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Image motion feature extraction for recognition of aggressive behaviors among group-housed pigs

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ABSTRACT

The aim of this study is to develop a computer vision-based method to automatically detect aggressive behaviors among pigs. Ten repetitions of the same experiment were performed. In each of the experiment, 7 piglets were mixed from three litters in two pigpens and captured on video for a total of 6 h. From these videos, the first 3 h of video after mixing were recorded as a training set, and the 3 h of video after 24 h were recorded as a validation set. Connected area and adhesion index were used to locate aggressive pigs and to extract key frame sequences. The two pigs in aggression were regarded as a whole rectangle according to their characteristics of continuous and large-proportion adhesion. The acceleration feature was extracted by analyzing the displacement change of four sides of this rectangle between adjacent frames, and hierarchical clustering was used to calculate its threshold. Based on this feature, the recognition rules of medium and high aggression were designed. Testing 10 groups of pigs, the accuracy of recognizing medium aggression was 95.82% with a sensitivity of 90.57% and with a specificity of 96.95%, and the accuracy of recognizing high aggression was 97.04% with a sensitivity of 92.54% and with a specificity of 97.38%. These results indicate that the acceleration can be used to recognize pigs' aggressive behaviors.

1. Introduction

Since group-housed pigs are confronted with capacity limited, poor environment, low fiber diet and repeated changes of group composition in the intensive farming conditions, they express higher levels of aggression than they do in the natural environment (Stukenborg et al., 2012). Aggression usually occurs in the artificial pigpen allocation after weaning and at the beginning of the fattening period, the mixed pigs will frequently attack each other within 2 days until the new hierarchy is established (Keeling and Gonyou, 2001). The aggression among pigs can cause skin trauma, infection and even fatal injuries (Turner et al., 2006). The injured pigs intake food more difficultly, thereby the growth rate is getting low, which influences pork production (Stookey and Gonyou, 1994). Additionally, the stress produced by aggression will reduce the reproductive performance of the surrounding sows (Kongsted, 2004). Therefore, aggressive behaviors are regarded as one of the most important health, welfare and economic problems in modern production systems (D'Eath and Turner, 2009). Currently, the recognition of aggression among pigs mainly depends on manual observation and video surveillance, these means are time-consuming, laborious and hysteretic, it is difficult to achieve the real-time aggression detection in large-scale farms. Using computer vision technology to recognize aggressive behaviors will improve the efficiency of recognition, increase animal welfare and reduce the economic losses of farms (Faucitano, 2001; Bracke et al., 2002).

The pigs aggression is a complex interactive behavior which has continuous and large-proportion adhesion of pig-body, it can last from a few seconds to a few minutes (McGlone, 1985). The process of animal mating has the similar phenomenon of continuous adhesion, the computer vision-based mating recognition has been achieved mainly by analyzing the shape of animals in mating. For instance, Tsai and Huang (2014) used the length of circumscribed rectangle of cattles in mating as the feature, when this length lasted about 2 s and 2 times of cattle length then turned into about 2 s and 1.5 times of cattle length, this process was recognized as a mating event. Nasirahmadi et al. (2016) used the pixel area of the fitted ellipse of pigs in mating as the feature, when this ellipse area

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changed into 1.3–2 times of pig-body area, it was recognized as mating behavior. Compared with the mating behavior, although the geometry shape and displacement of the two pigs in high and medium aggression have the mutation, they always maintain adhesion or a very small distance. Thus, the aggressive pigs are regarded as a whole for motion analysis in this paper.

Recently, computer vision technology has been widely used for animal behavior analysis such as pigs comfort discrimination (Shao and Xin, 2008), pigs drinking water detection (Kashiha et al., 2013), pigs tripping and stepping behavior recognition (Gronskyte et al., 2015). However, the computer vision-based research for recognizing pigs aggressive behaviors has still been few. In order to detect pigs aggression using motion history image (MHI), the moving pixels of all individuals were extracted as the mean intensity, and the ratios of moving pixels account for all pixels of pig-body were extracted as the occupation index. Linear discriminant analysis (LDA) was used to classify these two categories of features and to recognize aggression with an accuracy of 89% (Viazzi et al., 2014). In order to classify aggression, the average, maximum, minimum, sum and deviation of the occupation index were extracted as features, a multilayer feed forward neural network was used to train these features and to classify the high and medium aggression with an average accuracy of 99.2% (Oczak et al., 2014). In the above methods, the number or proportion of the moving pixels of all individuals was selected as the feature, while these features contained the moving pixels of not aggressive individuals, it would increase the data amount of feature and the computation amount of algorithm. Additionally, using the mean in a period of time as the feature will lose the aggression details of each frame in this period.

Hence, the objective of this paper is to develop a computer vision-based method to further separate the aggressive pigs from all the moving individuals and to automatically recognize aggressive behaviors by analyzing their acceleration between adjacent frames. Connected area and adhesion index were used to locate aggressive pigs and to extract key frame sequences. Among them, the diagonal length of circumscribed rectangle of aggressive pigs in the former frame was used to predict the aggression range in the latter frame to achieve the continuous tracking of aggressive pigs. The aggressive pigs were regarded as an entirety to analyze their motion between adjacent frames and to extract the acceleration feature. Hierarchical clustering was used to calculate the threshold of acceleration. Based on this feature, the recognition rules of medium and high aggression were designed. Accuracy, sensitivity and specificity were used to evaluate the effectiveness of this method.

2. Materials and methods

2.1. Experimental setup

2.1.1. Video acquisition

The videos used in this study were collected from pig farms of the Danyang Rongxin Nongmu Development Co., Ltd., which is the experimental base for key disciplines of the Agricultural Electrification and Automation of Jiangsu University. The pigs were monitored in a reconstructed experimental pigsty. The pigsty was 1 m high, 3.5 m long and 3 m wide. A camera was located above the pigsty at the height of 3 m relative to the ground. The camera was the Canadian point grey industrial camera FL3-U3-88S2C-C (Sony Exmor technology, Canada). The camera used a Kowa LM6NCL 6.0 mm lens (Kowa Company Ltd., Japan). It recorded at a resolution of 1760×1840 pixels. The camera enabled top-view RGB colour images of group-housed pigs to be captured. The camera was connected to the computer with software Point Grey FlyCap2, and the videos were recorded in MJPEG. The computer processor was the Intel (R) Core (TM) i7-2670QM CPU @ 2.2 GHz with 8 GB of physical memory. The operating system was Microsoft Windows 7 Ultimate.

Ten repetitive experiments were conducted between the 16th of June 2015 and the 4th of September 2016. In each of the experiment, 7 piglets with the average weight of 24 kilograms were mixed from three litters in two pigpens after weaning. Videos were captured for the first 3 h (08 h00–11 h00) after the groups were established and then for 3 h after approximately 24 h. The rationality of video acquisition in this way is that the mixed pigs have the most violent aggressive behavior during the first 3 h after mixing and they will continuously attack within 2 days (Erhard et al., 1997; Spoolder et al., 2000). Sufficient data can be collected to meet the needs of research.

2.1.2. Data labelling

In order to evaluate the proposed algorithm, the frames with aggression in videos were labelled to compare with the recognition results of algorithm. The aggressive and not aggressive behaviors are very close and difficult to be distinguished at the early stage of pigs aggression. Additionally, the initial aggression doesn't cause much harm to the pigs. Therefore, only the high and medium aggression were studied in this paper (Jensen and Yngvesson, 1998). The veterinary experts in morphology proposed that head to head knocking, head to body knocking, parallel pressing, inverse parallel pressing and other behavior processes were recorded as medium aggression. Neck biting, body biting, ear biting and other behavior processes were recorded as high aggression (Gonyou, 2001; O'Connell et al., 2005). These two categories of aggression were manually labelled frame by frame in the recorded videos using the software "Labelling Tool" developed in Matlab (R2012a, The MathWorks Inc., MA). Labelling the 60 h of video cost about 145 person-hours.

2.1.3. Dataset allocation

The first 3 h of video after pigs mixing were recorded as the training set, and the 3 h of video after 24 h were recorded as the validation set. The test set was built by 10 groups of pig videos using the same sampling method. Table 1 illustrates the datasets of the first pig group, the number (N), minimum, maximum and mean duration time of each category of episode were shown.

2.2. Algorithm

2.2.1. Key frame sequence extraction

In order to remove part of the frames without aggression and to reduce the amount of computation by using key frame technology (Wang et al., 2015), the behavior characteristics at the beginning, in the process and at the end of aggression were analyzed to extract the key frame sequence which may has aggression in it. The specific steps are as follows:

(1) Image preprocessing. The pigpen scenes include light changes, the influence of ground water stains, urine stains, manure and other sundries, varying colors of foreground objects, and pigs slow movement patterns. Comparing the segmentation effects of combining image enhancement (e.g. wavelet enhancement, histogram equalization, pseudo color transformation, etc.) with commonly used threshold segmentation (e.g. Otsu method, maximum entropy, percentage threshold, etc.), histogram equalization and percentage threshold segmentation were used to initially segment images to get the results as shown in Fig. 1(c) (Gonzalez and Woods, 2001). Since the wall around the image is not the pigs activity range, and the position of feeder is fixed. The pixels outside the red box and inside the blue box were set to zero to remove wall and feeder (Lao et al., 2016). The