The influence of lighting on fingerlings counting

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***Abstract*—The search for the automation of processes within fish farms has encouraged the research of new methods for counting fingerlings. The purpose of these devices is to reduce manual labor, increase counting precision and reduce fish stress. The automatic counting system consists of software that uses computer vision techniques to process captured images and a mechanical structure to manipulate fingerlings. A difficulty encountered in image processing is the influence of lighting, which may vary according to the environment, position, and time of day that the device is used. In this paper, we vary the illumination intensity, measured by luxmeter, to identify if this variation interferes in the counting precision. We analyzed five video blocks recorded in the Pacu Project environment in Terenos-MS. A MSE of 9.85 was achieved. The conclusion was that the illumination interferes in the recognition of fingerlings in the video and, consequently, in the counting.**

I. Introduction

The growth of fish farming has required many demands for technological solutions [1]. Techniques that reduce costs, increase productivity and, consequently, the profitability of the business is the main purpose for research [2]. Fingerling counting devices are equipment that facilitate handling and improve the accuracy of the production monitoring. Currently, the fingerlings counting is done manually in almost all Brazilian fish farms, as well as, according to Ibrahin et al. [3], in most developing countries, requiring a significant number of employees in this process that leads to inaccuracies[4, 5] related to the failures inherent to the human being. In addition, this procedure can stress the fish, increasing the probability of death and diseases. In a multidisciplinary project of the research group Inovisão at UCDB, equipment consisting of mechanical structure, image acquisition system, and specific software based on computer vision techniques was developed to automate the counting labor [6]. The computer vision seeks to simulate human vision once the input is an image and the output is an interpretation of that image [7]. The recognition of objects by human vision is a trivial task [8], but it is quite difficult for a computer system. To achieve better results, a very important factor is the quality of the images since several external factors can change them, such as the luminosity of the environment and the shadows, modifying the fingerlings identification [4]. In Le and Xu [9], it has been pointed out that lighting is one of the main problems to be solved. Therefore, this work aims to evaluate the counting under the controlled effect of lighting, with the purpose of inhibiting the influence of the environmental factors variations so that the generated images present the same quality and homogeneity.

II. Related Work

In Zion [10], the author states that lighting is one of the limiting conditions for the development of technological solutions for aquaculture. The interference of the lighting was pointed out by Cadieux et al. [11] that used automated system for counting fish by species through the system from Vaky enterprise that use sensor infrared diodes to acquire images of objects passing through the fishway and in Karplus et al. [12], that worked with positive phototactic and rheotactic responses of the guppies that can be manipulated to enable sorting by computer vision.

In the development of an ornamental fish counting instrument presented in Hernández-Ontiveros et al.[5], it was established an aquarium background and lighting system so that the software could correctly recognize the image captured by the camera, the counting was done by digital image processing obtaining an average accuracy up to 96.64% using different species of fishes and different sizes, according to the authors.

As shown in Chen et al. [13], they used Domain Adaptive Faster R-CNN for Object Detection to real-world object detection that still faces challenges due to the wide range of factors involved, such as appearance of objects, backgrounds, lighting, image quality, focus, etc. The authors in Choi and Banerjee [14] also pointed out that despite recent advances, the estimation of optical flow remains a challenging problem caused by the changes of light, large occlusions, or fast movements. In the works Salazar et al. [15] and Salazar and Mesa [16], the authors concluded that lighting conditions directly affect the results of algorithms based on computer vision.

The illumination variation is also an important factor to be considered for tracking animals in the laboratory [17] and for face recognition [18]. In their tests, using a Haar Cascade filter followed by a neural network application, they were able to work around the problem of brightness variation. Still, they concluded that this method has a very high computational cost, requiring better hardware performance. In their fish tracking and counting experiment, the authors in Lumauag and Nava [19] identified that the shadows caused by illumination lead to an excessive count.

In Park and Cho [20], a method of improving the images was proposed by changing parameters that simulate the alteration of the image illumination itself, resulting in different images from the original.

The authors in Toh et al. [21] related the problem of establishing an ideal boundary to separate the fish from the background image when the illumination is not uniform. In Labuguen et al. [22], it was analyzed the behavior of milkfish and tilapia under blue, green, and red lights, observing that there were differences in the behavior of these animals under these lighting conditions.

In more recent work, a machine learning approach for estimating the biomass of Pintado Real fingerlings was developed by Pache et al. [23], comparing an environment with lighting and without lighting. The approach showed better results for the illuminated dataset, and the Linear Regression algorithm obtained 76% R2. On the other hand, Hong Khai et al. [24] developed a model based on Mask R-CNN applied to count shrimp from images collected by an underwater camera and using three different densities of shrimp, low, medium, and high, where they obtained R2 of 0.99, 0.97 and 0.87 respectively for these densities. In Costa et al. [25], Convolutional Neural Networks were used to count tilapia larvae utilizing a smartphone, obtaining 97% mAP.

As presented in the above-mentioned works, we emphasize that the techniques, procedures, and methods used are different from those presented in our proposal, not allowing an explicit comparison between them. With our article, we intend to present a new approach to the influence of lighting on fingerlings counting.

III. Materials and methods

A. First prototype

Initially, a device was used where the fingerlings were displaced by a ramp for counting. The surface of the ramp was painted light gray in order to contrast with the color of these fingerlings (Figure 1). A Logitech C920 PRO WEBCAM HD camera model with autofocus was used for the image acquisition. The resolution of the camera is 640 x 480 with a 30 frames per second rate. The camera was fixed at an appropriate distance from the ramp to cover the entire length of the ramp and capture the images. The counting was performed by software based on computer vision techniques. In Figure 1, we can visualize the structure of the device, which was the first prototype used for the initial counting tests.

As mentioned previously, object detection in images depends on the variation of illumination and shading. In the capture of images by the first prototype, we can observe in Figure 1, item A, the presence of shadows caused by illumination.

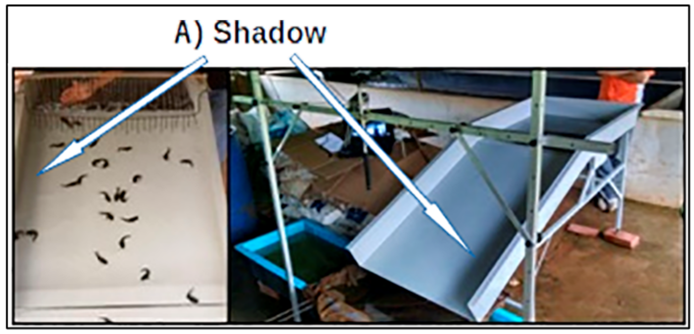

Fig. 1. Structure of the Fingerlings Counter - First Prototype.

In Figure 2, we have a complete picture of the first fingerlings counter prototype. To reduce the shadows, we added reflectors which had a good performance for the experiment.

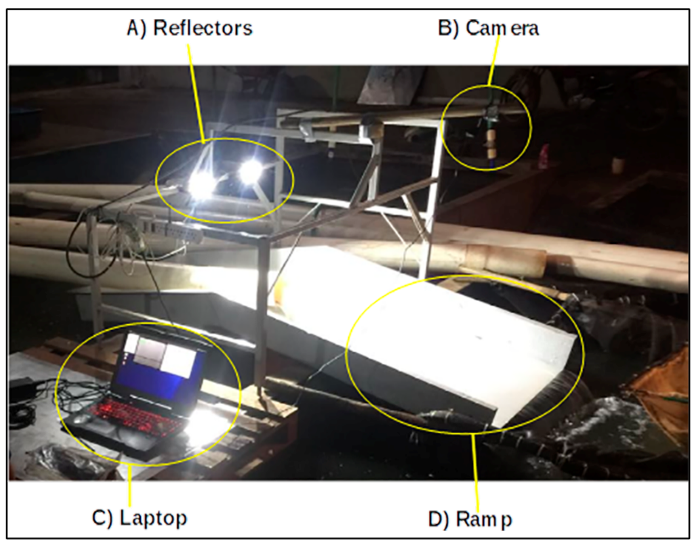

Fig. 2. Artificial lighting system by reflectors.

Figure 2 also shows two reflectors positioned in the upper part (item A), the camera responsible for capturing the images (item B), the ramp where the fingerlings pass (item D) and the Laptop that receives the information from the camera and run the fingerlings counting software (item C). In this section, we presented the first open prototype that is influenced by ambient lighting; in the next, we will present another prototype with some improvements.

B. Second prototype

The second method was designed in such a way that a structure isolated the counting environment (ramp) and the influence of the illumination could be observed more objectively in the result of the counting. There was no need for adjustments in the software for each experiment that was carried out. The reflectors were positioned at the bottom of the ramp, obtaining an illumination with no external influences. The overall view of the structure is shown in Figure 3, in which the red arrow indicates the direction of the fingerling flow in the equipment.

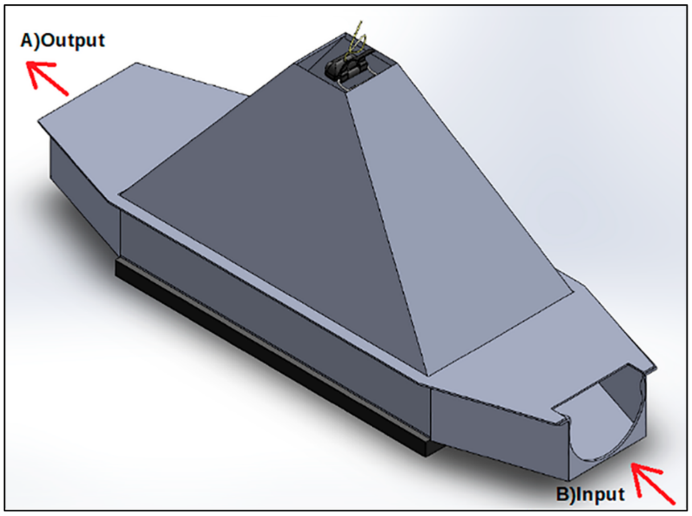

Fig. 3. Overview of the second prototype.

In Figure 4, we have the exploded view of the counter structure - the camera (item A) is positioned to capture the images of the fingerlings; a device top (item B) isolates the inner part; the ramp (item C) and the translucent plate (item D).

In the new prototype, the illumination interference analysis was carried out in three stages: in the first, 50 videos were recorded with 50 fingerlings in each one. The water flow was not constant because a bucket was used to put water on the ramp. The acquisition of images was performed in groups of videos, in which the variation of illumination was measured with a luxmeter Instrutherm ld-240 model. The videos were made with the following configuration:

- First group: 10 videos with slope of 29 degrees, natural lighting, 30 Lux;
- Second group: 10 videos with a slope of 19 degrees, natural lighting, 30 Lux;
- Third group: 10 videos with a slope of 19 degrees, artificial lighting, 51 Lux;
- Fourth group: 10 videos with a slope of 19 degrees, artificial lighting, 222 Lux;
- Fifth group: 10 videos with a slope of 19 degrees, artificial lighting, 467 Lux.

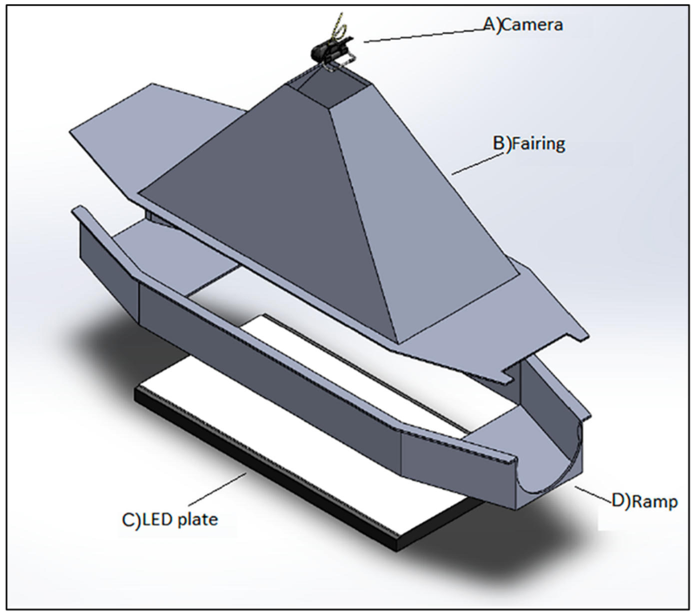

Fig. 4. Exploded view of the new prototype version.

The values of the ramp inclination angle relative to the horizontal and the illuminance values were experimentally defined by trial and error. For the second stage, a set of values, presented in Table I, was established for the software parameters to be used in this case. The parameters were chosen by trial and error to achieve the best hit rate.

TABLE I
PARAMETERS USED IN THE FINGERLINGS COUNTING SOFTWARE.

Parameters	Values						
distance between fingerlings (dt)	50	60	70				
candidate fingerlings (ct)	1	2	3				
maximum area (uds)	1.3	1.4	1.5				
minimum area (lds)	0.9	1.0	1.1				
blob area (ba)	60	64	68	72	76	80	
blob threshold (bt)	28	30	32	34	36	38	40

Briefly, the parameters indicate:

- Distance between fingerlings (dt): indicates the minimum distance between the blobs of a frame.
- Candidate fingerlings (ct): indicates the number of frames in which a blob should be traced to be considered a fingerling.
- Maximum area (uds): used to calculate the number of fingerlings in a cluster; corresponds to the maximum area.
- Minimum area (lds): the minimum area required for a drop to be counted as fingerlings.
- Blob area (ba): blobs with areas smaller than this value are discarded.
- Blob threshold (bt): value for blob segmentation.

In the third step, we executed the software in each group of videos, recorded in the second stage, using all 3.402 parameter combinations, and recorded the results.

IV. Results

As a result of the unstable illumination in the first prototype, which varied according to the time of day, location, and position of the device, it was necessary to calibrate the software constantly. For this reason, this prototype was only used for software development. It was verified that, in the assembly with the reflectors, the obtained illumination was heterogeneous with the presence of light focuses (light concentration at one point). In Figure 5, we can see this variation of brightness in the acquired images. It is observed that the brightness is not homogeneous throughout the image, with some parts lighter than others, showing the presence of shadows.

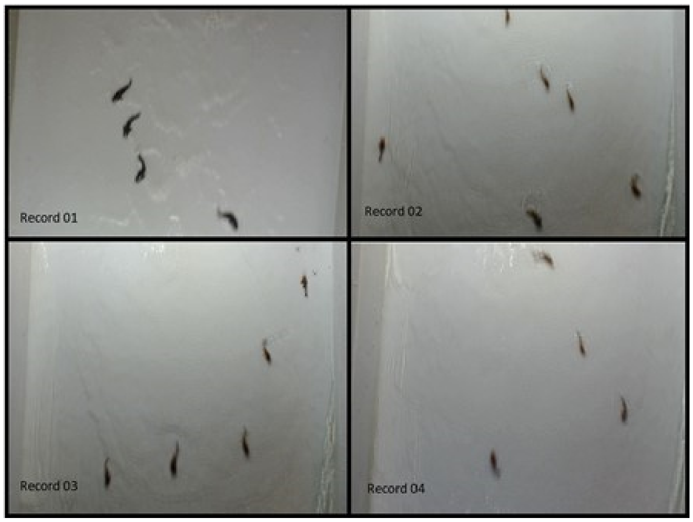

Fig. 5. Brightness variation in four different registers.

In Figure 6, we can see in item C the ramp without lighting and in item D, with illumination. In the same figure, it is also possible to see the predominance of intermediate tones, approximately between 50 and 150, item A. In item B, there is a predominance of light tones and a darker part, which can be identified on the left. We can observe that there is a scattering of the tones in the histogram when a reflector is applied at the bottom of the ramp.

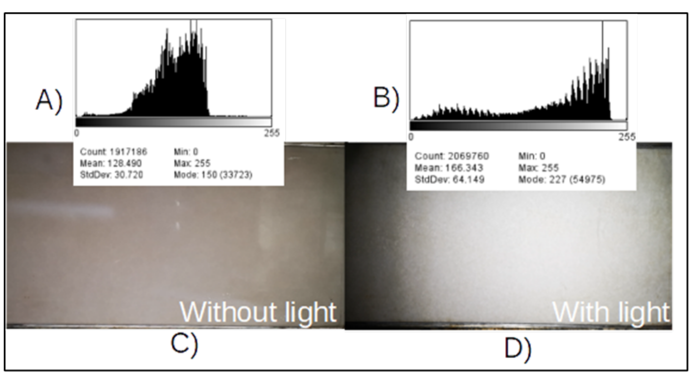

Fig. 6. Image without fingerlings in the first and second prototype.

Figure 7 shows the ramps of the prototypes with fingerlings. In C we observed that the histogram has variations like that of Figure 7-A, leading us to infer that the color of the fingerling could be confused with the background color. In addition, in Figure 7- B and D, with a more homogenous and lighter background illumination, the fingerling stands out in relation to the background.

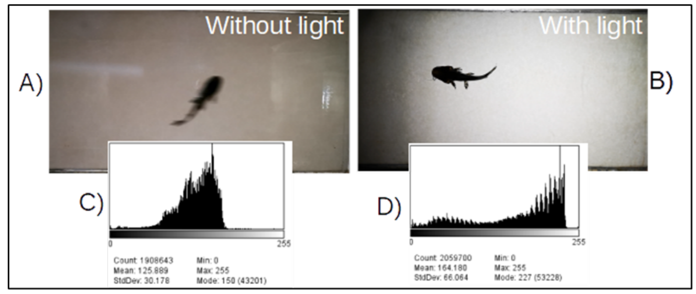

Fig. 7. Images with fingerlings.

In Figure 8, when items A and B are compared to each other, it is possible to see graphically the amplitude of the level that represents the tonality distribution of the fingerling. In A, the level is much smaller than in B. Therefore, the difference between the background color and the object increases the difference between the object's black tones and the proximity of the white tone relative to the background. This difference aids in the segmentation of the fingerling in the image.

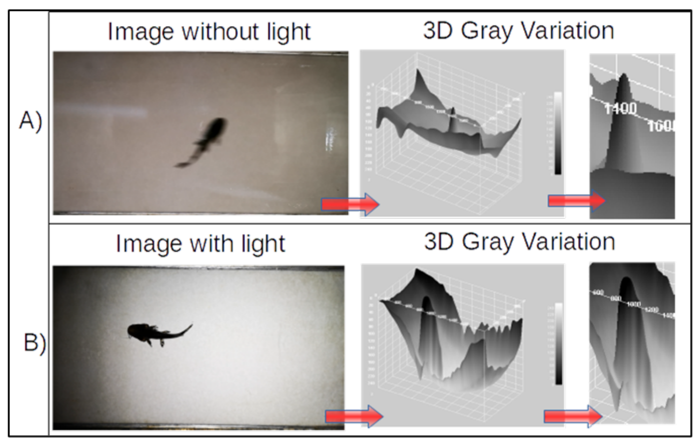

Fig. 8. Fingerling representation in 3D in grayscale chart with light and without light.

V. Discussion

Thus, from the results obtained, statistical methods were used to discuss. For the Anova test, a p-value of 2.2e-16 is obtained. Since it is less than 0.05, it indicates a statistical difference between treatments.

Considering that there are significant statistical differences between the groups, we can better understand the results. Table II shows the descriptive statistics for each group. It is observed that the best result occurred in group 3, where the mean was closest to the reference count (50), and all combinations resulted in some counting, with a minimum of 22 and a maximum was 72. The most frequent value in group 3 was 44, and a lower standard deviation and variance were achieved. The ”minimum” equals zero (Group_1, Group_2, Group_4, Group_5) indicates that the software in at least one of the combinations did not recognize any fingerling. In general, the metrics identify group 3 as being the one closest to the reference count.

TABLE II
DESCRIPTIVE STATISTICS.

	Group_1	Group_2	Group_3	Group_4	Group_5
			50		
Mean	28.78	25.98	45.59	25.67	10.46
Mode	0	0	44	0	4
Standard deviation	16.98	12.72	8.81	18.80	7.25
Variance	288.40	161.86	77.56	353.59	52.63
Interval	80	57	50	60	36
Minimum	0	0	22	0	0
Maximum	80	57	72	60	36

Group 3 was recorded with the ramp at 19º and illumination of 51 lux. Table 4 shows the root mean square error (RMSE), the number of combinations where the automatic count was equal to the reference count (AC_equal_MC), and the number of combinations that didn’t recognize fingerling in the video. It is identified that group 3 was the one that obtained the greatest number of hits in the count and did not have a score equal to zero.

TABLE III
MEAN SQUARED ERROR AND EQUAL COUNTS.

Groups	RMSE	AC_equal_MC	AC_ZERO
Group_1	27.18	297	3402
Group_2	27.18	73	3402
Group_3	9.85	1569	0
Group_4	30.75	444	10206
Group_5	40.20	0	2088

In the tests carried out, it was verified that the variation of the luminosity influences the precision of the fingerlings counting. The first prototype was used only for development but presented unsatisfactory results in the initial counting tests. However, these results were essential for the development of the second prototype since the designed structure makes lighting independent of the external environment. A mean square error of 9.85 was achieved. The results are promising for further improvements throughout the system. It is suggested to apply other methods to obtain a more homogeneous illumination of the internal part of the structure.

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