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Research Paper

Object discrimination in poultry housing using spectral reflectivity

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To handle surrounding objects, autonomous poultry house robots need to discriminate between various types of object present in the poultry house. A simple and robust method for image pixel classification based on spectral reflectance properties is presented. The four object categories most relevant for the autonomous robot PoultryBot are eggs, hens, housing elements and litter. Spectral reflectance distributions were measured between 400 and 1000 nm and based on these spectral responses the wavelength band with lowest overlap between all object categories was identified. This wavelength band was found around 467 nm with an overlap of 16% for hens vs. eggs, 12% for housing vs. litter, and less for other combinations. Subsequently, images were captured in a commercial poultry house, using a standard monochrome camera and a band pass filter centred around 470 nm. In 87 images, intensity thresholds were applied to classify each pixel into one of four categories. For eggs, the required 80% correctly classified pixels was almost reached with 79.9% of the pixels classified correctly. For hens and litter, 40–50% of the pixels were classified correctly, while housing elements had lower performance (15.6%). Although the imaging setup was designed to function without artificial light, its optical properties influenced image quality and the resulting classification performance. To reduce these undesired effects on the images, and to improve classification performance, artificial lighting and additional processing steps are proposed. The presented results indicate both the simplicity and elegance of applying this method and are a suitable starting point for implementing egg detection with the robot.

1. Introduction

In current poultry production systems in Western Europe, and more and more in other parts of the world, laying hens in commercial farms have more freedom to move around in their living environment. Compared to earlier cage housing this requires more advanced management and more human labour under unfavourable conditions, for example for the collection of floor eggs (Blokhuis & Metz, 1995; Claeys, 2007). In earlier work (Vroegindeweij, van Willigenburg, Groot

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Nomenclature

TP	True positive, i.e. correctly classified as object
TN	True negative, i.e. correctly classified as non-object
FP	False positive, i.e. incorrectly classified as object
FN	False negative, i.e. incorrectly classified as non-object
TPR	True positive ratio, ratio of TP divided by TP + FN
FPR	False positive ratio, ratio of FP divided by FP + TN
T1	Threshold 1, separating litter and housing
T2	Threshold 2, separating housing and hens
T3	Threshold 3, separating hens and eggs
GT	Ground truth
ROC	Receiver operating characteristic
R	Measured spectral reflectance after correction
I	Measured spectral intensity
B	Black reference, relates to sensor noise
W	White reference, relates to full exposure of sensor
FWHM	Full-width half maximum, property of spectral filter
FPS	Frames per second, speed of camera shutter
F-number	Relative aperture of lens
PCA	Principle component analysis
LDA	Linear discriminant analysis

Koerkamp, & van Henten, 2014), a poultry house robot (designated *PoultryBot*) that will assist the farmer in such tasks was introduced. For this robot, path planning and localisation methods were previously presented and evaluated (Vroegindeweij, Ijsselmuiden, & van Henten, 2016; Vroegindeweij, et al., 2014). In addition to knowing their location and following a desired path, autonomous poultry house robots should also be aware of objects in their surroundings, especially those objects that affect their functioning, such as hens, poultry house elements and eggs. As the required response to such objects differs between object types, objects should not only be detected but also be classified into different categories. In robotics, vision-based methods are commonly applied for such detection and discrimination of objects (Bac et al., 2017; Ball et al., 2016; Ekvall, Kragic, & Jensfelt, 2007; Pillai & Leonard, 2015). Thus, the aim of this research was to investigate if vision based methods are suitable for creating environmental awareness for an autonomous poultry house robot.

A poultry house is a challenging environment for a robotic system with sensing based on camera vision. For details on the layout and properties of aviary poultry houses the work by Blokhuis and Metz (1995), Sandilands and Hocking (2012), and Vroegindeweij et al. (2016) is recommended. The houses are in general rather dark, with light intensities varying between 5 and 30 lux (Ellen, van Emous, & Kruit, 2007; Prescott & Wathes, 1999). In general, fluorescent or LED sources provide white light with a fairly flat spectral distribution. However, as light colour is used to control animal behaviour, light sources with different colours can be used, and light colour can change in the poultry house within a single production cycle (Ellen et al., 2007; Lewis & Morris, 2000).

An additional challenge for camera vision is the fact that aviary poultry houses are densely populated with metal housing objects that offer various facilities to the animals. The remaining free space is occupied by tens of thousands of animals that move around at will. Finally, the ambient air contains high concentrations of dust and vapour. All of this reduces clear and free sight and leads to continuous variation in image content.

As a first step in the development and evaluation of a vision system for this application, the aim was to detect and classify of objects at pixel level. For image classification and object detection, a simple method was preferred since that would reduce the computing power required for image processing and would not require additional lighting which would avoid undesirable influence on animal behaviour. As an initial objective, correctly classifying 80% of pixels was set as a target. Correctly classifying 80% of the pixels would mean that all objects are at least partially classified correctly, which was expected to be satisfactory for operating PoultryBot.

A relatively simple way to detect and identify objects in an agricultural scene is to exploit the differences in spectral reflection properties of the various objects present in the scene. Based on prior acquired reflection properties of the most common objects in such a scene, common and cheap monochrome cameras can be equipped with suitable filters to provide an image that may require less processing for object detection and classification.

This method has been used in agriculture to distinguish between various kinds of green plants (Nieuwenhuizen, Hofstee, van de Zande, Meuleman, & van Henten, 2010; Piron, Leemans, Kleynen, Lebeau, & Destain, 2008) and to distinguish between fruits, leaves and stems in cucumber harvesting (van Henten et al., 2002). A literature review revealed that spectral reflection properties have also been investigated before in poultry farming. Prescott and Wathes (1999) have presented an extensive review of reflective properties of poultry, their housing and the light characteristics therein. They presented results of 15 hen species, of which several are closely related to current commercial hybrid species. Furthermore, they showed spectral properties of various materials present in commercial poultry houses, which turned out to be distinct from the spectral properties of hens. Spectral characteristics of hen eggs were used mainly for transmission measurements to determine the quality of shelled eggs (De Ketelaere, Bamelis, Kemps, Decuypere, & De Baerdemaeker, 2004; Mertens et al., 2010). Less work has been done on spectral reflectance of eggs. In Prescott and Wathes (1999), only the spectral reflectance of a brown egg was reported. Gloag, Keller, and Langmore (2014) presented also work on other egg colours, although from a different bird, but with similar results.

This paper investigated the hypothesis that the spectral features of objects commonly found in poultry houses could be used for discriminating between these objects by PoultryBot. The laboratory experiment described in Section 2 determined the spectral features of objects that are common in poultry houses, such as eggs, hens and housing elements. This extends the preliminary results published in Vroegindeweij, van Hell, IJsselmuiden, and van Henten (2015). The field experiment in Section 3 used these spectral features to discriminate between the various object categories relevant for the operation of an autonomous poultry robot.

2. Laboratory experiment

In the laboratory experiment, the spectral features of several object categories relevant for the operation of PoultryBot in a commercial aviary poultry house were determined. This involved four main steps, leading from the selection of relevant objects (**step 1**) to the selection of the most discriminating wavelength for object separation (**step 4**), which were all executed under lab conditions:

1. Define which object categories in a poultry house are relevant to create environmental awareness for an autonomous poultry robot.
2. Measure the spectral reflection for each object category at all wavelengths relevant for application in a poultry house.
3. Determine for each object category the distribution of all measured reflectance values at a given wavelength. Do this for each combination of wavelength and object.
4. Identify the wavelength with the largest discriminative power, i.e. the one with the least overlap in reflection between the object categories of interest.

In this section, which is based on (Vroegindeweij et al., 2015), details of the approach used in the laboratory experiment are described, the results are presented, and their suitability is discussed.

2.1. Materials and methods

2.1.1. Materials tested

In **step 1**, four main object categories were found that are relevant for the functioning of an autonomous poultry robot inside a poultry house, as they represent the majority of the objects present. These were: 1) eggs, being target objects that have to be collected, 2) hens, being moving obstacles that can be ignored while driving, because they move voluntarily away from the robot, 3) housing, being static obstacles that should be avoided, like metal poles and walls, and 4) litter, covering the floor area and indicating the driveable surface. As representatives of these categories, white eggs, feathers of white hens (Dekalb White), galvanised steel, and a litter sample from a poultry house were used. In **step 2**, spectral reflection of these objects was measured using the setup described below. For each measurement, 1 or more objects were placed on a white cardboard plate, which was then put into the measurement setup. Subsequently, spectral reflectance of these objects was measured by performing a single scan over the area within the setup.

2.1.2. Spectral measurement setup

The spectral reflection data was collected using a hyperspectral line scan setup, similar to the one described in Polder and Young (2003) and Polder, Pekkeriet, and Snikkers (2013). The setup is shown in Fig. 1, and consisted of an ImSpector V10E spectrograph (SPECIM Spectral Imaging Ltd., Oulu, Finland) with a slit size of 30 μm, attached to a Photonfocus MV1_DV1320 camera (Photonfocus AG, Lachen, Switzerland) and a 25 mm lens. In the ISAAC2 software that controlled the imaging setup, the acquired reflectance data was binned by 2 cells spatially and 4 cells spectrally, and outside spectral cells were removed as they contained no relevant data. Thus, each scan contained a line of 656 pixels with 192 spectral bands between 400 and 1000 nm. As light source two tungsten halogen lamps of 150 W with a fibre and a rod lens were placed below the camera. The wavelength range of these lamps was similar to those commonly found in poultry houses. The camera, spectrograph and the light source were driven by a stepper motor, moving them over the object with a fixed step size of 0.5 mm over a length of 150 mm. As result, an area with a length of 150 mm and a width of about 300 mm was measured. Camera and light source were on for at least 20 min before measurements to avoid start-up effects. Furthermore, the experiment was carried out in a dark room to avoid influence from ambient light. Also, the ISAAC2 software automatically normalised the reflectance of the object R from the measured intensity I to correct for influences from light source and background light. Reflectance was corrected for the background noise B, and expressed as fraction of the white reference W using

$$R = \frac{I - B}{W - B} \tag{1}$$

which is based on Polder and Young (2003). Both references were acquired at the start of the measurement. The background noise B was acquired using a covered lens, while the white reference W was acquired using a 98% reflecting white plate (ColorChecker White Balance, X-rite Pantone, Grand Rapids MI, USA).

2.1.3. Processing spectral data

Processing of the acquired spectral reflectance data was performed using Matlab 2015b (The MathWorks, Natick, MA, USA). For pixel selection, colour images were reconstructed from the hyperspectral data. As these were only used for visual inspection and to allow manual identification of the objects for ground truth generation, no effort was put in correct representation of the colours in these images. For each object category, between 38,000 and 45,000 pixels were manually selected from the acquired spectral data, by taking rectangular areas within the objects. From these samples, the reflectance distribution over all selected pixels was determined at each wavelength band (**step 3**). Next, a normal distribution was fitted to these samples, as a smoother representation of the data. In **step 4,** at each of the 192 wavelength bands the percentage of overlap was calculated per combination of object categories. For the measured distributions, this was done by applying Riemann integration on

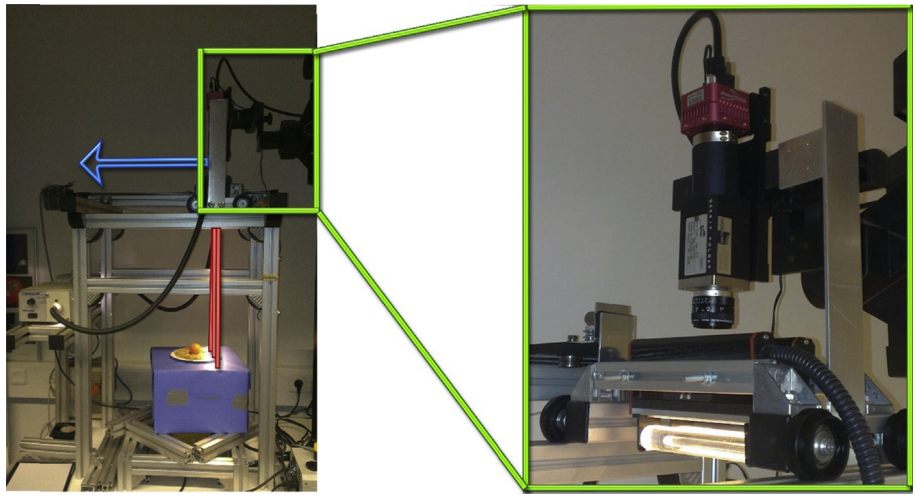

Fig. 1 – The hyperspectral imaging setup used for acquiring the spectral data in step 2 of the laboratory experiment. On the left, the full setup is shown, with an indication of the linear motion of the camera (blue arrow) and the scan line (red triangle). The blue box is used to place the sample upon, in this case a brown egg on wood shavings. On the right is a close up of the moving construction for the camera, spectrograph and light source.

the overlapping area between the distributions of two object categories at a single wavelength band, while trapezoidal integration was used for the fitted distributions. The overlap percentage was calculated by dividing the overlapping area by the area under the distribution of the second object category. Next, the total amount of overlap per wavelength band was calculated by summing the overlap percentages of all object categories for that wavelength. Based on this, the wavelength band with the lowest sum of overlap between the four object categories was selected as the most discriminative wavelength for classification of the objects considered.

2.2. *Results and discussion*

For each of the four object categories selected in step 1, *eggs, hens, housing* and *litter,* spectral reflectance data was acquired. Hyperspectral imaging (step 2) created for each pixel in a 2D frame a stack of 192 wavelength bands with the associated reflectance. From the hyperspectral data, pictures as shown in Fig. 2 were produced to visually inspect the results before further processing. Figure 2 shows on the left side a colour image containing the four main object categories. This image was reconstructed from the wavelength bands for display purposes only, and no effort was put in creating a correct representation of the colours. On the right side, the spectral responses at locations indicated in the left image are given. It shows that eggs had the highest reflectance, followed by hens and then housing and litter, although the latter two change place when it comes to the amount of reflectance above 615 nm. Furthermore, the difference between litter and both eggs and hens was large at lower wavelengths, but declined with increasing wavelengths. For housing and litter, the difference was initially small, but it increased at larger wavelengths.

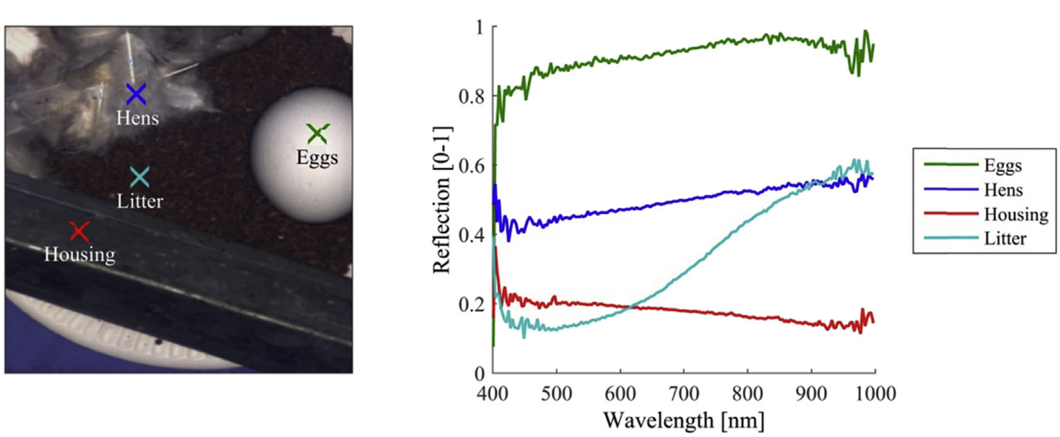

Fig. 2 – Results of hyperspectral imaging for the four object categories. On the left side a colour image is given, reconstructed from the spectral data for display purposes only, on the right side the spectra that correspond to the locations indicated on the left image.

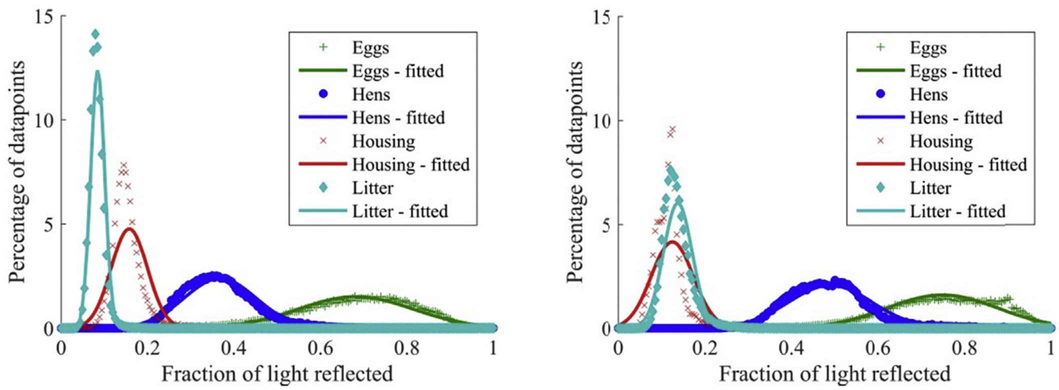

Fig. 3 – Distribution of reflectance for the 4 main object categories, at the 467 nm (left) and 663 nm (right) wavelength bands. Points indicate measured data, while lines represent the fitted distributions.

In step 3, between 38,000 and 45,000 pixels for the same object category were selected to estimate the distribution of the reflectance. For the four object categories and two wavelength bands the resulting reflectance distributions are shown in Fig. 3, together with normal distributions fitted to these data (step 3). Clear differences were found in the reflectance distributions of the various object categories. Litter and housing had narrower distributions than hens and eggs. In addition, there was some overlap between litter and housing, as well as between feathers and eggs. Furthermore, this overlap turned out to be different between the various wavelength bands.

In step 4, overlap between all combinations of object categories was quantified for each wavelength band to identify the wavelength with the most discriminative power for the objects considered. The least overlap was found for wavelength bands between 430 and 515 nm, with the 467 nm band showing the lowest overlap. Based on the measured distributions, the percentage overlap of the measured distributions is given in Table 1 for the most discriminating wavelength band (467 nm, least overlap) and an arbitrary one with much more overlap, especially for housing and litter (663 nm). Data in Table 1 correspond to Fig. 3. There were clear differences in overlap between both wavelength bands and the various object categories. At the 467 nm band the overlap was quite evenly distributed over the categories, with the largest overlap between eggs and hens (16.2%) and housing and litter (11.5%), and some overlap between hens and housing. At 663 nm, most overlap was found between housing and litter (78.1%), while also the overlap between eggs and hens was higher (from 16.2% to 23.0%). The combinations eggs and housing, eggs and litter and hens and litter contained minimal overlap.

Table 1 – Results of wavelength selection, showing the percentage of overlap between various object categories. Data is presented for the measured distributions, at the most discriminating wavelength band (467 nm) and a less suitable wavelength band (663 nm) with more overlap. Overlap percentage is calculated by dividing the overlapping area by the area under the reflection curve for the second object category.

Overlap between	467 nm	663 nm
Eggs and *hens*	16.2%	23.0%
Eggs and *housing*	1.7%	1.0%
Eggs and *litter*	0.0%	0.3%
Hens and *housing*	6.9%	2.7%
Hens and *litter*	0.2%	0.8%
Housing and *litter*	11.5%	78.1%

In general, the measured spectral reflectance (step 2) results matched those reported by Prescott and Wathes (1999). In the presented results, significant variation can be observed at the ends of the measured spectra. Prescott and Wathes (1999) indicate similar findings from their measurements, especially around 400 nm, which is the spectral band of UV. They did not indicate whether this originated from technical limitations of their setup or whether it was a specific feature of the sample measured. As in our experimental setup the light source emitted hardly any UV light (around 400 nm), this seems a plausible explanation for the effects seen at the lower end of the acquired spectra. Combined with limited sensitivity of the camera chip at the limits of its spectral range, this can result in reflectance values that are largely determined by sensor noise (Polder & Young, 2003). As the amount of UV light available in a poultry house is limited and adding artificial UV light might have undesirable consequences for animal welfare, further investigating this spectral band seems of limited use for the application considered.

The obtained spectral reflectance, particularly for the housing material, was based on relatively clean materials, providing a rather constant response throughout the spectrum. However, in the poultry house contamination with dust and poultry droppings can be expected. As housing objects are mainly made from metal with rather shiny surfaces, the angles between light source, object and imaging device influence the measured reflection. The spectral response of housing objects under practical conditions might therefore be different in shape and intensity. As the spectral response forms the basis for the discrimination between object categories, this might affect correct separation of housing elements from other object categories.

For the selection of the most discriminating wavelength band (step 4), the overlap between each combination of object types was weighted equally and the minimum in the sum of overlap percentages was used to identify the most suitable wavelength. For practical applications, however, it might also be relevant to apply different weight factors, to allow better discrimination of object categories that have higher importance. Failing to detect a housing element, for example, might have more impact on the functioning of the robot than misclassifying litter as hens. Furthermore, more advanced statistical methods, such as principal component analysis (PCA) or linear discriminant analysis (LDA) might provide better identification of the most discriminating wavelength.

Also, using multiple spectral bands simultaneously seems promising for improving the classification results. For example, by selecting separate wavelength bands for different object categories, differences in reflectance can become more distinct. When using the 437 nm band for separating hens and eggs and the 940 nm band for housing and litter, overlap reduced from 16.2% to 15% for hens and eggs, and from 10% to 4% for housing and litter. For brown hens and eggs (data not reported) the overlap is reduced by more than 50% when using two wavelength bands instead of one. Alternatively, the responses at different wavelengths can be combined arithmetically, for example by considering the ratio of the responses at separate wavelength bands. However, a disadvantage of using multi-spectral imaging is that a more complex optical setup is required.

3. Field experiment

In the field experiment, the effectiveness of the chosen wavelength band for pixel classification was evaluated under the conditions found in a commercial poultry house. To this end, images were acquired with a monochrome camera using a wavelength filter around the most discriminating wavelength, and intensity-based pixel classification was performed and evaluated. This involved 6 steps, starting with the selection of a suitable wavelength filter (**step 5**) and ending with a performance evaluation (**step 10**):

5. Select a suitable band pass filter for the wavelength found in step 4.
6. Acquire images in a commercial poultry house, using the selected band pass filter and a standard monochrome camera.
7. Find for each object category the distribution of pixel intensity values in these images.
8. Use this information to define threshold values for classification of pixel intensities.
9. Classify the image pixels using thresholds defined in step 8.
10. Evaluate pixel classification performance.

Also, steps 7–9 allow for additional image processing to improve classification, for example by filtering image noise. This section describes the approach followed and the results obtained for these steps.

3.1. *Materials and methods*

3.1.1. *Experimental environment*

Images were acquired in a commercial poultry house of Het Anker BV, Opheusden, The Netherlands, with animals of the same breed as used for the collection of the spectral data (Dekalb White). The house contained 6 interior rows (Natura Step, model year 2014, Big DUtchman AG, Vechta-Calveslage, Germany) and was split into 7 compartments, each housing some 6000 hens, being 76 weeks old at time of measurement. Unfortunately, the hens were rather anxious, and thus kept a clear distance from the measurement setup. Original ambient light intensities were measured using a Voltcraft MS-1300 photometer (Conrad Electronic SE, Hirschau, Germany), and ranged between 5 and 15 lux at floor level. For the experiment, ambient light settings were increased from their normal value of about 30% of full intensity to 100% of full intensity for HF tube lights (Aura Light T8 Universal, Cool White, Auro Light International, AB, Karlskrona, Sweden) between rows and LED strips within interior rows (Big Dutchman FlexLED, Warm White colour, Big Dutchman AG, Vechta-Calveslage, Germany) and to 80% of full intensity for LED strips below interior rows (Big Dutchman FlexLED). All light sources appeared white to the human eye.

3.1.2. *Image acquisition*

For image acquisition (**step 6**), a standard monochrome camera and a band pass filter at the selected wavelength band were used. In **step 5** a band pass filter was selected with its centre wavelength at 470 nm (MidOpt BN470, 45 nm FWHM, Midwest Optical Systems, Inc, Palatine, IL, USA), as being the one closest to 467 nm, which is the wavelength with the lowest amount of overlap between categories. This filter was fitted in front of a lens with 5 mm focal distance (KOWA LM5JCM10M, Kowa Optical Products Co. Ltd., Tokyo, Japan), attached to an extra sensitive DMK 23UX174 monochrome camera (The Imaging Source Europe GmbH, Bremen, Germany). Camera settings were set to resemble application on a mobile robot, with a frame rate of 30 fps to avoid blur resulting from camera and animal movements. Furthermore, the diaphragm was fully opened (F1.8) and a fixed gain of 33.7 dB was applied at image read-out inside the camera to have sufficiently exposed images. For practical reasons, the camera was placed on a tripod at a height comparable to the mount on the robot (approximately 380 mm above floor level). The tripod was moved and rotated by hand while capturing images. Images and related camera and system settings were registered using a dedicated application in NI LabVIEW 2013 (National Instruments, Austin, TX, USA). In total, 87 images were collected, covering most of the environmental variation that was present in the poultry house. In Adobe Photoshop CS6, corresponding ground truth images were obtained by manually labelling the pixels in each image that belonged to one of the four indicated object categories: eggs, hens, housing, and litter. A fifth category ‘other’ contained all pixels from other objects, such as pecking blocks, or that were too dark to be reliably assigned to a category. The built-in magic-wand tool in Adobe Photoshop was used to handle groups of pixels at the same time, to allow faster annotation.

3.1.3. *Image processing*

Image processing in **steps 7** through **9** and performance evaluation in **step 10**, were carried out in using Matlab R2015b (Mathworks Inc., Natick, MA, USA). The images contained clear intensity distortion, which resulted from the optical components, and was visible in the images as a vignette effect. To correct for this phenomenon, first the distortion was estimated using the method of Zheng, Yu, Kang, Lin, and Kambhamettu (2008), based on a set of 12 images of the grey concrete floor specifically obtained for this purpose in the front of the poultry house. These images were captured using similar camera settings as used during the remaining image collection. From the distortion estimated for each of these 12 images, an average correction for the vignette effect was calculated, which was subsequently applied to each image collected in the house. To set appropriate thresholds for intensity-based pixel classification, for each image collected in the poultry house, the intensity distribution within each object category was estimated based on the associated ground truth (**step 7**). These distributions were then averaged over all 87 images in the set to obtain an average intensity distribution for each object category (eggs, hens, housing and litter). Using these average intensity distributions, a single set of thresholds was defined for intensity-based pixel classification of all 87 images (**step 8**). In fact, steps 7 and 8 repeated steps 3 and 4 in the laboratory experiment, but now used for placing thresholds on pixel intensities to facilitate proper object classification, instead of selecting the wavelength band that allows for the best discrimination based on object reflectance as was the case in steps 3 and 4. Here, threshold T1 was used to separate litter and housing, threshold T2 separated housing and hens, and threshold T3 separated hens and eggs. Ideally, the selected thresholds T1 through T3 are located between the intensity peaks for the various object categories, to minimise overlap between object categories. Thus, their position was determined by taking the intensity peaks of the object categories to be separated, and selecting the middle between these peaks as threshold value. The last step in the image processing used the selected threshold values for the pixel classification of the images into four object categories: litter, housing, hens and eggs (**step 9**).

3.1.4. *Performance evaluation methods*

In **step 10**, the result of the classification step was compared on pixel level with the ground truth image to determine classification performance. This resulted in a confusion matrix indicating for each ground truth category how many pixels were classified as each of the four object categories. Various performance metrics were then calculated for each object category. First, the values for true positive (*TP*), true negative (*TN*), false positive (*FP*) and false negative (*FN*) were determined in a 1 vs. all approach. Based on this, the true positive rate (TPR) and false positive rate (FPR) were calculated per object category and image by

$$TPR = \frac{TP}{TP + FN} \tag{2}$$

$$FPR = \frac{FP}{FP + TN} \tag{3}$$

Confusion matrix values were expressed as a fraction of the number of ground truth pixels for this category. To represent the quality of the classification results over the full dataset, the calculated performance metrics and confusion matrices were averaged over all images.

Finally, by varying the values used for thresholds T1 through T3, also the sensitivity of the classification performance for changes in the threshold values was evaluated. This evaluation was done in a brute force manner, by testing all possible combinations of thresholds T1, T2 and T3 that complied with the requirement T3 > T2 > T1. Used values ranged between 3 and 24 for T1, between 8 and 30 for T2 and between 15 and 45 in steps of 2 for T3. Based on these results, TPR and FPR were calculated for each combination of object category and threshold setting, and were then used to create plots showing the receiver operating characteristic (ROC) to indicate the change in classification performance. As the pixels in the 'other' category had no reliable ground truth annotation (i.e. in reality they might or might not belong to one of the first four object categories), they could not be classified correctly and therefore were ignored when varying thresholds and determining the resulting performance. Thus, with eggs as example, TP pixels are defined as pixels which have a ground truth annotation (GT) as eggs and are also classified as eggs. FP pixels are defined as pixels with housing, hens or litter as GT, which are classified as eggs. FN pixels are defined as pixels with eggs as GT, which are classified as housing, hens or litter. TN pixels have housing, hens or litter as GT, and are also classified in one of these groups.

3.2. *Results and discussion*

3.2.1. *Results of image acquisition*

Image acquisition in the poultry house (step 6) using the selected wavelength filter (step 5) resulted in 87 images covering most of the variation present in the environment. One of these images is shown in Fig. 4. In this figure the top row contains the original image, while the bottom row shows the results after vignette correction. On the left, the original brightness is used, while on the right the brightness is increased by 75% for presentation purposes only.

In Fig. 4 it can be seen that the original image has clear differences in image intensity in the radial direction due to optical properties of the lens. Corners and image side borders did not receive light at all, as result of the optical diameter of the lens being smaller than the diagonal of the camera chip. Correcting for the vignette effect strongly reduced the radial intensity differences, as shown in the images in the bottom row, although some minor variation remained. As expected from the laboratory results at this wavelength, eggs were the brightest objects, followed by the hens. Between housing and litter no clear difference in intensity can be observed in this image. The hens being rather far away from the camera and operator might be due to the anxious behaviour of this particular flock, as this was not observed while testing among other flocks. Also, the hens in the image contain several bright spots, as a result of being close to the light sources in the poultry house, which resulted in variation in the observed intensity for this object category. On the floor level, however, the images have a more uniform distribution of ambient light.

3.2.2. *Intensity distribution of object categories*

Based on the associated ground truth, the intensity distributions for each object category could be determined for each image. In Fig. 5 (left) the intensity distributions for each object category are shown for the image in the lower-left of Fig. 4, and as the mean over all 87 images in the set (right). In theory,

Fig. 4 – Image resulting from the application of the selected 470 nm wavelength filter and a monochrome camera for imaging in a poultry house. The original image is shown top-left, while in the top-right image a correction of +75% on brightness was applied for presentation purposes. In the bottom-left image a correction was applied to compensate the vignette effect, while in the bottom-right image also the +75% brightness correction was applied for presentation purposes.

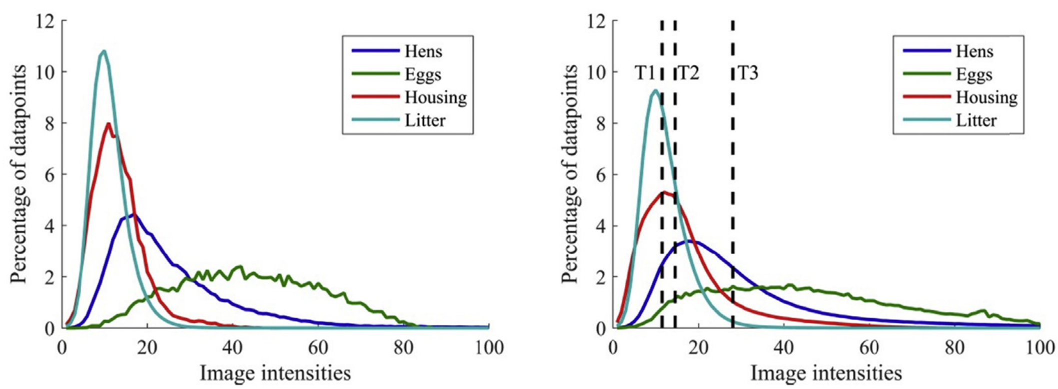

Fig. 5 – Intensity distributions per object category, after correction for the vignette effect. The left graph corresponds to the lower-left image in Fig. 4, while the right one shows the mean distribution over all 87 images. Vertical dashed lines in the right graph indicate thresholds T1, T2 and T3 going left to right. As the images hardly contained pixels with intensities higher than 100, the x-axis omits the range between 100 and 255.

these distributions should be comparable to those in Fig. 3 (left), as they describe similar objects at the same wavelength. However, as result of the intensity variation within the images, the distributions in Fig. 5 show more overlap of the categories. This overlap is especially present for housing and litter, which limits the correct discrimination of these object categories, whereas for hens and eggs correct separation seems still possible based on these distributions. Threshold values for image classification (step 9) were placed in the middle between the peaks of the mean intensity distributions, and are indicated by the dashed vertical lines in the right hand graph of Fig. 5. Threshold T1, separating the categories litter and housing, was placed at 11.5, while threshold T2, separating the categories housing and hens, was set to 14.5. Threshold T3, separating the categories hens and eggs, was set to 28.

3.2.3. *Pixel classification performance*

Based on these thresholds, pixel classification was applied on the collected images. Average classification results over all 87 images are given in Table 2, as percentage of the number of pixels in the related GT category. For each element, also the performance range is indicated by the lowest and highest values found. Furthermore, the classification results on two of the acquired images are shown in Fig. 6, together with the original image and the associated ground truth (GT) image.

For hen pixels, on average 41.5% were classified correctly (Table 2), with values ranging between 25 and 55%, while on average 79.9% of the egg pixels were classified correctly, with a number of images also reaching more than 90% (not shown). Incorrectly classified hen pixels were mostly mistaken as eggs and most of the incorrectly classified egg pixels were considered to be hens, thus indicating the clear overlap between

Table 2 – Classification results averaged over all 87 images, represented as percentage of the average number of pixels in each ground truth (GT) category. Numbers between brackets indicate the lowest and highest values found. Diagonal values (in bold) indicate correct classifications or true positives (TP). False positives (FP) for a given category are the sum of the remaining values in the column of the corresponding TP value, while false negatives (FN) are the sum of the remaining values in the row of the corresponding TP value. True negatives (TN) consist of the sum of all remaining values.

GT category	Percentage of GT classified as:				Number of pixels in GT
	Hens	Eggs	Housing	Litter	
Hens	**41.5% (25.7%–54.5%)**	41.3% (17.8%–68.3%)	8.6% (4.1%–17.2%)	8.5% (2.0%–21.7%)	109,831 (0–226,168)
Eggs	16.5% (1.1%–67.1%)	**79.9% (23.2%–98.9%)**	2.2% (0.0%–11.9%)	1.4% (0.0%–17.4%)	4817 (0–21,090)
Housing	31.0% (7.1%–53.7%)	8.2% (0.8%–54.8%)	**15.5% (4.9%–29.1%)**	45.2% (3.8%–80.1%)	71,569 (10,924–320,914)
Litter	25.0% (9.2%–53.9%)	1.1% (0.1%–6.7%)	21.5% (9.3%–26.0%)	**52.3% (19.5%–79.4%)**	1,921,486 (1,305,161–2,116,129)
Other	46.3% (16.3%–58.5%)	8.6% (1.1%–28.0%)	17.4% (10.4%–21.1%)	27.6% (8.5%–67.9%)	196,297 (55,913–686,343)

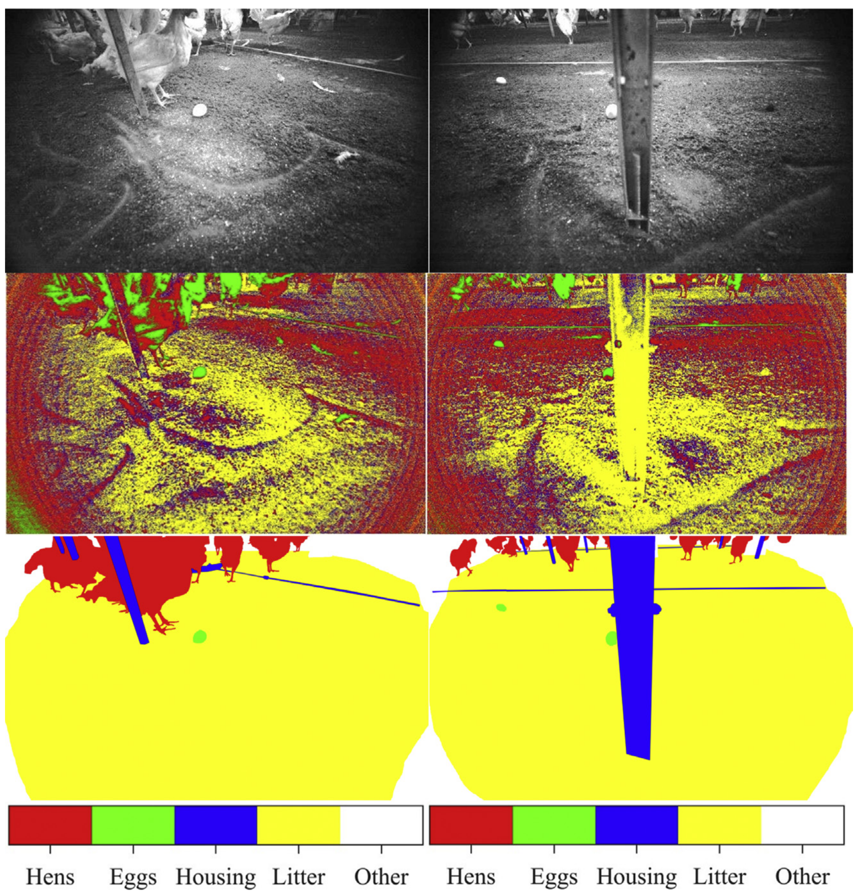

Fig. 6 – Results of pixel classification on two images. Values are set to 11.5 for T1, 14.5 for T2, and 28 for T3. The top row contains the original images (brightness increased by 75%), the middle row the classified images, while the bottom row contains the associated manually generated ground truth.

these categories as shown in Fig. 5. This is also shown in the images in Fig. 6 where the hens have varying brightness and part of the hen pixels are therefore incorrectly classified, mostly as eggs, but also sometimes as housing or litter. Similarly, the border pixels of the eggs are somewhat darker and therefore incorrectly classified as hens. Incorrect classification of eggs as housing or litter occurred less frequently.

With respect to housing pixels, classification performance was rather poor, with on average only 15% of the pixels classified correctly and overall values did not exceed 30%. Although some pieces of the housing poles were classified correctly, many parts (up to 80%) were classified as litter, such as the pole in the right image in Fig. 6. Misclassification as hens also occurred in up to half of the cases, mainly with objects more towards the borders of the image, like on the poles on the left image in Fig. 6. The litter scraper, visible as the horizontal thin blue line in the GT in Fig. 6, is partly classified as egg. Thus, the difference in spectral behaviour of housing elements under practical conditions, as indicated in Section 2.2, indeed seems to affect the performance here.

Litter pixels showed similar classification performance as hens, as over 50% of the litter pixels were classified correctly

(Table 2) but also misclassification as housing or hens was observed. On average, 20–25% of the litter pixels were classified in each of these categories, although misclassifying up to 50% of the litter pixels as hens also occurred. From Fig. 6, it seems that this mostly happened at locations under the housing interior (visible in the top half of the images), probably as result of higher light intensities in that area. Furthermore, the structure and uneven distribution of the litter seemed to influence the reflection of ambient light. Especially areas with visible patterns or variation in the litter structure were incorrectly classified as housing or hens, as can be seen from the middle of the left image in Fig. 6. Similarly, hen feathers present in the litter were frequently assigned to the egg category.

During ground truth annotation, on average about 10% of the pixels remained unclassified, mainly at the image borders, and were therefore assigned to the 'other' category. The classification procedure indicated that these pixels tended to belong to hens or litter, but this could not be verified, as most of them were too dark to be reliably assigned to a category in the ground truth annotation.

The radial rings showing up in the classified images in Fig. 6 most likely originate from internal reflections in the optical setup used, resulting in varying intensities spanning multiple object categories. Furthermore, the bright spots from ambient light observed in Fig. 4 are also present in the classification result, which together with the radial rings, seem at least a partial cause for the limited overall classification performance and large variation in the results. Another explanation, especially for the moderate performance seen for housing, litter and hens, might be the relatively large distance hens kept from the camera. As result, spatial variation in ambient light intensity is more likely to affect image intensity, leading to wider and potentially overlapping intensity distributions for the individual object categories in the acquired images. Close range imaging, on the other hand, is expected to yield less variation in object intensity and an improved classification performance. In the practical application, i.e. with the camera mounted on a robot operating in the poultry house, this is likely to happen, as hens quickly get used to the robot (Vroegindeweij, Boots, & Bokkers, 2014), and thus remain closer to the camera.

3.2.4. *Effects of changing the threshold values*

To see how the threshold settings affect classification, values for all three thresholds were varied and classification performance was assessed. Results are presented for each threshold separately, using the TPR and FPR, as average value over all 87 images. After that, interaction effects will be discussed shortly. As the 'other' category contained no reliable information on pixel content, i.e. pixels in reality might or might not belong to one of the four object categories, these pixels were ignored in processing and excluded from the performance results shown below.

The expected difficulty to separate between litter, housing and hens as result of overlapping intensity distributions (Fig. 5) is confirmed by the limited performance for these objects in both ROC plots in Fig. 7. The singular datapoints in the figures indicate performances for the object categories that are not affected by the threshold varied, and thus remain stationary. As a 4-category problem is considered, performance for random-guess classification into 4 categories (blue dotted line) was added for comparison. Since each threshold separates only 2 categories, also random-guess classification into 2 categories is shown (red dotted line), as this might be a more representative benchmark.

In the left half of Fig. 7, an ROC curve is shown with the effect of varying threshold T1, which separates litter and housing, between 3 and 24, with T2 set to 19 and T3 to 25. The result for the lowest threshold value ($T1 = 3$), is indicated here by the filled diamonds. In general, performance for litter outperformed random-guess classification, whereas that for housing was at the level of random-guess classification in 2 groups. Increasing T1 led to more litter pixels being detected correctly, while the number of false positives increased at a lower rate, showing a performance improvement for litter. Also, classification performance for housing pixels decreased, both for TPR and FPR, although for FPR at a faster rate. This indicates that while litter might be detected properly, for housing elements this method has limited added value.

The right half of Fig. 7 shows the effect of varying T2, which separates housing and hens, between 8 (results indicated by filled diamonds) and 30, with T1 set to 8 and T3 to 37. Increasing the value for T2 gave higher TPR for housing, but also increased FPR, such that performance slightly increased but remained between binary and 4-class random-guess classification. As T2 separated housing and hens, increasing correct classification of housing pixels likely reduced correct classification of hen pixels, which is visible from the mirrored behaviour of the curves. The perceived upper limit for correct classification of hen pixels originates from the setting of T3, as this threshold influenced the classification performance for hens by separating hens and eggs. As result, changing T2 allows for proper detection of hens, while performance for housing can hardly be improved over a "random-guess" classification.

The separation between hens and eggs by threshold T3, ranging from 15 to 45 in steps of 2, with T1 set to 8 and T2 set to 15, is shown in Fig. 8. Here, a similar trend as for T2 is seen, since lowering T3 led to better egg detection with higher TPR, at the cost of proper recognition of hens (decreasing TPR). Egg FPR remained rather constant until egg TPR approached 0.8, indicating reasonable performance for egg detection. Beyond this point, hens were also considered as egg, thus increasing the egg FPR. The position of the ROC-curve for hens on the FPR axis was determined by the setting of T2. This also explains the cut-off point at an FPR of 0.25, as the T2 setting limited the amount of FPs at the lower end of the distribution of hen pixels. Except for the two lowest threshold values, classification for both hens and eggs clearly outperformed the random-guess alternatives. For both categories reasonable performance can be achieved, although there was a clear trade-off as result of overlap between the intensity distributions of both categories. Thus, proper classification of hens could be done, but only when missing part of the eggs. Alternatively, eggs could be well detected, but would include a number of FPs for hen pixels.

Varying multiple thresholds at the same time did not affect the ROC curves given for litter and eggs, as they were dependent on T1 or T3 only and changing the settings for other

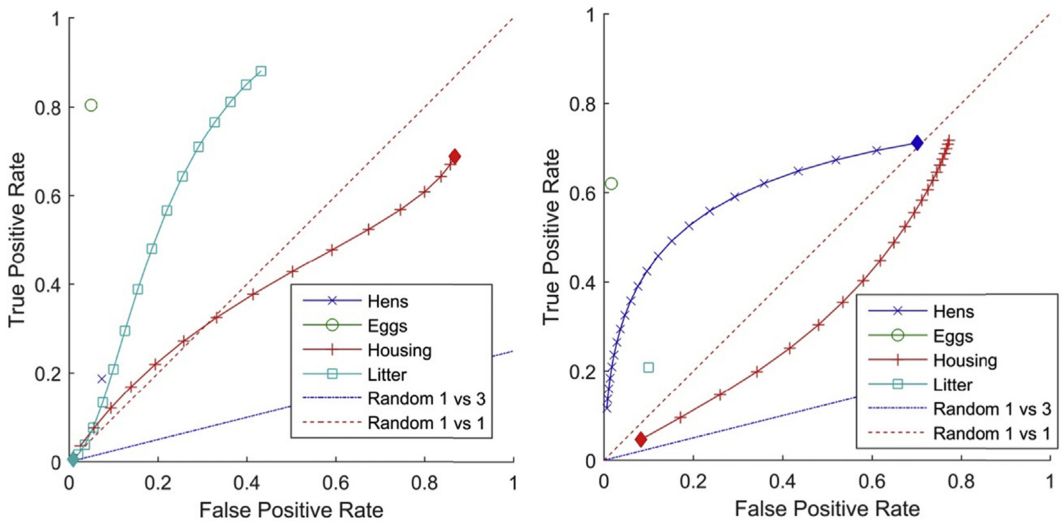

Fig. 7 – Left: Effect of changing threshold T1 between 3 and 24, which separates Litter and Housing pixels. Values for the other thresholds were set to T2 = 19 and T3 = 25; Right: Effect of changing threshold T2 between 8 and 30, which separates Hens from Housing pixels. Values for the other thresholds were set to T1 = 8 and T3 = 37. Filled diamonds (◆) indicate the result for the lowest threshold value used. As baseline, random-guess classification into 2 groups is shown by the red dashed line and random-guess classification into 4 groups by the blue dash-dot line. Singular datapoints indicate performance for the object categories not affected by this threshold. (For interpretation of the references to color/colour in this figure legend, the reader is referred to the Web version of this article.)

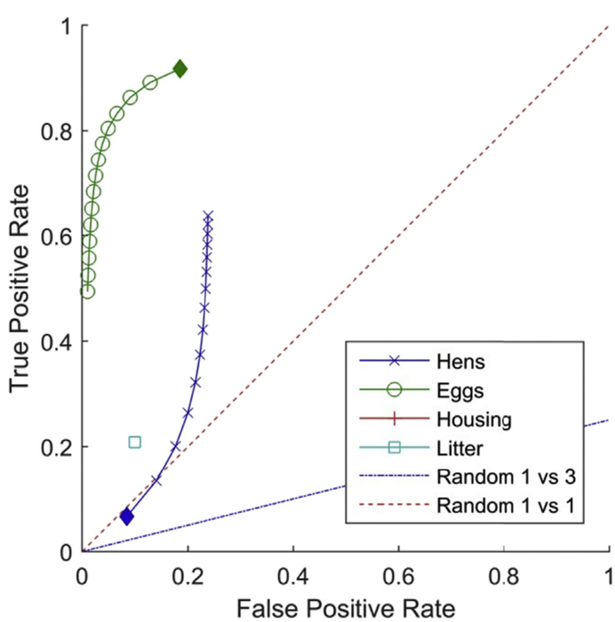

Fig. 8 – Effect of changing threshold T3, which separates pixels into Hens and Eggs, between 15 and 45 in steps of 2. Values for the other thresholds were T1 = 8 and T2 = 15. Filled diamonds (◆) indicate the result for the lowest threshold value used. Random-guess classification into 2 groups is shown by the red dashed line and into 4 groups by the blue dash-dot line. Singular datapoints indicate performance for the object categories not affected by this threshold. (For interpretation of the references to color/colour in this figure legend, the reader is referred to the Web version of this article.)

thresholds did not affect the results. For hens and housing however, there was a clear effect of varying the combination of threshold settings. For hens, the line moved either left/right (T2, Fig. 7 – right) or up/down (T3, Fig. 8) but did not really change its shape. For Housing, similar behaviour was observed, but now with T1 and T2, while also some changes in the shape of the performance curve were visible. The low performance and overlapping distributions rendered further investigation of these effects of limited use.

4. Discussion

4.1. *Effects of imaging approach*

Avoiding the use of artificial light sources as part of the imaging setup in the field experiment created a number of new challenges, which are discussed below. As poultry houses are in general rather dark, with a light intensity between 2 and 20 lux (Prescott, Wathes, & Jarvis, 2003), an extra sensitive camera was selected to avoid the need for artificial lighting. This seemed beneficial, as artificial lighting might affect image quality through uneven light distribution and this requires additional electrical power to be supplied and carried by the robot. Lens selection was also affected by this choice. The low light conditions required a very translucent lens with a large diameter and short focal distance. For this research the best available option as indicated by the supplier was selected, with a minimum F-number of 1.8 and 5 mm focal distance. Still, its diameter was not large enough to allow sufficient exposure on all areas of the camera chip, leading to unexposed areas in the corners of the image. Light intensity was further reduced by the wavelength filter. Next, the spherical shape of the lens combined with the wavelength filter led to radial distortion that is visible in the images as radial intensity fall-off and concentric rings. This is most likely caused by light being reflected or refracted between the filter and the convex lens. Thus, avoiding the use of an artificial light source led to a suboptimal imaging setup, which turned out to have clear influence on the classification results. This choice may need to be reconsidered and possibly investigated in future research.

For practical application of this object discrimination method, sufficient illumination at the selected wavelength band is required. If this is not the case, there is clear influence of ambient light on the imaging results, of which an example was seen during testing in another poultry house. Here, the used wavelength of 470 nm was abundantly available from the white lights in the corridors in the rear part of the image in Fig. 9, but hardly presented below the interior rows (front part of the image) where illumination was achieved by orange LEDs. This led to insufficient illumination or shading in the front part of the image, as shown in Fig. 9, with very low signal to noise ratios in the shaded areas and a need for different classification thresholds in each region. Thus, for the presented method to function properly in a poultry house, it is required that the wavelengths used are sufficiently present in the ambient light and have an even spatial distribution.

As ambient light plays a role in both problems, including ambient light conditions in the selection of the most suitable wavelength (step 5) might present a possible solution. Also, light conditions in the house could be adapted to better match the needs for image acquisition. However, as this might lead to problems with animal behaviour and could involve considerable costs, this approach seems less desirable. Alternatively, using artificial lighting as part of the imaging setup might be reconsidered, to avoid or reduce adverse effects from both the imaging setup and the housing conditions, while having only a limited influence on animal behaviour. In preliminary research (Vroegindeweij et al., 2015), artificial lighting was already added to have sufficiently illuminated images; specimen results are shown in Fig. 10.

Fig. 9 – Image captured in another poultry house, showing clear shading effect as result of ambient light. In the front part of the image, the ambient light was orange-coloured and missed wavelengths around 470 nm, while in the rear part, there was white light that did include these wavelengths and thus showed higher intensities.

Compared to the images in Figs. 4 and 6 , using an additional light source results in a more even light distribution but it also creates shading effects due to the directed beam of the light source. Such shading results in more variation in the observed reflection within object categories, leading to wider distributions. Thus, more overlap between distributions will be observed, which will complicate intensity-based classification. Proper selection of the illumination system and calibration of the setup might avoid such undesirable illumination effects, and still result in a more even distribution of light over the area. As result, the intensity distributions for the object categories are expected to be more distinct, allowing for better separation using intensity thresholds under practical conditions. As the classification results in this case are likely to improve beyond those presented in this paper, it seems worthwhile to reconsider this approach in future experiments.

4.2. *Processing methods*

In the image processing all labelled image data, i.e. all labelled pixels, were considered. As an alternative a region of interest (ROI) excluding pixels at specific locations in the image from the analysis can be used. This allows image regions that were prone to adverse effects of using a suboptimal imaging setup (such as the image corners) or unequally illuminated areas (as seen in the top of the images) to be excluded from the data. Most likely, classification results will then improve, since part of the data that is difficult to classify correctly is then ignored. Preliminary investigations showed that using an ROI focussing on the centre of the image could improve performance by 2.5% for hens and 8.6% for litter. Using an ROI during classification, however, requires that only the ROI area that is of relevance for robot operation and other pieces of the image can safely be excluded because it will not affect the operation of the robot. This is the case, for example, when the excluded parts of the image will be handled at a later moment, when the robot is closer to these objects. As PoultryBot moves through the house, this seems indeed a feasible approach, and thus should be considered in continuation of this work.

Furthermore, current processing was based on a number of fixed intensity thresholds, using only information from the individual pixel in a specific spectral band. This made the method rather simple, while still offering reasonable performance. Other thresholding methods have also been evaluated such as manually varying the threshold values per image or auto-defining them using Otsu's method (Otsu, 1979), but found to be harder to apply or less suitable for the current dataset. This was mainly caused by the overlapping intensity distributions of object categories and variations within the images. Using an improved imaging setup might reduce these effects. To further improve classification results, and allow for object detection using this method, other processing methods should be added to the processing pipeline, especially around steps 7–9 that deal with classifying the images. For example, adding filtering steps such as a median filter can reduce image noise. Also, eggs and housing elements have a specific shape that can be used in image processing and classification using morphologic image processing methods like erode, dilate and shape filtering. As such methods include specific object

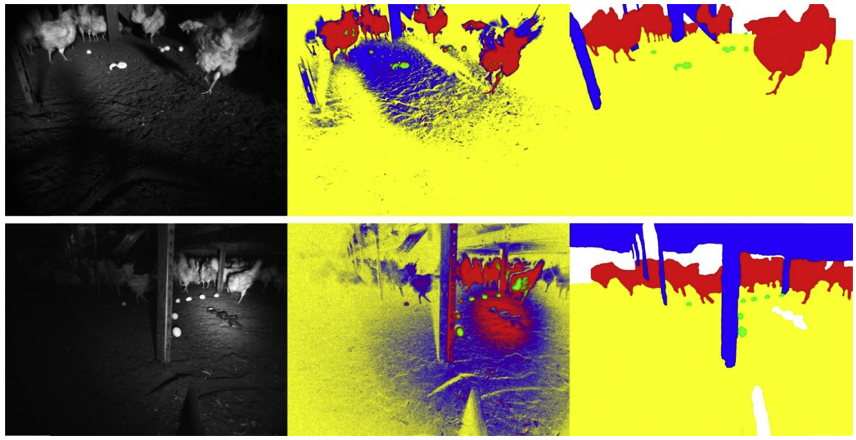

Fig. 10 – Preliminary classification results, as presented in (Vroegindeweij et al., 2015). Top and bottom show 2 example images. From left to right: original image (brightness increased by 100% for presentation purposes), classification result, ground truth.

properties, they will potentially lead to better classification results, especially when moving from pixel to object level.

Alternatively, a completely different approach could be taken, by replacing steps 7–9 with a more advanced method that considers adjacent pixels or other features for the classification process. This might reduce the problems with individual intensity values, and connects better to the current state of the art in machine vision. For example, Yang et al. (2010) used fuzzy classification to classify hens in a processing facility based on measurements in specific spectral bands, achieving over 95% correct classification. Also, the use of various advanced methods such as conditional random fields, support vector machines and neural networks is common for image classification and semantic segmentation (Abe, 2005; Giacinto & Roli, 2001; He, Zemel, & Carreira-Perpiñán, 2004). Then, the image is segmented into superpixels based on specific image features such as intensity or texture. Next, for each superpixel a vector containing a range of features like intensities, size, and texture is generated. After training a classifier system using a labelled dataset, this method can subsequently classify the superpixels. Although such methods can be used on the current data, they might be even more suitable for use on colour images, as they use 3 instead of 1 spectral band and might contain a wider range of features. However, these methods require extensive training using dedicated datasets, and have clear computational demands and constraints. Thus, these methods might provide more possibilities for image classification, but at the cost of more complex and demanding implementations, which in turn might limit their current application in mobile robotics for livestock applications. However, as the availability of computational power increases, these algorithms present an interesting option for future investigations.

4.3. *Performance versus requirements*

In this work, an approach was presented for a pixel based classification method that discriminates between various objects in a poultry house based on their spectral reflection properties. Although development of this approach requires a complex hyperspectral imaging setup in the laboratory experiment, in its final application standard hardware components and simple processing methods can be used. For imaging, a monochrome camera with a wavelength filter and no additional light are sufficient, while the classification method is based on intensity thresholds only.

As the choices made when implementing this approach mainly depend on the properties of the objects considered, the presented method and results are largely insensitive to changes in environmental properties. Thus, if the method is to be applied in a different environment, but with the same type of objects (i.e. white hens and eggs, regular litter and housing elements), only the setting of the thresholds in the classification step might need some fine-tuning as result of different ambient light conditions. If different object types are present, such as brown hens and eggs, or different material is used for litter or housing elements, their spectral reflectance has to be determined first. This requires re-running the laboratory experiment, to see which wavelength band is in this case the most suitable one for discrimination of these objects. Initial investigations for brown eggs, for example, indicated that a different one should be selected.

When comparing the achieved performance of this approach, as presented in Section 3.2, against the stated performance requirements, quite reasonable results were achieved using manually defined thresholds. For eggs, the requirement of 80% correctly classified pixels was almost reached, with on average 79.9% of TPs. For hens and litter, on average about 40–50% of the pixels were classified correctly, thus not yet reaching the requirement of 80% of the pixels being classified correctly. Modification of the vision setup is needed to remove undesired side effects, as well as extending the processing with other methods based on adjacent pixels or object shape. This seems a very feasible way to reach the desired level of 80% correctly classified pixels for hens and litter, and is expected to also improve the results for eggs. For housing, such adaptations are definitely required, but given the amount of overlap between the intensity distribution for housing and the intensity distributions for litter and hens, it is not sure whether the desired level can be reached at all. As alternative, image data might be combined with additional data sources such as a map or a laser scanner to properly identify housing elements.

Thus, the current method is clearly suitable for implementing egg detection on PoultryBot, and with some improvements it is also likely to be able to provide information on the presence of hens and the availability of free driving space. Even more, as long as objects can still be recognised correctly, also the performance of the current system might already be sufficient for the functioning of a poultry robot, especially when this is combined with information from other sensors to create a high level of environmental awareness. In that case, the requirement of 80% correctly classified pixels serves merely as a performance guideline, instead of being a lower limit on the acceptable performance. With these results, the desire for a universal solution using simple methods for object detection as basis for creating environmental awareness for a poultry house robot is clearly met by this approach, although the use of artificial light might be reconsidered in future.

5. Conclusions

In this work, a simple pixel based classification method based on spectral reflectance properties was presented. This method is characterised by the simplicity in its application, where a wavelength filter is applied on a standard monochrome camera for image acquisition. For classifying the pixels of the acquired images into multiple object categories, the use of multiple intensity thresholds is sufficient. Based on the results presented, it can be considered as a first step in discriminating between various object categories present in an aviary poultry house, to generate environmental awareness for a poultry house robot.

In the laboratory experiment, the spectral reflectance of four object categories that are relevant for the robot (eggs, hens, housing and litter) was investigated in the range between 400 and 1000 nm. Clear differences could be observed in the amount of reflectance between object categories, and overlap was lowest around 467 nm, being 16% for hens and eggs, 12% for litter and housing, and lower for the other combinations.

In the field experiment, 87 images were taken in a commercial poultry house, using a standard monochrome camera and a band pass filter around 470 nm. On these images, pixel classification into the four object categories was evaluated. For eggs, the requirement of 80% correctly classified pixels was almost reached (on average 79.9% TPs). For hens and litter, 40–50% of the pixels were classified correctly, thus not yet matching the requirement of 80% correct classification. For housing, performance was rather low with 15.6% of the pixels classified correctly. Effects of threshold settings were evaluated using ROC curves, displaying a clear relation between the performance for the various object categories.

As the imaging setup relied solely on ambient light, collected images were influenced by both the ambient light conditions and the optical properties of the setup. Thus, object intensities in the acquired images overlapped more than in lab conditions which made discrimination difficult. This influenced classification results, limiting the performance for pixel classification in this research. However, simplicity and elegance in its application remain a major advantage. With about 80% of the egg pixels classified correctly, this method seems a feasible starting point for implementing egg detection on PoultryBot. A further increase in performance is expected from using additional processing of the images, or replacing the processing of the acquired images with more advanced computer vision methods.

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