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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 within 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 modeling of the individual animals. Many studies are based on elliptical models because they sufficiently reproduce the positions of the pigs with a few parameters. However, the existing methods for adapting the ellipses require an almost perfect segmentation as they depend on the clear delimitation of individual animals. Although the animals are usually visually distinct from the background, a uniform segmentation is not always feasible. Due to occlusions, dirt or shadows in the barn, incomplete or faulty segmentation can occur even with advanced segmentation techniques. So 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 minor errors in segmentation and helps to process images even under sub-optimal conditions, such as poor lighting or unfavourable camera positioning.

1. Introduction

Recently published studies show a frequent use of video cameras to automatically 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). Combining the position information of multiple animals also gives information about interactions (Nasirahmadi et al., 2016) and social or aggressive behaviour (Viazzi et al., 2014).

To determine the position of the piglets, McFarlane and Schofield (1995) used chain coding to form blobs from segmented pixels. These blobs were then transformed into ellipses by analyzing the spatial distribution of the related pixels. An ellipse can be fully described by only five parameters 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 sense. Although other techniques are known (Ahrendt et al., 2011; Guo et al., 2014), both ellipse-fitting approaches were successfully 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.

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

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Fig. 1. Example images from the used data-set. For individual identification the piglets were marked with pattern of paint on their backs. Immediately after application, the color was clearly visible, but later it faded noticeably. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2. Materials and methods

2.1. Data-set

The data-set for this work originates from a behaviour study of piglets where the piglets were recorded by top-down-facing surveillance cameras (*VTC-249/IRP/W* by *Santec*) to monitor their activity over time. The images used in this work were recorded on two consecutive days and show the same pen (1.61 × 2.8 m) with 12 piglets. No special preparations were made to enhance the lighting or to improve the distinguishability of the animals from the background. To reduce the amount of storage needed, only four images per second were captured in a highly compressed format. The original intention was to analyze the images by humans so the individual piglets were all marked with painted patterns on their backs (four different colors, three different symbols) to allow individual identification. Immediately after application, the color was clearly visible, but later it faded noticeably. Fig. 1 shows some images of the data set as an example.

To be able to compare the proposed technique to ground truth data, the positions of all 12 pigs in the first 500 frames of the two recording days were labeled by hand. The labeling was done by depicting the two major axis of an ellipse that would cover the pig and correspond to its contours. From this input the position, size and orientation of the ellipse could be calculated. For long term evaluation one pig was also labeled over the complete first recording (1992 frames). If pigs were covered by structures or other pigs, this was also registered (*occlusion-label*).

2.2. Experiments

To measure the accuracy of the proposed technique, five different experiments were defined in which the correlation of the ellipses proposed by the method were compared with the hand-labeled ellipses. To check if hidden pigs could falsify the evaluation, it was also distinguished whether not successfully detected pigs marked as hidden by the human observer were counted as errors or not (see Table 1).

Table 1
Listing of the five experiments. The last column describes the consideration of the occlusion-label in case of an unsuccessful detection. If the label is considered, an unsuccessful detection is not counted as an error.

#	Data-set	No. pigs	No. frames	Occlusion interpretation
1	Day 1	12	500	Occlusion-label considered
2	Day 1	12	500	Occlusion-label ignored
3	Day 1	1	1992	No occlusions
4	Day 2	12	500	Occlusion-label considered
5	Day 2	12	500	Occlusion-label ignored

2.3. Segmentation and probability map

As mentioned in the introduction, the quality of the segmentation of individual pigs can be crucial for the subsequent image processing and detection of the pigs. In cases where the original image footage is of poor quality or stored in a highly compressed format even advanced threshold methods like Otsu (1979) may fail to create a basic foreground/background segmentation to build upon. The painted pattern on the pigs' back add an additional level of difficulty, since in many cases they prevent the animals from being segmented in a continuous way. Fig. 2 shows some examples where the present markings on the pigs prevented an optimal continuous segmentation of the animals.

As irregular segmentation is not problematic in the proposed method, the initial binary segmentation was obtained by simple histogram-equalization and thresholding. Next the imperfect segmentation-image was transformed to a probability map. This was done by applying an unnormalized box filter with a kernel-size of 19 pixels. This filter sums the activated pixel in the binary segmentation within a 19 × 19 pixels window 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 (background) got negative values, pixels in clustered surroundings (pig) got positive values. To separate background and segmented areas even more, all pixels with values below −100 were set to the minimal value of −255. The result gave the final probability map. Fig. 3 depicts the individual steps of this process.

2.4. Ellipse fitting

As pixels in the probability map have positive values when probably belonging to pigs and negative values if not, summing pixel-values covered 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. This can be exploited to define a fitness-function which converts a five-dimensional (centroid, major axes and orientation of the ellipse) position-proposal into a probability-value (the sum of the pixels covered by the proposed ellipse). Such a fitness-function can then be used by an optimization algorithm to fit the ellipses to the individual animals.

The 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. This corresponds exactly to the characteristics of the given problem, since the form of the defined fitness function is not known and can have unattractive characteristics such as discontinuity.

CMA-ES is an evolutionary algorithm that builds a population in each iteration and then selects the best entities to initialize the next iteration. The population is built by sampling from the fitness-function. Based on the parameters of the guesses with the best fitness-score, the internal state of the optimizer is updated and the next iteration is initiated, until the fitness value converges.

Per pig in the pen a separate optimizer was initiated with the hand-labeled position of one pig in the first frame of recording. In the successive frames the optimizers started with the valid position of their pigs in the last frame. If a pig had moved, this position would be slightly

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