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Towards on-farm pig face recognition using convolutional neural networks

Mark F. Hansen[a,*], Melvyn L. Smith[a], Lyndon N. Smith[a], Michael G. Salter[b], Emma M. Baxter[c], Marianne Farish[c], Bruce Grieve[d]

[a] Centre for Machine Vision, BRL, UWE Bristol, Bristol BS16 1QY, UK
[b] AB Agri Ltd., Innovation Way, Peterborough, UK
[c] Animal Behaviour and Welfare, Animal and Veterinary Sciences Research Group, SRUC, West Mains Road, Edinburgh EH9 3JG, UK
[d] School of Electrical and Electronic Engineering, University of Manchester, M13 9PL, UK

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ABSTRACT

Identification of individual livestock such as pigs and cows has become a pressing issue in recent years as intensification practices continue to be adopted and precise objective measurements are required (e.g. weight). Current best practice involves the use of RFID tags which are time-consuming for the farmer and distressing for the animal to fit. To overcome this, non-invasive biometrics are proposed by using the face of the animal. We test this in a farm environment, on 10 individual pigs using three techniques adopted from the human face recognition literature: Fisherfaces, the VGG-Face pre-trained face convolutional neural network (CNN) model and our own CNN model that we train using an artificially augmented data set. Our results show that accurate individual pig recognition is possible with accuracy rates of 96.7% on 1553 images. Class Activated Mapping using Grad-CAM is used to show the regions that our network uses to discriminate between pigs.

1. Introduction

The need for on farm identification of individual animals has become more pressing in recent years as sustainable intensification has become commonplace, and the ability to monitor inputs to, and outputs of each animal is increasingly desired. The major method of livestock identification is via passive Radio Frequency IDentification (RFID) tags. These low-cost tags are commonly fitted to the animals' ears through piercing – a time consuming and distressing activity for the animal. They also have a limited range (even long range readers state a maximum distance of 120 cm) at which they can be activated and read successfully, and multiple tags cannot be read concurrently. Even fitting two tags per pig (to improve the chance of a successful reading) was found to only identify the animal at close range with an accuracy of 88.6% [1]. Common elements in the farm environment can also be detrimental to the antenna's effectiveness. Metal apparatus and tag readers from other equipment (e.g. shedding gates or weigh scales) can reduce the range further and interference can prevent some equipment from functioning at all.

Human face recognition has been an active area of research for at least five decades [2]. From geometric feature matching to holistic methods in the 1990s [3,4], the recent trend of using deep networks has advanced the state-of-the-art to near human level performance [5,6]. It is commonly used for non-intrusive access control and monitoring/surveillance purposes, and as such represents a potentially useful research area to apply to the problem of pig identification. Although there has been related work to automatically identify behaviours of pigs [7] and feeding/standing of cattle [8–10], biometrics on cattle [11–14], sheep [15] and canines [16] showing promising results, to date there has been very little research into using a pig face as a biometric, although [17] show some preliminary results of applying the Eigenfaces technique to pigs and achieve a recognition performance of 77% on 10 pigs using the full manually cropped face. They reported better results for smaller regions (i.e. the nose, or the eyes), but this relied on further manual segmentation of the regions so is not very applicable to an on-farm system. They also only collected 16 sequential image frames per pig, so the generalisation of such a system to different environmental conditions when imaging the same pigs is unknown.

This paper presents the results of three face recognition methods applied to a dataset of pig faces that have been captured on a farm under natural conditions: Fisherfaces [4], transfer learning using the pre-trained VGG-Face model [6] and our own

* Corresponding author.
E-mail address: mark.hansen@uwe.ac.uk (M.F. Hansen).

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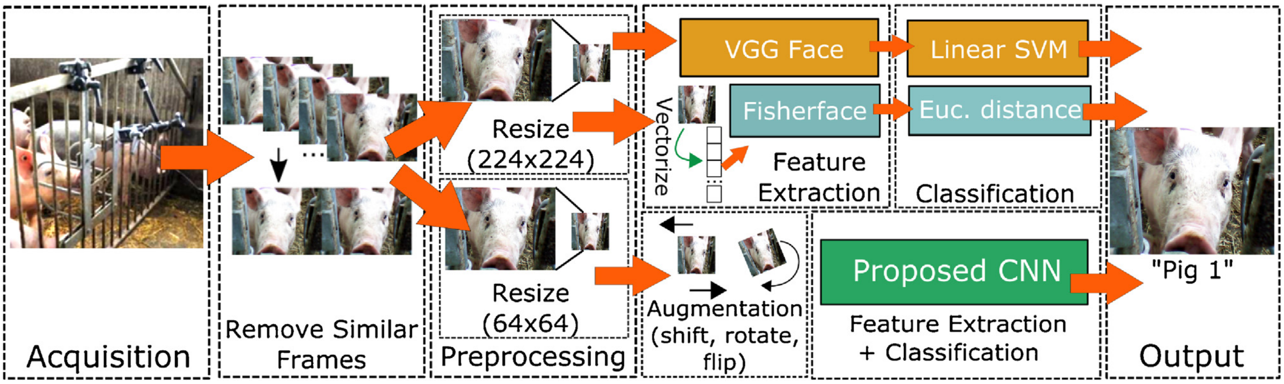

Fig. 1. Processing pipeline showing the acquisition, pre-processing steps, feature-extraction and classification for the three methods used in this paper for pig face recognition.

convolutional neural network which has been trained using our own dataset captured using an off the shelf web camera at the drinker in a pen. This represents a machine vision application in a challenging, poorly structured environment and even though the pigs are technically under cover, ie in a shed, the subjects position and pose as well as other aspects, such as the lighting, expression, contamination from dirt, etc., are relatively uncontrolled and highly variable. We demonstrate the efficacy of the system on recognising unconstrained, and un-preprocessed images of pig faces and present an analysis of those features and activation areas which our system has learned in response to training.

The rest of the paper is organised as follows: Section 2 outlines the data collection methodology, the video preprocessing approach to remove very similar frames, and the implementation details. Section 3 gives the background to the chosen approaches before the results being given in Section 4. A discussion follows which puts these results into context together with limitations and suggestions for future work.

2. Material and methods

This section describes the data capture, data cleaning and implementation details. An overview of the processing pipeline can be seen in Fig. 1.

2.1. Data collection

The pigs were Large White × Landrace × Hampshire breed, approximately four months old and housed at SRUC's research farm (Midlothian, Scotland). The pigs were filmed using a Sogatel USB2.0 webcam, with VGA resolution (640×480 px) at 30 frames per second. The camera was connected to a Dell Precision laptop running "iSpy Connect" software to allow motion-detection capture of the pigs each time they voluntarily approached the drinker. The camera was positioned behind the drinking nipple as shown in Fig. 2. A Manfrotto universal clamp and articulated arm were used to mount the camera to the pen frame at sufficient distance to ensure it was out of reach but close enough that the bars did not obscure the pigs' face as they drank. Access to the drinker was altered slightly through addition of shoulder bars which help to keep the pig face-on to the camera and other pigs from being in frame. No other changes were made to the drinker and the experiment was approved by the SRUC's Animal Ethics Committee.

Data of 10 pigs were collected in 2 sessions (31/03/2017 and 03/04/2017). The camera was left running unattended and manually labelled afterwards in order to create the training and test data required. As can be seen in the images, the pigs have been spray-painted to aid manual identification, and this is not required by the automated system itself. It should also be noted that some care was taken to mount the camera in such a way as to ensure that direct sunlight did not fall on the pigs' faces at the drinker as this led to saturated images. Other than this, natural variation in lighting levels was handled automatically by the camera. Examples of the pigs can be seen in Fig. 3.

2.2. Data cleaning

To avoid the shortcoming noted in [17] regarding low variance between consecutive frames, the structural-similarity index measure (SSIM) [18] is employed to measure similarity between

Fig. 2. Photographs showing the modified drinking nipple (left) and the arrangement of the webcam behind it (right).