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Research Paper

Foreground detection of group-housed pigs based on the combination of Mixture of Gaussians using prediction mechanism and threshold segmentation

Yizheng Guo [a,b], Weixing Zhu [a,*], Pengpeng Jiao [b], Jiali Chen [a]

[a] School of Electrical and Information Engineering, Jiangsu University, Zhenjiang 212013, Jiangsu, China
[b] Nanjing Normal University Taizhou College, Taizhou 225300, Jiangsu, China

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In this paper, a foreground detection method to obtain the foreground objects of pigs in overhead views of group-housed environments is proposed. The method is based on the combination of Mixture of Gaussians (MoG) using prediction mechanism (PM) and threshold segmentation algorithm. First, the "valid region" is manually set according to a priori knowledge. Second, the foreground objects of pigs are detected using the PM-MoG algorithm. The algorithm uses the detected binary image of the previous frame to predict the current frame in the valid region for pixels that fulfil background updating conditions. Different update strategies are used to update the background for different circumstances. Third, the maximum entropy threshold segmentation algorithm is used according to the colour information of foreground objects. Finally, the results of the two previous steps of foreground detection are fused. The experimental results show that the method is effective and can extract relatively complete foreground objects of pigs in complex scenes. These complex scenes include light changes, the influence of ground urine stains, water stains, manure, and other sundries, pigs' slow movement patterns, and varying colours of foreground objects. The average foreground detection rate is approximately 92%. The experimental results set the foundation for further exploration of individual identification of group-housed pigs, their behaviour analysis, and other objectives.

1. Introduction

The study of foreground detection, tracking, and identification, as well as behaviour analysis of pigs in overhead views of group-housed environments based on machine vision, have important theoretical value and significant application potential. Among these, research on the accuracy of foreground detection of pigs is basic work for advancing subsequent research (Kashiha et al., 2013).

Foreground detection of individual pigs is mentioned to varying degrees in some literature (Ahrendt, Gregersen, &

* Corresponding author. Tel.: +86 051188797200.
E-mail addresses: guoyizheng0523@163.com (Y. Guo), wxzhu@ujs.edu.cn, zwxbest@126.com (W. Zhu).
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Karstoft, 2011; Hu & Xin, 2000; Lind, Vinther, Hemmingsen, Hansen, 2005; McFarlane & Schofield, 1995; Navarro-Jover, et al., 2009; Wang, Yang, Winter, Walker, 2008). In that literature, however, foreground detection technology is not the focus; rather, it is used to address requirements of specific applications. For example, Shao and Xin (2008) developed a real-time image processing system that is used to segment pigs, detect their movements, and classify their thermal behaviours (i.e., cold, comfortable, or warm/hot).

Some current computer vision systems that are used for video surveillance of group-housed pigs require that the pigs are marked (Navarro-Jover et al., 2009). Tu, Karstoft, Pedersen, and Jørgensen (2013) proposed a foreground detection algorithm based on loopy belief propagation. This method can overcome the influence of sudden light changes, dynamic backgrounds, and motionless foreground objects. For environments lacking sufficient a priori knowledge, research on effective foreground object detection methods for video sequences of group-housed pigs in complex scenes remains a challenge (Kashiha et al., 2014).

Among the mainstream foreground detection methods such as background subtraction, frame difference, and optical flow, background subtraction is the most common. The key concept of the background subtraction method is to model and update the background. Background modelling methods mainly include statistical average, median filtering, single Gaussian background modelling (Wren, Azarbayejani, Darrell, Pentland, 1997), Mixture of Gaussians(MoG) background modelling, W4 (Haritaoglu, Harwood, & Davis, 2000), ViBe (Barnich & Droogenbroech, 2009), and the SOBS (Maddalena & Petrosino, 2008) methods. Each method has its scope of application, and no general method can accurately handle all complex scenes such as light changes, shadow problems, or long-term motionless foreground objects. Stauffer (Stauffer & Grimson, 1999, 2000) presented the MoG model to build the background based on a K Gaussian distribution. It can handle multi-modal situations in the background modelling process, and has been widely used and improved in many studies since then (Bouwmans, 2011; Bouwmans, Baf, & Vachon, 2008). In addition, for large and slow foreground objects, a foreground detection method based on a space–time combination can detect objects more completely and boundary contours more accurately (Zhou & Zhang, 2006). Therefore, by combining the characteristics of video overlooking group-housed pigs, a new foreground detection method is proposed.

The complex scenes discussed in this paper include light changes, the influence of ground urine stains, water stains, manure, and other sundries, pigs' slow movement patterns, and varying colours of foreground objects. The proposed method consists of four stages. In the first stage, the "valid region" is manually set according to a priori knowledge. In the second stage, a foreground detection algorithm based on (MoG) using a prediction mechanism (PM)—herein referred to as the PM-MoG algorithm—is proposed. The detected binary image of the previous frame is used to predict the current frame; the background or foreground of the previous frame may be the respective foreground or background of the current frame. Four possibilities may occur: the background remains the background, the background becomes the foreground, the foreground remains the foreground, and the foreground becomes the background. Different update strategies are used to update the background of the relevant pixels. In the third stage, the maximum entropy threshold segmentation algorithm is used according to the colour information of foreground objects. Finally, the results of the two previous steps of foreground detection are fused. The experimental results show that the method is feasible and effective.

2. Materials and methods

2.1. Video acquisition

The videos used in the present 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 used was a Sony FL3-U3-88S2C-C with an image resolution of 1760×1840 pixels. The camera enabled top-view RGB colour images of group-housed pigs to be captured.

2.2. Methods

The flowchart and functional components of our foreground detection method are illustrated in Fig. 1. The method is a space–time combination technique based on the temporal correlation of video sequences and the spatial correlation of a single frame among pixels. First, a foreground detection result is obtained using the PM-MoG algorithm after the valid region is set. Another foreground detection result can be obtained using maximum entropy threshold segmentation (Kumar, Pant, & Ray, 2012) after the current frame is used in the image enhancement (Raju, Dwarakish, & Venkat Reddy, 2013). An example of the image enhancement is shown in Fig. 2. The fusion of results primarily occurs with AND and OR operations and mathematical morphology processing (Gonzalez & Woods, 2001), which are performed on the basis of the first two steps. The AND operation is performed within the valid region; the OR operation is completed outside it. At that point, isolated noise is removed using the erosion and dilation operation of the morphology algorithm. Then a priori knowledge is used to perform the follow-up treatment to ensure that the region with the detected object is less than a certain number of pixels and that it is the non-foreground-object region. Finally, the foreground detection results are obtained.

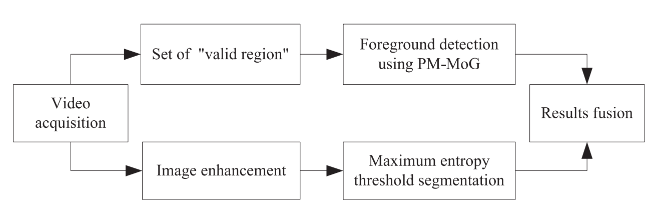

Fig. 1 – Flowchart and functional components of the proposed foreground detection method.