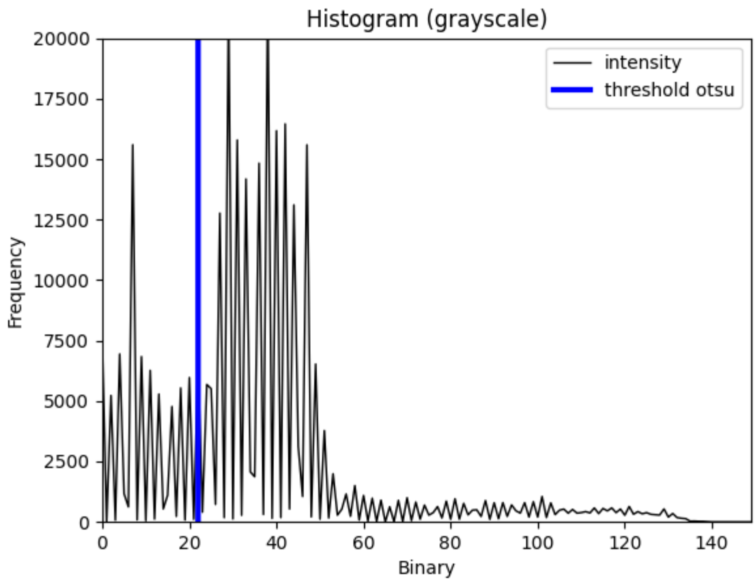
$$\mu_1(T) = \sum_{i=0}^{T} i\,\frac{I_i}{\omega_1} \tag{3}$$

$$\mu_2(T) = \sum_{i=T+1}^{L} i\,\frac{I_i}{\omega_2} \tag{4}$$

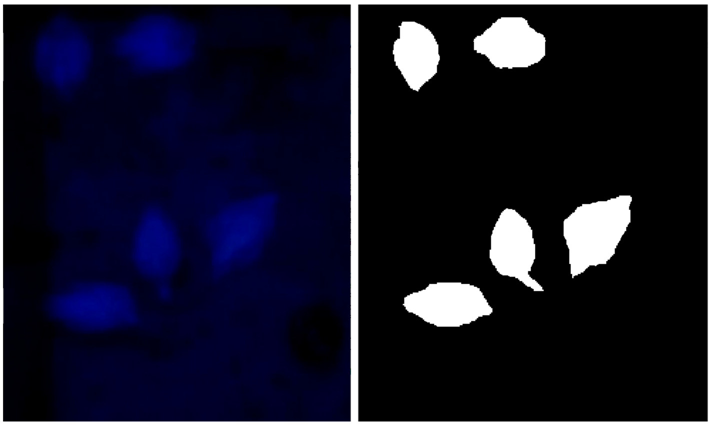
$$\sigma_T^2 = \omega_1(T)\omega_2(T)(\mu_1(T) - \mu_2(T))^2 \quad (5)$$

From that equations, $\omega_1(T)$ and $\omega_2(T)$ represents the probability of number of pixels for each class at threshold T and $\sigma_T^2(T)$ represents the variance of color values. Where the weight is defined on equation (3)-(4), P_i is sum of pixel with value grayscale i and N is the total pixel in one image. The result of equation (5) is the effective result of the gray level histogram where the Threshold value can produce the highest inter-class variation. If multiple targets are incorrectly divided into backgrounds or multiple backgrounds divided into targets, the difference between the two halves will be smaller. Therefore, during as the variance between clusters is maximized, probability misclassification will be minimized, thus realizing the perfect segmentation of an image.

This method involves an iterative process where it calculates the total value in the background class (enclosure floor), dividing it by the total number of pixels. Following this, it determines the mean intensity of the background. Once these parameters are established, the method employs the same equation to calculate the foreground (chickens). The process iterates through equations (1)-(5), taking input values ranging from 0 to 255 in grayscale. Crucially, the method strategically selects the threshold value that maximizes the inter-class variance (σ_T). This variance, indicating the dissimilarity between background and foreground intensities, is pivotal in the Otsu method of adaptive thresholding. The ultimate goal is to find the threshold that optimally discriminates between these classes, ensuring effective segmentation in image processing.



(a)



(b) (c)

Figure 3. (a) Histogram result of otsu method (b) Raw image taken from camera (c) Image after thresholding using otsu method

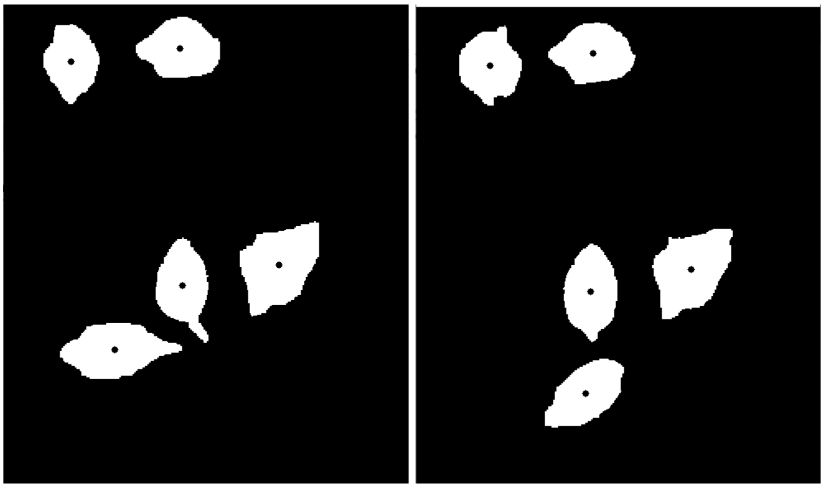
In Figure 3, it is evident that the Otsu method successfully achieved favorable results in discriminating between the chicken and the enclosure floor. This success can be attributed to the stable light intensity maintained within the enclosure throughout the video capture, and the minimal interference from external light sources. The histogram of the image frame also displayed a graph showcasing maximum inter-class variance, underscoring the mechanism that operated behind the system to ensure the accurate selection of the threshold value.

Following the thresholding procedure that generated black and white contours, the pivotal step in measuring chicken movement or calculating the area of the chicken flock involved establishing a center point for each chicken contour to serve as a reference for calculations. This approach simplified the tracking process, as opposed to relying on optical flow, occasionally guided by Shi-Tomasi, to select tracking points from the contour. Our chosen method involved creating artificial points for tracking, offering a simpler and easily computable alternative. The equation to compute contour analysis can be seen in the equation (6)-(8).

$$m_{ij} = \sum_{i=0}^{w}\sum_{j=0}^{h} x^i y^j I(x,y) \tag{6}$$

$$C_x = \frac{m_{10}}{m_{00}} = \frac{\sum_{i=0}^{w}\sum_{j=0}^{h} x^1\, y^0\, I(x,y)}{\sum_{i=0}^{w}\sum_{j=0}^{h} x^0\, y^0\, I(x,y)} \tag{7}$$

$$C_y = \frac{m_{01}}{m_{00}} = \frac{\sum_{i=0}^{w}\sum_{j=0}^{h} x^0\, y^1\, I(x,y)}{\sum_{i=0}^{w}\sum_{j=0}^{h} x^0\, y^0\, I(x,y)} \tag{8}$$



(a) (b)

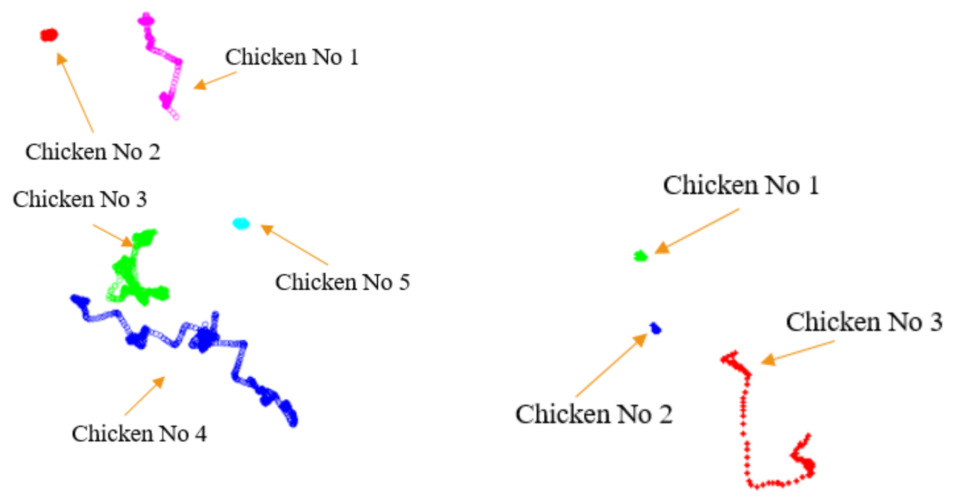
Figure 4. Result image with center from each contour from (a) frame 98 video number 2 and (b) from frame 367 video number 2

In Equation (6), the system iterated from the top-left corner to the bottom-right corner of the image. The iteration involved searching for a white pixel, and upon finding one, the system circled that point, declaring it as a contour. In Equations (7) and (8), the system calculated the center of the contour using a moment. This process involved searching for the most horizontally aligned white pixels for each contour and dividing it by the total area (moment) of that contour, determining the x center of that contour. A similar process was applied to find the y center of the contour, but instead of horizontally aligned pixels, vertically aligned white pixels were used. As we can see from figure 4, the center generated by this method is sufficient for data associations.

5. Data Associations for Tracking

In this research, the importance of data associations was evident in the chicken tracking process. As frames advanced, establishing a connection between the contour in the current frame and the one in the preceding frame was crucial. These associations were instrumental in maintaining a consistent labeling of the same chickens through successive frames. To achieve this, we employed a method that identified the smallest distance between the new frame contour and the last frame contour, categorizing the new frame contour closest to the last frame contour as the same chicken. This assumption was grounded in the relatively slow speed of chickens compared to the area of pixels divided by the frame rate. The equation for performing data associations can be seen in the equation (9).

$$\sum_{i=0}^{nfc}\sum_{j=0}^{lfc} r_{i,j} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \quad (9)$$

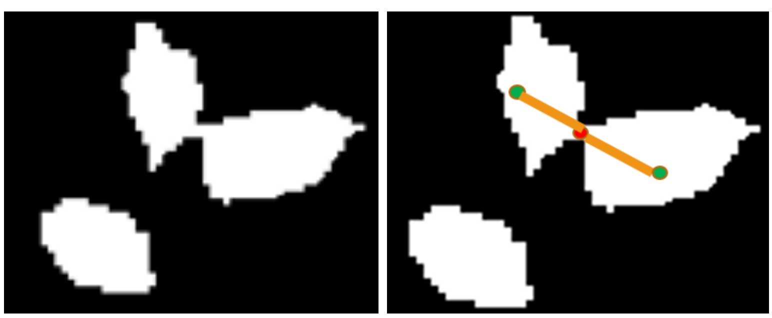


(a) (b)

Figure 5. (a) Result chicken tracking with 5 chickens (b) Result chicken tracking with 3 chickens

In Figure 5, the outcomes of the executed data associations within the system are visually depicted. The dots observable in the illustration represent the centroids of chicken contours derived from individual frames. This visual representation serves as a comprehensive elucidation, illustrating the dynamic patterns of chicken movement across successive frames throughout the entire video sequence. The figure provides an insightful retrospective view of the tracked chicken trajectories, showcasing their motion and spatial relationships over the course of the video.

A challenge arises in tracking due to the inherent nature of contour detection. When two or more chicken contours merge because the chickens are moving closer, data associations can fail. To address this issue, we introduced a system capable of identifying the location and number of contours that have merged. By calculating the area of the contours, we can identify unusually large contours that typically represent two or more chickens positioned side by side. Subsequently, we copied the last known positions of these merged contours into an array, preserving the chicken positions for the current timeframe. This preventative measure was implemented to ensure robust data associations during tracking.



(a) (b)

Figure 6. (a) Contour joining do to the chicken position is side by side (b) Preventive method to prevent data association process fail

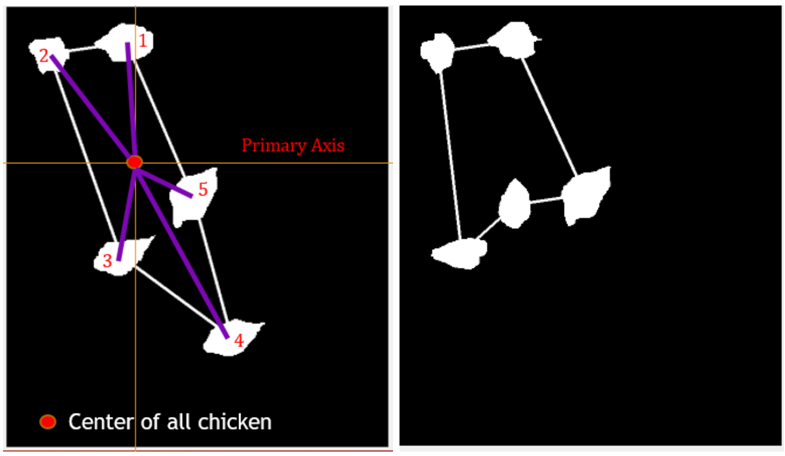
6. Measurement of Area and Movement

The measurement of the area in this research involved a process that included searching for the center of all contours using equation (10), sorting each contour based on the degree determined by the primary axis from the center of all contours in a clockwise direction using equation (11), and applying shoelace calculation to determine the area according to equation (12). This procedure was carried out to ensure that all calculated areas were derived from the overall area of the chicken flocking behavior, maintaining consistency. Subsequently, after calculating the area for each frame, the difference between two consecutive frames was computed to ascertain the rate of change in the area of chicken flock behavior.

$$\bar{C}_{x,y} = \frac{\sum_{i=1}^{N} C_{x,y}}{N} \tag{10}$$

$$tan^{-1}\left(\frac{y_n - y_c}{x_n - x_c}\right) \tag{11}$$

$$A = \frac{1}{2}\sum_{n=1}^{M}|x_n y_{n+1} - x_{n+1} y_n| \tag{12}$$



(a) (b)

Figure 7. (a) Procedure for establishing clockwise orientation prior to chicken area calculation (b) Description of the chicken area to be calculated

To ensure the accuracy of the area measurements, we also quantified the movement of each chicken. The measured movement encompassed the distance traveled by each chicken from the beginning to the end of the video, the velocity of the chicken's movement based on the differences in position of the chicken's center from frame to frame, and finally, the acceleration, calculated as the derivative of the velocity. This set of measurements may, in future research, provide insights into the social hierarchy of the chicken flock. The equations for calculating these three parameters can be found in equations (13)-(15).

$$v_i = \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} fps \quad (13)$$

$$s_i = \sum_{i=0}^{N} \frac{v_i}{fps} \quad (14)$$

$$a_i = (v_i - v_{i-1}) fps \quad (15)$$

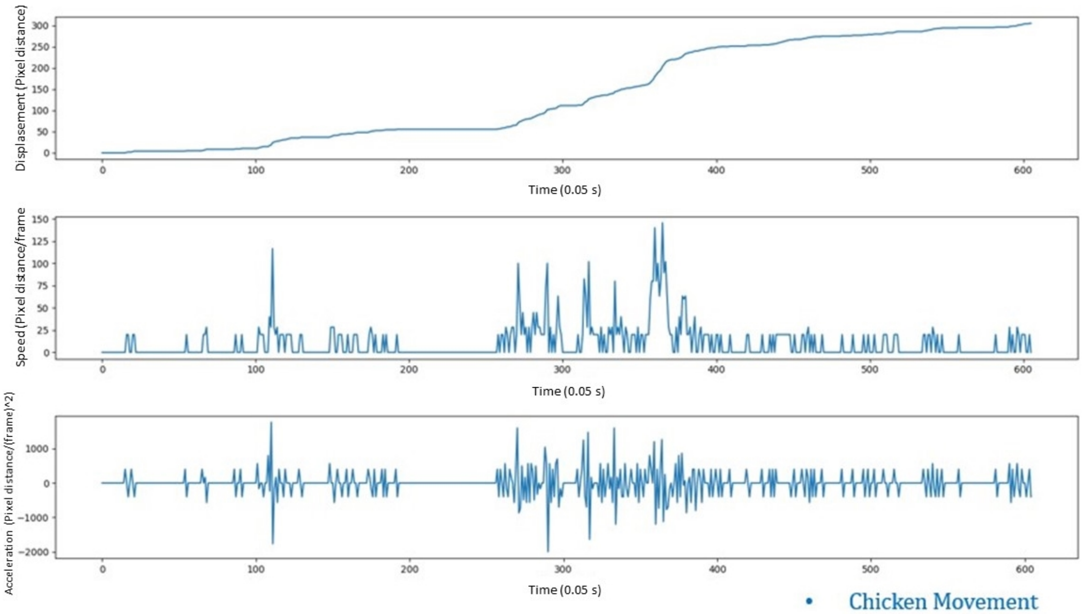
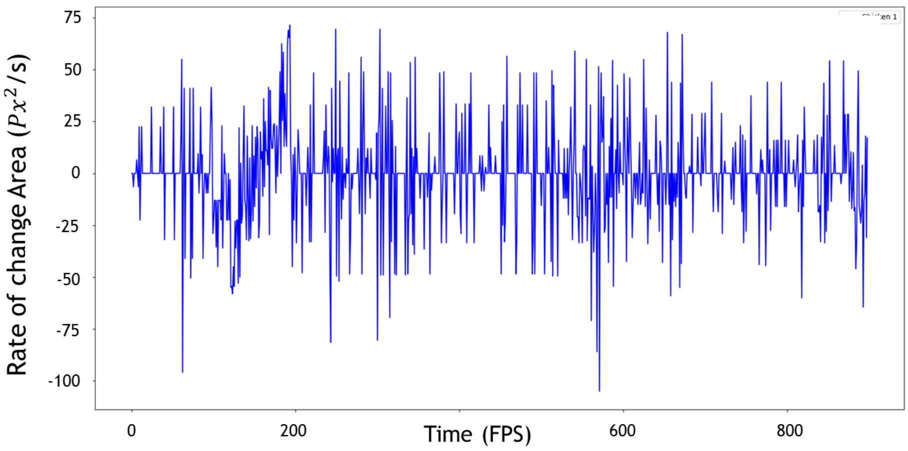


Figure 8. From top to the bottom is the chicken movement distance travelled, velocity, and acceleration

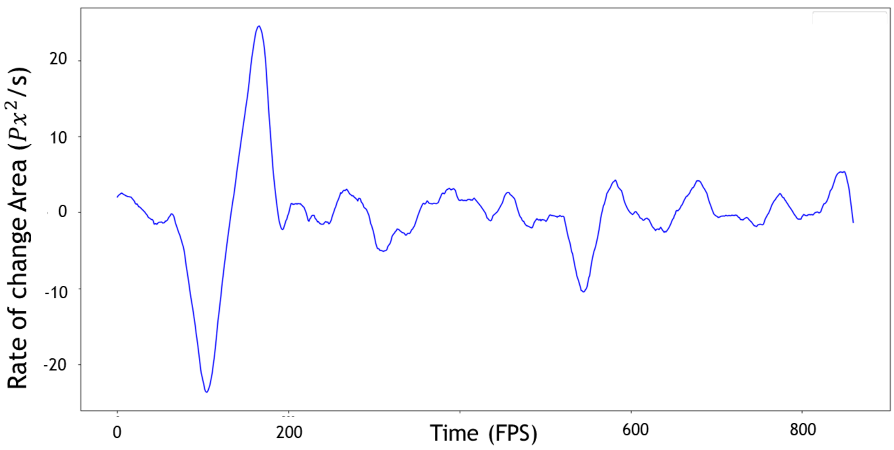
7. Savitzky-Golay Filter

To refine the measurements of area, rate of change of area, distance traveled, velocity, and acceleration in this research, we employ the Savitzky-Golay filter. This choice is based on the filter's characteristic of not distorting the measurements [21]. To implement the filtering process, we utilize constants outlined in the original paper of the filter, as specified in equation (16).

$$Y_j \quad (16)$$



(a)



(b)

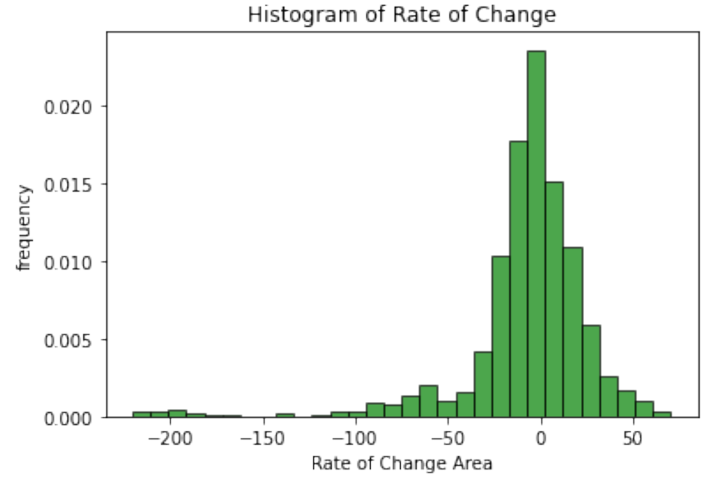
Figure 9. (a) rate of change area from the chicken flock before the savitzky-golay filter (b) rate of change area from the chicken flock after the savitzky-golay filter

8. Histogram of Total Rate of Change Area

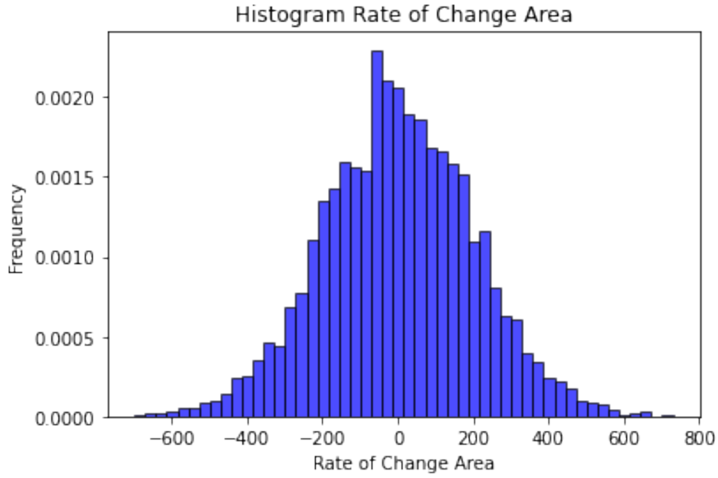
In this research, histograms were employed to visualize the overall rate of change in area, providing insights into chicken behavior during both normal and scared states. This method was chosen due to the inherent unpredictability in chicken responses. The histogram result is detailed in result and discussion, reflecting the analytical approach taken to capture and understand the diverse and dynamic nature of chicken behavior observed in the study.

C. Result and Discussion

This research focuses on the typical behavior of chicken flocks and their scared behaviors. A statistical analysis will be conducted using histograms to examine the rate of change in the area of chicken flocks. The test results indicate that the rate of change in the area of normal chicken flocks is centered around 0, suggesting that chickens, particularly broiler chickens, do not move much. Additionally, the test findings reveal that the rate of change in the area of scared chicken flocks is more scattered and distributed. This result emphasis that there are some connection between the scared/freightened chicken flock with the movement activity.



(a)



(b)

Figure 10. (a) Histogram of the normal chicken flock (b) Histogram of the scared chicken flock

To guarantee accurate calculations of the area and rate of change of the area, we examine the movement graph. If there are rapid fluctuations in the rate of change, we investigate whether any chickens are in motion. The absence of movement in response to significant differences in the rate of change of the area indicates a false reading. However, for future research endeavors, it is imperative to formalize this process in a more statistically robust manner.

For comparison, we include a roughly trained YOLO-V1 to detect chicken contours. This YOLO model was trained using 200 images generated from one of the captured videos and underwent training for 9 hours and 34 minutes. The current performance of the trained YOLO-V1 indicates that it is not performing well. It can be concluded that YOLO-V1 requires more images for training and additional computing time. Therefore, our proposed method is quicker to implement, although it comes with certain restrictions that have already been specified.

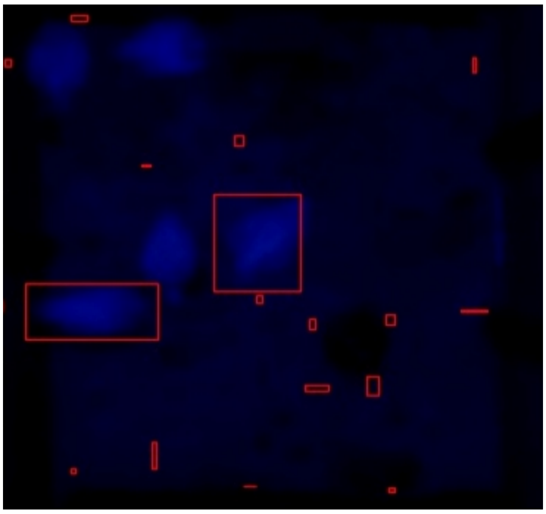


Figure 11. Chicken contour area detection using yolo-V1.

D. Conclusion

By implementing a bandpass filter centered around 470 nm and employing procedural tracking, a closed system has been established to effectively measure the behavior of chicken flocks. It is important to note that the results discussed here are derived from observations on small chicken flocks, and it is conceivable that different outcomes may arise when applying this setup and methodology to larger chicken flocks.

The bandpass filter, operating in the vicinity of 470 nm, facilitates focused monitoring and data collection, ensuring a more refined examination of chicken behavior within the designated spectral range. The procedural tracking methodology enhances the precision of the system, allowing for a thorough assessment of the intricate movements and interactions within the chicken flock.

It is crucial to recognize that the current findings primarily pertain to small-scale chicken groups, and extrapolating these results to larger flocks warrants caution. The dynamics and behavioral patterns observed in smaller flocks may not be directly translatable to more extensive poultry populations.

In conclusion, the rate of change in the area of the chicken flock emerges as a valuable metric influenced by fear-induced chicken behavior. The integration of a bandpass filter and procedural tracking contributes to the establishment of a comprehensive and adaptable system for behavior measurement, paving the way for potential applications in various poultry management scenarios. Further investigations on larger chicken flocks are recommended to validate and extend these findings.

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