Model-based detection of pigs in images under sub-optimal conditions

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Abstract

The automatic detection of pigs in camera images from the barn helps scientists and farmers to detect abnormal behaviour or problematic housing conditions and to investigate the causes. An established method for determining the position of pigs is the binary segmentation of the image and the subsequent modelling of the individual animals. Many studies are based on elliptical models because they reproduce the positions of the pigs sufficiently with few parameters. However, the methods used require a perfect segmentation of the individual animals from the stable subsoil. Since such a segmentation is not easy to create, this paper introduces a novel method for adapting the ellipses, which is not based on the edges of the segmentation but looks at all segmented pixels. This makes it easier to compensate for minor errors in segmentation.

Keywords: behaviour of pigs, automatic detection of pigs, animal housing surveillance, ellipse-fitting, randomized black-box optimization

1. Introduction

Lately published studies showed a frequently use of video cameras to automatic detect the position of pigs in livestock environment. The use of image data in combination with automatic detection methods enable the researchers to evaluate different behavioural measurements by bypassing the time-consuming and error-prone manual interpretation. The position of the pigs in the pen alone

gives information about activity (Ott et al. (2014)), feed/water uptake (Kashiha et al. (2013a)) or lying behaviour (Nasirahmadi et al. (2015)). Also interactions (Nasirahmadi et al. (2016)) and social behaviour (Viazzi et al. (2014)) have been monitored and evaluated.

To determine the position of the piglets McFarlane and Schofield (1995) used chain coding to form blobs from segmented pixels. These blobs then were transformed into ellipses by analyzing the spatial distribution of the related pixels. An ellipse can be fully described by only five parameters (centroid, major axes and orientation) but approximates the body of a pig in images from down-looking cameras sufficiently. Alternatively Zhang et al. (2005) proposed an optimization approach where ellipses were found by minimizing the algebraic distance over a set of segmentation border-points in the least-square sens. Although other techniques are known (Ahrendt et al. (2011); Guo et al. (2014)), both ellipse-fitting approaches were successful applied in recent studies (Nasirahmadi et al. (2016, 2017); Kashiha et al. (2013a,b)). Since the first algorithm uses chain coding to combine the segmented pixels into blobs, and the second algorithm uses the segmentation limits of individual blobs, it is crucial for both methods that each pig is represented by exactly one blob. The adjustment results of both approaches therefore depend to a large extent on correct segmentation. Unfortunately, such a correct segmentation is not easy to obtain, since individual animals may not be represented as a whole due to structures in the barn or markings on the pigs, which means that animals can be depicted by parts of different blobs. Figure 2 shows an example of such an interrupted segmentation.

In this work a different approach for fitting ellipses to the pigs is presented. It is much more insusceptible to disruption in the segmentation and can therefore be used on image footage with sub-optimal conditions like heavy compression, occluding structure or disruptive markings on the pigs backs. It works by transforming the defective segmentation into a probability map where pixels are rated depending on their probability of belonging to a pig or to the background. On this probability map a specially designed fitness function is evaluated by Covariance Matrix Adaptation - Evolution Strategy (CMA-ES) a global stochastic

Figure 1: Example images from the used data-set. For individual identification the piglets were partially marked with pattern of paint on their backs. The results of the proposed technique on this images are depicted in Figure 6.

non-convex optimizer that fits ellipses to the pixels representing the pigs with the highest probability.

2. Materials and methods

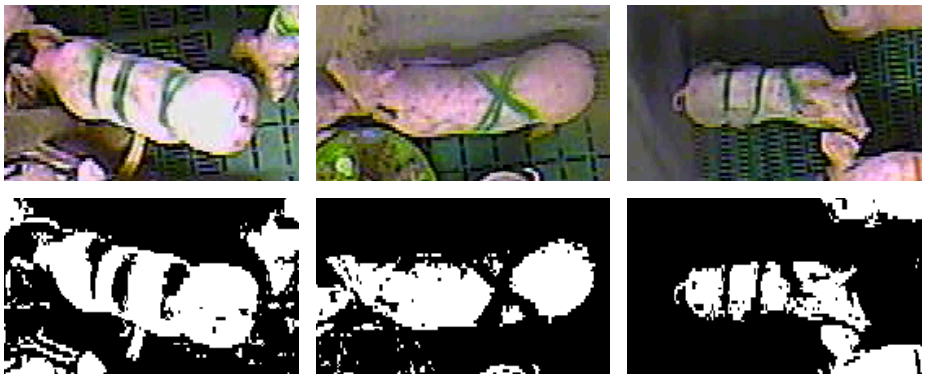
2.1. Data-set

The data-set for this work was originated from a behaviour study of piglets where the piglets were recorded by top-down-facing surveillance cameras to monitor their activity over time. To manual evaluate the activity and behaviour of individual animals, the piglets were marked with pattern of paint on their backs (four different colors, three different symbols). As the images were intended to be analyzed by humans no special preparations were made to improve the distinguishability of the animals from the background. All records show standard-sized pens (1.61 x 2.8 m) with 12 piglets each. As the original behaviour study was designed as long term study only four image per second were captured with *VTC-249/IRP/W* cameras by *Santec* and stored highly compressed on a storage system. Figure 1 shows some example images of the data set.

2.2. Segmentation and probability map

For the initial binary segmentation the images were converted to histogram-equalized grayscale and a threshold was applied. As shown in Fig. 2, the partly present markings on the pigs did prevent an optimal continuous segmentation of the animals.

To counteract this the segmentation was transformed to a probability map.



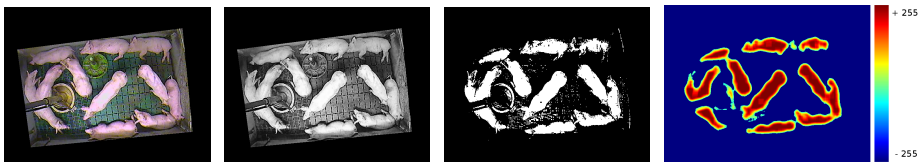
(a) (b) (c)

Figure 2: First row: Different image details showing some of the marked pigs. Second row: The problematic segmentations.

Therfore an unnormalized box filter with a kernel-size of 19 pixels was applied. This filter sums the activated pixel in the binary segmentation within an 19×19 pixels radius around the sampling-point, resulting in high values on locations where many segmented pixels are clustered in the local neighbourhood. The value-range of the resulting feature-map is [0, 361]. Next the values were normalized to a range of [-255, 255], so pixels with no or few segmented pixels in the neighbourhood get negative values, pixels in clustered surroundings get positive values. Setting all pixels with values below -100 to the minimal value of -255 gave the final probability map. Fig. 3 pictures the individual steps of this process.

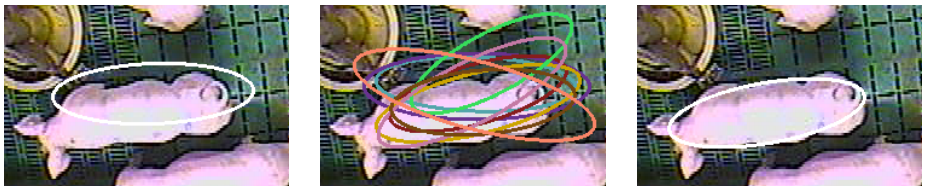
2.3. Ellipse fitting

As pixels in the probability map have positive values if they probably belong to pigs and negative values else, summing pixel-values covert by an ellipse at an assumed position can be interpreted as fitness of this guess. The higher the summed value the higher the probability of covering the complete animal. Hence the fitness-function which converts an proposed position (five ellipse parameters) into an probability-value (the sum of the pixels covert by the proposed ellipse) can be defined and used by an optimization algorithm to fit the ellipses.



(a) (b) (c) (d)

Figure 3: The stages of segmentation: masking (a), histogram-equalization (b) binary threshold (c) and the resulting (colorized) probability-map (d).



(a) Starting position for the optimization (b) The samples in an early iteration (c) Final result

Figure 4: Illustration of the optimization. The optimizer starts with the last valid position (a). In each iteration samples are evaluated and the internal distribution is updated (b). If the optimization converge, the final result is found (c).

As optimization algorithm Covariance Matrix Adaptation - Evolution Strategy (CMA-ES) developed by Hansen and Ostermeier (2001) was used as it has shown great performance[1] in the domain of randomized black-box search techniques. In the Black-box search domain the optimizer has no knowledge about the fitness-function and the only information about it can be obtained by sampling the function at certain points. CMA-ES uses an evolutionary strategy by sampling from the fitness-function and selecting the best guesses. Based on their parameters the internal state of the optimizer is updated and the next iteration initiated.

Per pig in the pen a separate optimizer was initiated and overlap with the remaining animals was penalized (subtraction from the fitness-score) to take the

[1]see 2009 Black-Box Optimization Benchmarking Competition (BBOB)

(a) 13.45 px (b) 19.42 px (c) 24.76 px (d) 25.00 px

Figure 5: Different Hausdorff distances between two ellipses with size 136×45 pixels (average pig-size in our datasets). The examples show classical cases of hits for the threshold of 25 pixels. The dark line between the ellipses marks the point of maximum Hausdorff distance.

natural displacement of the animals into account. Deviations in the estimation of the major axes from the average size of the animals (136×45 pixels) were similarly penalized. Each optimizer was initialized with the position of one pig in the first frame. In the successive frames the last valid position was used as starting position for the optimizer. Fig. 4 depicts an example for the process of testing different guesses starting from the initial starting position and the final result. If no valid starting position was available (e.g. due to occlusion), the search space for the position parameters was enlarged to recover the hidden animal.

3. Results

To measure the accuracy of the proposed technique the ellipses for all 12 pigs in the first 500 frames of two different recordings were labeled by hand. For long term evaluation one pig was also labeled over the complete first recording (1992 frames). The labeling was done by depicting the two major axis of the ellipses consistent with the pigs outlines. From this the position, size and orientation of the depicting ellipses could be calculated. If pigs are obviously occluded by structures or by other pigs this has also been recorded for separate evaluation. The detection were evaluated by matching the hand-labeled ellipses to the one proposed by the optimizers. To classify if the detection were correct, the Hausdorff distance was used (Hausdorff (1957)). Interpreting the ellipses as set of points this measure gives the *maximum distance of a set to the nearest point in the other set* (Rote (1991)). A detection was counted as a *hit* if the Haus-

(a) (b) (c) (d)

Figure 6: The results of the proposed technique for the frames from Figure 1. Note the partially occlusion of individual pigs by structure or other pigs in (b) and (d).

dorff distance between a hand-labeled ellipse and a proposed ellipse was under a threshold of 25 pixels. This threshold was chosen with respect to the average pig size in the data set (136×45 pixels). Figure 5 shows different Hausdorff distances as an illustration. To ensure a clear assignment of the ellipses proposed by the optimizers, the ellipses were exclusionary assigned to the best fitting hand-labeled position. Pigs that are not marked by an optimizer are counted as a miss. Misses where pigs were obviously occluded can optionally be ignored to assess the performance of the detection without falsification.

Three different experiment-types were defined:

- (A) 12 pigs over 500 frames ($\sim$ 2 min. in the recording) whereby misses of occluded pigs are ignored.
- (B) 12 pigs over 500 frames ($\sim$ 2 min. in the recording) whereby misses of occluded pigs are not ignored.
- (C) 1 pig over 1993 frames ($\sim$ 8 min. in the recording) whereby occlusions did not occur.

The experiments were carried out on the two hand-labeled recordings. Table 1 shows the average percentage of hits (correct detections). As CMA-ES is a randomized procedure each experiment was repeated 50 times. The maximum standard deviation of 0.93% over all experiments confirms the stability of the proposed method.

Table 1: Average percentage of hits (correct detections) on five different experiments on the two recordings.

Recording (Exp.-type)	**Hit-rate**	**Avg. Hausdorff distance of hits**
Recording 1 (A)	91.92%	12.88 px
Recording 1 (B)	88.94%	12.51 px
Recording 1 (C)	93.60%	11.31 px
Recording 2 (A)	91.22%	13.15 px
Recording 2 (B)	87.63%	12.68 px

4. Discussion

The detection of pigs based on elliptical models has been successfully used in a wide variety of scenarios. However, since the procedures depend on good segmentation, they are also susceptible to certain problems. In the material available for this investigation, in some cases it was not possible to clearly segment the individual animals. Therefore, the presented procedure was introduced and successfully tested. Although it could only be tested on short sequences, there is no reason why it should not be used on longer sequences.

Of course, the presented procedure fails in some situations where even the established procedures fail. If the pigs jump up or lie on top of each other, it is not possible to reconstruct the position unambiguously. Due to the recovery-process the animals can be found again reliably after the situation has been resolved.

5. Conclusion

The position detection of pigs based on ellipse-fitting is the basis for many further investigations (Nasirahmadi et al. (2015, 2016); Kashiha et al. (2013a)). The procedure for adapting the ellipses presented in this paper does not use the edges of the individual segmentation but all segmented pixels and can therefore deal with incomplete segmentation. As the evaluation on the presented data record shows, this method can be used to successfully detect the positions of

the animals in over 90% of all cases, even if the preceding segmentation is interrupted by occlusions or markings.

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