Live monitoring in poultry houses: a broiler detection approach

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***Abstract*—This paper presents a general framework for live detection of broilers in poultry houses. The challenges for image recognition of broilers are posted by crowded scenes, poor image quality and difficulty in acquiring a benchmark of labeled samples. The proposed framework consists on the use of image thresholding, morphological transformations, feature engineering, in addition to supervised and unsupervised learning techniques. Results show the effectiveness of the proposed framework to detect individual broilers in a poultry house image. Descriptive attributes related to the spatial distribution and movement of the broilers can be extracted using the resultant detections. These attributes can be used by automated warning systems, for the detection of anomalous events and thermal stress conditions.**

I. Introduction

According to Brazilian Association of Animal Protein (*ABPA*) [1], in 2015 Brazil has been responsible for 20% of world chicken meat production and 40% of the world chicken meat exports. Exporting around 4.3 million tons of chicken meat (7.2 billions USD in receipt), Brazil was the largest exporter and second largest producer of chicken meat in 2015.

Despite the high financial volume of broiler industry, this activity has very low profit margins [2]. In order to ensure that the activity is profitable, an intensive system is adopted for the simultaneous production of thousands of birds. In this intensive system, the proper management of the birds is crucial for the activity.

Broiler management is one of the main factors responsible for ensuring adequate levels of productivity, as well as ensuring good health and comfort conditions [3]. Considering the low profit margins, the economic viability of this farming activity is strongly dependent on good management practices.

In this scenario, live video monitoring can be used to collect helpful information for the proper broiler management. In particular, behavioral patterns can be monitored with image processing, for cheap and efficient solutions to guarantee the welfare, health and meat quality [2].

Several methods regarding broiler image monitoring have been proposed in the last years. These methods use image thresholding and optical flow to generate broiler movement and spatial distribution statistics.

In contrast to such methods, our proposal is to use an object detection approach to detect broilers, extracting the exact location of each broiler before generating any distribution or movement statistics. We search for particular texture patterns that permit to distinguish the center of each broiler in commercial broiler house images. The usage of this new approach is promising, because new studies can be done relating the detected broiler dynamics and the detection of interest events in commercial broiler houses. We show that, even with the poor image quality and the crowded scene challenges, it is possible to achieve a high accuracy level in such detection.

II. Related Works

In the context of live video monitoring, research has been developed to infer spatial distribution patterns, movement and behavior, allowing the detection of events unfavorable to bird development.

In the work of Aydin et al. [4], recordings of broilers were used to measure the movement intensity (activity index) of the birds. Analysis identified a correlation between changes in the historical series of this index and adverse conditions, like diseases that affect broiler locomotion.

In the work of Youssef et al. [5], the index of activity was modeled as a dynamic response of the broilers, subjected to ventilation system alterations in the confinement space. It was shown that when the ambient temperature inside the space deviated from the thermal comfort zone, the broilers began a search for more comfortable zones, suddenly increasing the global activity index.

Dawkins et al. [6] proposed the use of optical flow to analyze broiler movement patterns. It was shown that different metrics (mean, variance, asymmetry and kurtosis) calculated from the optic flow of the flocks were related to the behavior and individual well-being of the broilers. The asymmetry and kurtosis of the optical flow was related to the percentage of chickens with locomotion problems in each flock.

Kashiha et al. [2] proposed a spatial distribution index, using image thresholding. Anomalous behavior patterns were detected by analyzing the time series of this indicator. It was found that anomalies in the time series of the distribution index were associated with ventilation system failures, illumination changes and feeding problems.

In the work of Nääs et al. [7], patterns of behavior and spatial distribution were related to the thermal welfare of broilers. It was observed that the distribution of broilers in drinking and feeding areas varies according to the thermal welfare of the birds.

Vilas Novas et al. [8], [9] proposed a method using image thresholding, altogether with thermal sensors data for thermal welfare classification in commercial broiler houses. Applying an unsupervised learning algorithm, different broiler distribution profiles were detected.

In comparison to the previous works, our method improves the state-of-the-art by using image texture information to detect the center of each broiler in commercial broiler house images. Using the detected broilers, statistics related to the spatial distribution and the movement of the broilers can be easily obtained. These statistics calculated by the detected object tend to be more accurate, opening new possibilities of broiler behavioral studies.

III. Basic Concepts And Notations

In this section we present important concepts related to the problem under analysis. An image can be defined as a set of pixels $I = \{P_i | 0 \leq i < n\}$, where n is the total number of pixels in the image. Each pixel is a tuple $P_i = (R_i, G_i, B_i)$, where the values of R_i, G_i and B_i represents the intensity of each channel of the RGB color space. Global or local information can be extracted from images. A feature extraction is a function F that for a given image I, generates a feature vector $V \in \mathbb{R}^d$, of size d.

Let a set $\mathcal{T} \subset \mathbb{R}^d$ of tuples of size d and a set of possible labels $\mathcal{L}$. Given a training set in which every $t_i \in \mathcal{T}$ has a label c_i assigned by an expert, where $c_i \in \mathcal{L}$.

$$c_i = \begin{cases} 1, & \text{if } P_i \text{ is a broiler center} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

A supervised classifier C must build a model capable to predict the label of a new data item. Given a tuple $x \in \mathbb{R}^d$, a classifier can be defined as the function $C(x) = c$, where $c \in \mathcal{L}$. Among the most used classifiers are the K-Nearest Neighbors (*KNN*), Multi-layer Perceptron Neural Networks and Random Forests [10], [11]. We refer to the above definitions in the rest of this work.

Feature Extraction: Images are processed by means of extracted features. The features extracted from a given image correspond to numerical measurements that describe visual properties. Such properties are able to discover and represent connections between pixels of the whole image (global) [12], or of small regions of the image (local) [13]. Low-level descriptors [14], as those base on color, shape and texture, are frequently used.

The Local Binary Pattern (LBP) is a texture feature extractor that considers the neighborhood of a pixel. Perhaps the most important property of the LBP descriptor in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings [15].

The LBP descriptor is used in several applications, as fire detection [16], pedestrian detection, image matching, facial expression recognition and image segmentation [15]. The LPB can be performed in gray scale, in a region of nn pixels. For each pixel P_i from the neighborhood of the central pixel P_c, a binary code is created by assigning the value 1 if $P_i > P_c$, or 0, otherwise. Then, the histogram of codes is used as a feature vector.

In order to make the LBP rotation invariant, a variation of the original algorithm shifts the code until it reaches its minimum value. In our approach it will be used a LBP variation that is defined as uniform patterns [17]. A code is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 (or vice versa). This method is defined by its rotation invariance with uniform patterns and finer quantization of the angular space which is gray scale and rotation invariant.

IV. Our Proposal

We propose a framework that consists on the use of image thresholding, morphological transformations, feature engineering, together with supervised and unsupervised learning techniques for broiler detection. The goal of this framework is to provide an effective automated detection for the development of new studies relating broiler dynamics to interest situations in commercial broiler houses.

A. Image Pre-processing

Feature Engineering: We explore the fact that the texture can improve the detection of broilers, since they are more robust to changes in rotation, scale, illumination, viewpoint and different types of image degradation [15].

Our approach starts by using the uniform patterns LBP operator [17], [18] for each pixel P_i.

$$I_{texture} = LBP(I_{grayscale}) \tag{2}$$

Image Segmentation: Since the poultry house floor is darker than the white broilers, an image thresholding step is useful to restrict which pixels P_i are more likely to be broiler centers. Using Homogeneous Blur and Otsu's method [19], [20], the image $I_{grayscale}$ is converted to a binary image I_{otsu}. The homogeneous blur is performed using a normalized box filter, in order to reduce image noise before the segmentation.

$$I_{otsu} = Otsu(Blur(I_{grayscale})) \tag{3}$$

$$I_{dilate} = Dilate(I_{otsu}) \tag{4}$$

I_{dilate} is generated by applying a dilation (see Eq. 4) on the binary image. This morphological operation ensures that every broiler center must highlighted in I_{dilate}, respecting relation (5).

$$(c_i == 1) \Longrightarrow (P_i == 1 | P_i \in I_{dilate}) \tag{5}$$

Let $\mathbb{S}$ be the set of highlighted pixels in I_{dilate}. These pixels are the foreground P_i of the image, that must be classified by the supervised model C.

$$\mathbb{S} = \{i | P_i == 1 \text{ and } P_i \in I_{dilate}\} \quad (6)$$

B. Image Processing

Supervised Classifier: The binary image I_{dilate} is used to filter which pixels must be classified using a trained model C [10].

$$C(P_i) = \begin{cases} C(P_i), & \text{if } (i \in \mathbb{S} | P_i \in I_{texture}) \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

The result of the classification is the binary image $I_{classify}$.

$$I_{classify} = \{C(P_i) | 0 \leq i < n\} \quad (8)$$

Multiple detections of a given broiler can occur. To avoid multiple segmentations of the same broiler, a merging algorithm combines detected pixels, if they are in close proximity.

C. Image Post-processing

Clustering: Before merging the detected pixels, an opening morphological operation (9) is performed to remove part of the noise in the binary image $I_{classify}$. Opening is just another name of erosion followed by dilation.

$$I_{opening} = Opening(I_{classify}) \quad (9)$$

Since a single broiler must be leading to multiple local detections in the image, Mean Shift clustering algorithm [21] is used to merge detections relative to the same broiler.

Mean shift clustering aims to discover blobs in a smooth density of samples. It is a centroid based algorithm, which works by updating candidates for centroids to be the mean of the points within a given region. These candidates are then filtered in a post-processing stage to eliminate near-duplicates to form the final set of centroids [10].

$$I_{final} = MeanShift(I_{opening}) \quad (10)$$

The final output is the image I_{final} with only one detection for each broiler in the image I.

V. Experiments

A. Configuration

Following, we describe the configuration of our experiments.

Video Recordings: To perform the proposed computational experiments it will be used a sequence of videos collected in a commercial broiler house located in the region of Jundiaí, in the state of São Paulo. Video samples were collected for two flocks, totaling about 2 thousand hours of video.

All filming was done using a digital surveillance camera, with 480p resolution, connected to a DVR (Digital Video Recorder). The camera was attached to the ceiling of the poultry house, about 2.5 meters high. The camera lens had a 2.45 mm focal length and a 1/3-inch photosensitive sensor (CCD). With these specifications, the camera was capable of filming an area of about 22 square meters from the poultry house floor, capturing images from a fixed panorama as shown in Figure 1. Each pixel in the captured images represent approximately 1.3 cm^2 of the poultry house floor.

Camera Calibration: Since the surveillance camera had a wide-angle lens, the lens distortion have been corrected in the recordings before the experimental dataset preparation [20]. Figure 2 presents a grayscale image of the broilers after the lens distortion correction.

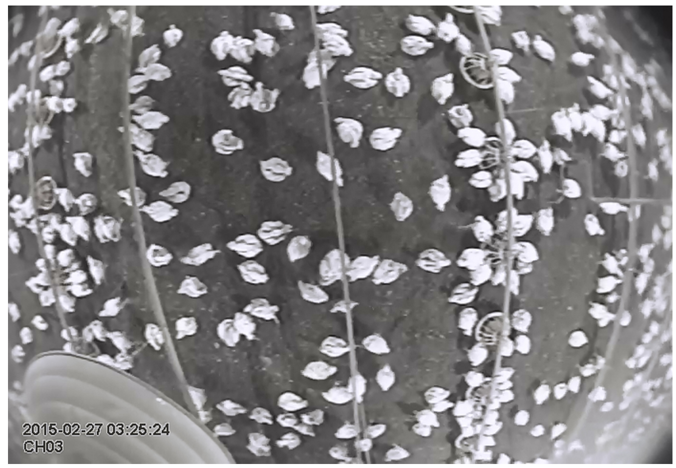


Fig. 1. Image captured in a commercial broiler house located in the region of Jundiaí, Brazil. Broilers with 28 days of life.

Labeling: Exhaustive labeling generation has been performed for a series of 40 images, with 9,695 labeled broilers of approximately the same size and age (21 days of life). Each of the 40 images were taken 1 second after the previous one.

Fig. 2. Image generated after the lens distortion correction. Broilers with 21 days of life ($I_{grayscale}$).

Starting from the labeled broiler centers, slight variations of the samples were created by randomly shifting the original points, resulting in a new set with more 9,695 samples. The shift has been generated randomly (with discrete uniform distribution) around ± 2 pixels of the originally labeled broiler center.

Negative samples were collected by random sampling pixels with distances between 9 and 29 pixels from the nearest broiler center (see Eq. 11), resulting in a negative set of 38,780 samples.

$$distance(c_{broiler}, c_{background}) \in \big(8, 30\big) \quad (11)$$

The experimental dataset (see Table I) had 58,170 samples, 33.3% labeled positive and 66.7% negative.

TABLE I
EXPERIMENTAL DATASET

Labeled Attributes	Number of Labeled Samples	Detector Size $(Width \times Height)$
Broiler Centers *(exhaustive labeling)*	9,695	13×13
Broiler Centers *(random shifting)*	9,695	13×13
Negative Samples	38,780	13×13
Total	**58,170**	

B. Description of the experiments

In this section we go through the proposed framework to detect the broiler centers labeled in the experimental dataset. Figure 2 will be used to illustrate each of the pre-processing, processing and post-processing framework operations.

Feature Extraction: The LBP descriptor has been applied to the 40 images of the experimental dataset. $I_{texture}$ has been calculated by LBP comparisons to neighboring 24 sample points at 12 pixels of radius (see Eq. 2).

Figure 3 shows an image representation of the LBP feature extraction result.

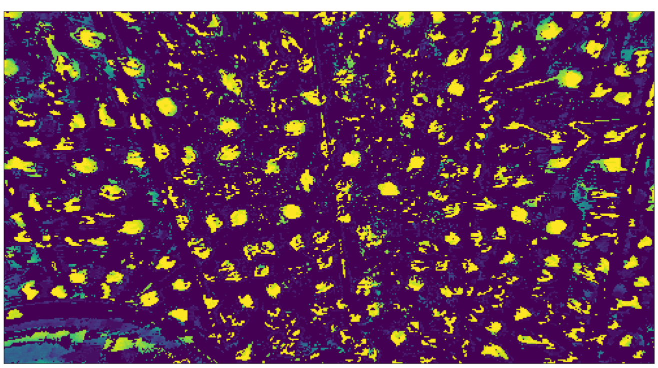
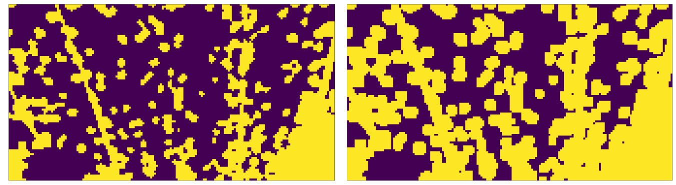


Fig. 3. LBP feature extraction representation ($I_{texture}$).

Image Segmentation: Figure 4a shows I_{otsu}, generated with Otsu thresholding and uniform blur (with a 9×9 uniform kernel).

Figure 4b presents I_{dilate}, the result of a dilation in I_{otsu} using a 3×3 uniform kernel.

Square windows with $width = 13$ were extracted around each of the labeled pixels.



(a) Blur + Otsu (b) Blur + Otsu + Dilation

Fig. 4. Image segmentation results (I_{otsu} *and* I_{dilate}).

In Figure 5, I_{dilate} (Figure 4b) is combined to $I_{texture}$ (Figure 3). The result is a new image with LBP features filtered only for the pixels highlighted in the image segmentation step.

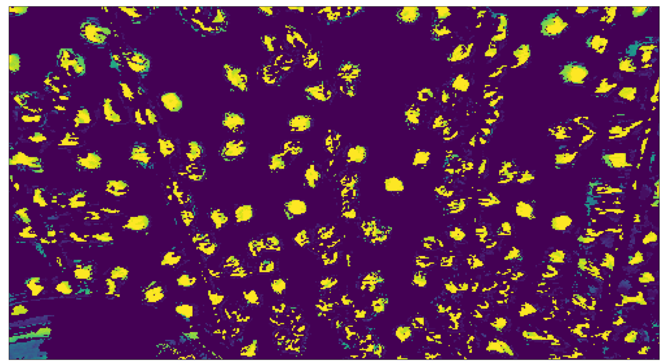


Fig. 5. LBP feature extraction combined with image segmentation filter.

Comparing Figure 5 with the original grayscale image (Figure 2), we can perceive significant differences in LBP activations between broiler and background pixels.

Training Classifier: First of all, the labeled samples from the last 5 poultry house images of the 40 experimental images were separated to serve as a testing dataset.

The 35 remaining images were then splitted for a 5-Fold Cross-Validation [10]. Using a grid-search approach, the hyperparameters of a Random Forest have been optimized to predict the dataset samples, using a 13×13 LBP window around the labeled pixels.

The following hyperparameters have been optimized using a grid-search approach:

1) Estimators number: Number of trees in the forest;
2) Split criterion: The function to measure the quality of a split (Gini Impurity or Information Gain);
3) Max features: Number of features to consider when looking for the best split;
4) Min samples leaf: The minimum number of samples required to be at a leaf node.

Scikit-learn implementation of the Random Forest Classifer [11] has been used in this experiment. More details about the hyperparameters above can be found in the Scikit-learn documentation [10].

The best model has been chosen by searching for the highest area under the ROC *(Receiver Operating Characteristic)* curve, for the 5-Fold Cross-Validation resultant mean. The evaluation and results of these experiments are reported in section VI.

Initial Detection: The trained classifier can be used now to detect which pixels are broiler centers. A sliding window is then applied for the highlighted pixels, resultant of the image segmentation step.

The window is slided with a step of size 3. If the interest pixel isn't highlighted in I_{dilate}, this pixel is automatically classified as background. Otherwise, if the interest pixel is highlighted in I_{dilate}, the classifier is used to predict the label using the LBP 13x13 descriptor around the pixel.

Figure 6 presents which pixels are automatically classified as background.

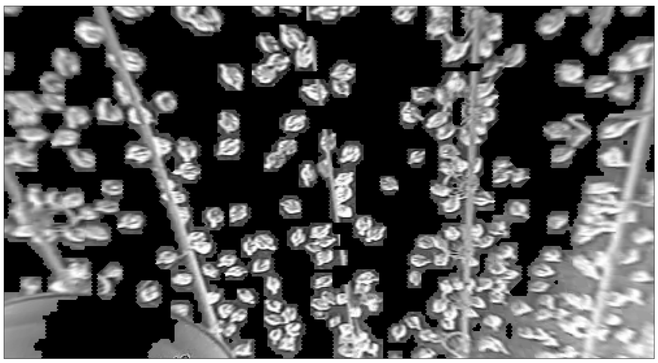


Fig. 6. Grayscale image $I_{grayscale}$ convolved by I_{dilate}.

Applying the trained model, we can generate a heatmap of broiler detection probabilities (see Figure 7).

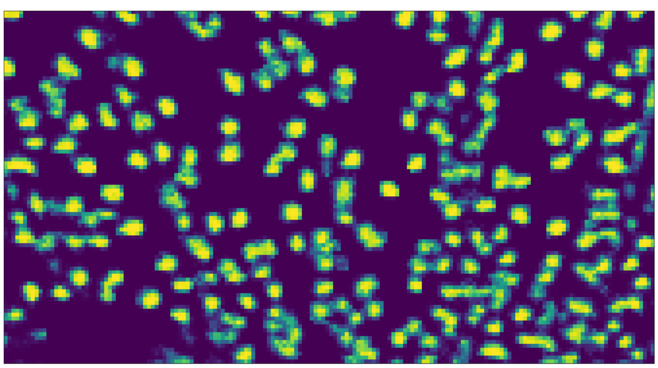
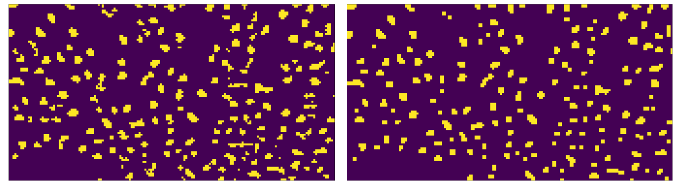


Fig. 7. Heatmap of broiler detection probabilities.

Only detections with probabilities of at least 70% will be considered valid in this experiment. Figure 8a shows the binary image resultant by dismissing the classified pixels with probabilities lower than 70%.

Opening operation is done in sequence to remove isolated detections (noise), placing them in the background (see Figure 8b). In our experiments, the opening operation has been applied using a 2×2 kernel.

Merging Detections: Finally, detections relative to the same broiler needs to be merged. Figure 9 presents the final result after the mean shift clustering, with a bandwidth of 2.



(a) Detection (b) Detection + Opening

Fig. 8. Binary broiler detection results ($I_{classify}$ *and* $I_{opening}$).

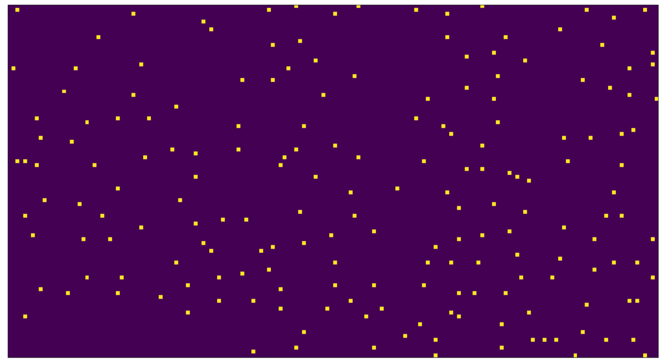


Fig. 9. Broiler detections after the mean shift clustering (I_{final}).

Figure 10 presents the original image (Figure 2) highlighted with the final detection results from the mean shift operation.

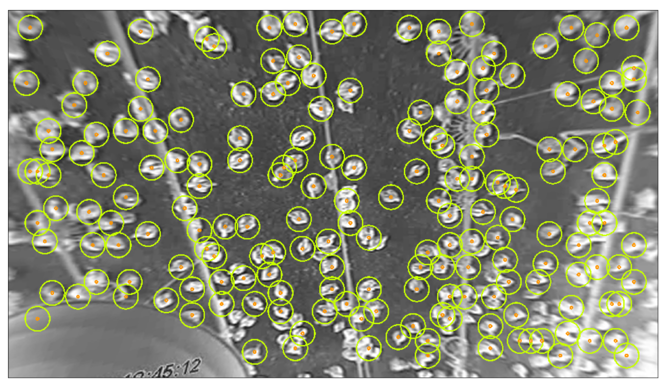


Fig. 10. Final result of the proposed approach for broiler detection.

VI. Results and Discussion

The performance of the experiments presented in the previous section have been evaluated by means of the trained classifier performance metrics. Since the experimental dataset was generated by exhaustive labeling poultry house images, labeling deviations and mistakes can interfere in the accuracy of the final model.

Table II presents the calculated perfomance metrics. The best model achieved a 0.9864 value for the ROC AUC *(Area Under Curve)* for the test dataset.

The LBP texture description of the poultry house images allowed the classifier to detect broilers even in the areas of the image with significative illumination and sharpness variations (see the bottom right corner of Figure 10).

False-negative classifications were the major problem in the final model, and these error were mostly related to broilers that were really close from each other.

TABLE II
TEST DATASET PERFORMANCE METRICS

Metric	Performance
ROC AUC	0.9864
F1 Score*	0.9202
Accuracy*	0.9470
Recall*	0.9134
Precision*	0.9271

*Note: Probabilities $\geq$ 50% were considered detections.

Significant differences between the texture of the background and the texture around the broiler centers are evidenced in the good discrimination between the two labeled classes. The quality of this discrimination is presented in Figure 11, with the ROC curve for the final model.

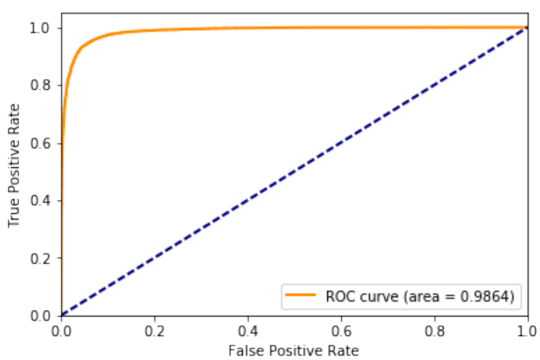


Fig. 11. ROC Curve of Class 1 (Labeled Broilers).

The optimal hyperparameters configuration chosen by the grid-search approach were the following:

1) Estimators number: 40 trees;
2) Split criterion: Information Gain;
3) Max features: 40%;
4) Min samples leaf: 9 samples.

Our broiler detection approach can achieve real-time performance, which is a requirement for live broiler monitoring applications. In our experiments, on a desktop computer, the total processing time for each image has averaged 10.2 seconds.

Parallel executions of the same broiler detection routine for each recorded image can guarantee a real-time detection performance. This approach would permit the detection in real-time, but with a 10.2 seconds delay between the recording of an image and the detection of the broilers. Through a better use of the CPU power and of the available memory, several parallelizations can also be performed in the framework's routines to reduce the processing time.

VII. CONCLUSIONS

In this paper, we presented a novel approach for live broiler monitoring in commercial poultry houses. Our results show that the proposed approach was capable of detecting broilers with high accuracy, allowing the calculation of spatial distribution statistics for the detected broilers.

Given its performance, our approach is suitable to integrate a tracking system that monitors short-term movements of the broilers. These spatial and movement attributes can be used by automated warning systems, for the study of anomalous events and thermal stress conditions in poultry houses.

The proposed technique should be considered in future works for the detection of broilers of different ages and sizes. In addition, another set of image descriptors and supervised classifiers should be investigated to improve the obtained results.

Finally, since the detection recall didn't meet exactly the number of broilers present in the poultry house scene, evaluations of the images obtained after the mean shift consolidation step should also be considered. This has the potential to further decrease the false-negative rate achieved with the proposed framework.

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