# Capturing 2D and 3D Biometric Data of Farm Animals under Real-Life Conditions†

Henry Stahl[1*], Kristina Schädler[1*], Eberhard Hartung[2]

[1] *Institute Ma.Vi.Tec - Westcoast University of Applied Sciences (FHW), 25746 Germany*
[2] *Institute of Agricultural Engineering – University of Kiel, 24118 Germany*
[*] *Corresponding author. E-mail: {stahl, schaedler}@fh-westkueste.de*

**Abstract**

Capturing biometric data of animals for the purpose of identification of individuals is a central challenge in precision livestock farming. Sophisticated, mature biometric methods of face, fingerprint or iris identification for humans cannot easily be applied to animal identification under practical conditions on a livestock farm (Gonzales Barron et al., 2009). Today, the state of the art in animal identification is the use of RFID tags. However, attaching or implanting chips can cause technical and health problems. Camera-based optical solutions are non-invasive and not stressful but very challenging to implement. Human faces, for instance, can mostly be detected and identified from a 2D view, whereas the detection of pose and position of an animal's head under difficult lighting conditions and in front of a complex background can be nearly impossible using usual 2D-cameras. Therefore the goal of the current project was to develop a device that uses multiple sensors for capturing 2D and 3D data. The information provided by the different cameras is fused in order to locate, measure and identify the animal's head. The current paper describes the device and method for the acquisition of biometric data. The chosen approach has been proven to work under practical conditions on a livestock farm and requires no special cooperation of the animals.

**Key words:** Image Processing, Biometric Data, Detection, Animal heads

## 1. Introduction

Face detection and recognition of humans is already used in a variety of applications used for security purpose and even in social networks. But still most algorithms suffer from a lack of robustness against different face expressions and illumination conditions. To identify animals means dealing with comparable challenges, since the animal will not co-operate on its own, and illumination under real-life conditions is not entirely controllable. Additionally animals have a much higher intraclass variance of different colored and structured coats compared to the human's facial color. This diversity in their appearance may facilitate face recognition, i.e. the discrimination between faces of different individuals, on animals but complicates the detection, i.e. finding the location of the face on the image.

Today's animal identification is based on ear notching, freeze branding or RFID tags, which are attached or implanted to the animal. These markers can get lost, cannot prevent fraud in trade and must be relocated at slaughter or for reasons of animal welfare (Gonzales Barron et al., 2008; Schatzmann, 2012). As alternatives to the marker the biometric identification from iris pattern (Musgrave and L., 2002), retinal patterns presented by Gonzales Barron et al. (2008), nose prints (Hirsch et al., 1952), muzzle patterns (Corkery et al., 2007) or facial detection and recognition makes applications of devices to the animal's tissue unnecessary.

†The project was funded by the *Bundesministeriums für Bildung, und Forschung* (Federal Ministry for Education and Research of Germany) under grant number 17N2009. The responsibility for the content of this publication lies with the author.

Recognizing animals by their muzzle pattern or their facial features does not need direct contact to the animal and enables the identification from a distant point of view. Thus, the animal will not be stressed or affected in its natural behavior. Face recognition on Japanese Black Cattle has been proven to be possible by Kim et al. (2005). The recognition of great apes, which have a more human facial arrangement, has been investigated by Loos et al. (2011a,b). Identifying individual zebras by their coat pattern (markings) has been presented in Lahiri et al. (2011).

In general the automatic facial recognition is a queue of several tasks. It starts with detecting the object (face), preprocessing the data e.g. pose estimation and the normalization and ends with the final recognition. Haar-like features (Viola and Jones, 2004) or Histogram of Oriented Gradients (HOG) (Danal and Triggs, 2005) are wide spread feature sets for object classification and are often used in human face detection. These features or similar variations can also be used to detect particular animal species by their face (Burghardt and Calic, 2006a,b; Zhang et al., 2008; Kozakaya et al., 2009; Kouda et al., 2011; Zhang et al., 2011).

Compared to the species examined in the above mentioned papers most farm animals e.g. cattle and horses have different head shape and their eyes are not oriented towards the front, but are positioned sideways on their heads. These species' head shapes are modified supplementary according their ear-positions, which may be pricked up or flattened to their heads. Additionally their coat drawings might be arbitrarily distributed over their head and body in different colors. Due to this similarity in structure and color, the animal's head might be indistinguishable from the body in 2D image data.

In comparison the depth information allows for a reliable detection, pose determination and measuring of the animal's head. In the current paper a device for capturing 3D and 2D image data synchronously from the animal's heads is presented. This allows a robust detection of the animal's head and is a prerequisite for the biometric identification of the individuals. The only paper found in recent literature using 3D information for animal identification/detection is from Burghardt and Campbell (2007). They introduced the 3D information to train a classifier for dealing with different appearances as the animal moves in front of the camera.

## 2. Approach

The system, which is presented in the following chapter, was developed in 2010 at our Institute *Ma.Vi.Tec*[1] in Heide (Germany). Right after its completion the device was set up in a nearby stable on the premises of *HIT Hinrichs Innovation + Technik GmbH* [‡]. In this barn, around ten horses are kept at most times. This is a typical size of a herd of horses in one barn. Eight of them were picked for the tests presented in this paper due to their continuous availability.

### 2.1 Capturing 2D and 3D data

Capturing the depth information in parallel to the standard 2D image data allows for a more robust segmentation of the animal's head from its body. Therefore a system was developed using a device, which combines a structured light projector and a camera, for 3D data acquisition with an integrated color camera and added two high-resolution monochrome cameras (Stahl et al., 2012). The high-resolution cameras are triggered by the event of 3D image data acquisition. Hereby the cameras are synchronized and capture several frames per second. Thus, a video-like image sequence of a moving animal is grabbed.

Every frame consists of four images: the depth image, a low-resolution color image and two (stereo) high-resolution gray images. On the left of figure 1 a single frame shot of the depth information, the color image and the two monochromatic camera images is depicted. For a better interpretation the given depth graphic is color-coded and fades with the distance towards

[‡] HIT Hinrichs Innovation + Technik GmbH, Kleine Straße 2, 25795 Weddingstedt (Germany)

the camera from cold to warm colors. Simultaneous capturing is required to fuse the depth information with the remaining camera images. In case of a time-shift the captured data would not match for a moving animal.

### 2.2 Background separation

The goal of background separation is to find the object in each camera image. Distinguishing the object from the background is carried out clearly by the depth information. Our system is installed in a stationary position, so the animal is easily identified because it appears as a deviation from the constant background. The cameras are capturing their data from different view-points. This means the depth-masked region, which outline the object, has to be transferred from the depth camera to the remaining camera's 2D images of our system. The result of this operation is shown in the right part of figure 1. The calibration, which is necessary for transferring the images, is done in a preceding offline step presented by Herrera et al. (2011).

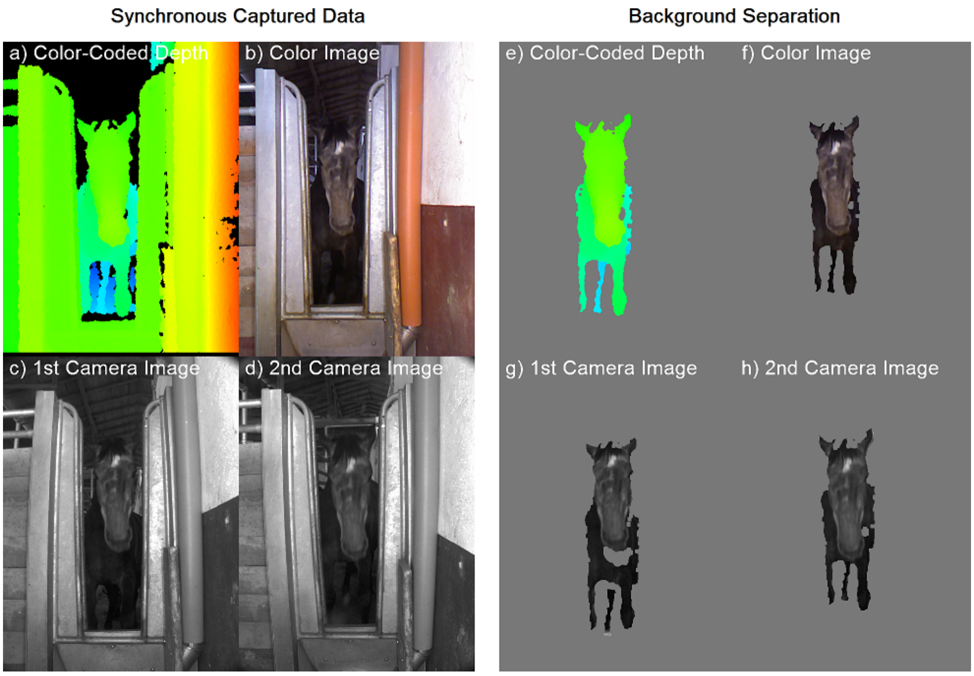


Figure 1: Left: Synchronous captured image data; Right: Background Separation *(a/e: color-coded depth image; b/f: color image; c/g and d/h: high resolution monochromatic camera images)*

### 2.3 Head separation

The developed noninvasive indentification device was installed in a feeding station for horses. The horse approaches towards the system's cameras head first. Thus the object's point with the shortest distance to the cameras is assumed to be part of the animals head. Starting from this point and moving rearwards to the animal's back a certain distance one collects all points belonging to the animal's head. The resulting head separation is shown on the left of figure 2. Those images where the face is most likely partially occluded by the background are filtered to be excluded from further processing.

In a second step an ellipse-like head model is created to distinguish whether the previously determined head candidate is actually an animal's head (in our case horse head) facing directly the cameras. The model is based on an ellipse fitted (Bookstein, 1979) to the borders of the original head-mask, the upper part is truncated and replaced by a semicircle with the ellipses minimal radius. Information is extracted from the intersection areas of the modeled head mask and its origin. The approach to evaluate an ellipsoid fitted to the 3D point cloud extracted from the depth according the previous step revealed no advantage over the presented 2D head model.

On the right of figure 2 the original mask (blue) is intersected with the cyan area, which is the mask generated according to the ellipse-like head model. Their intersected area is painted green. For being scale invariant the areas are compared to each other. The resulting factors are taken as features to separate the preferred views from the undesired ones. The strength of this classification can be adapted to set the tolerance in accepting images, which are determined for further processing.

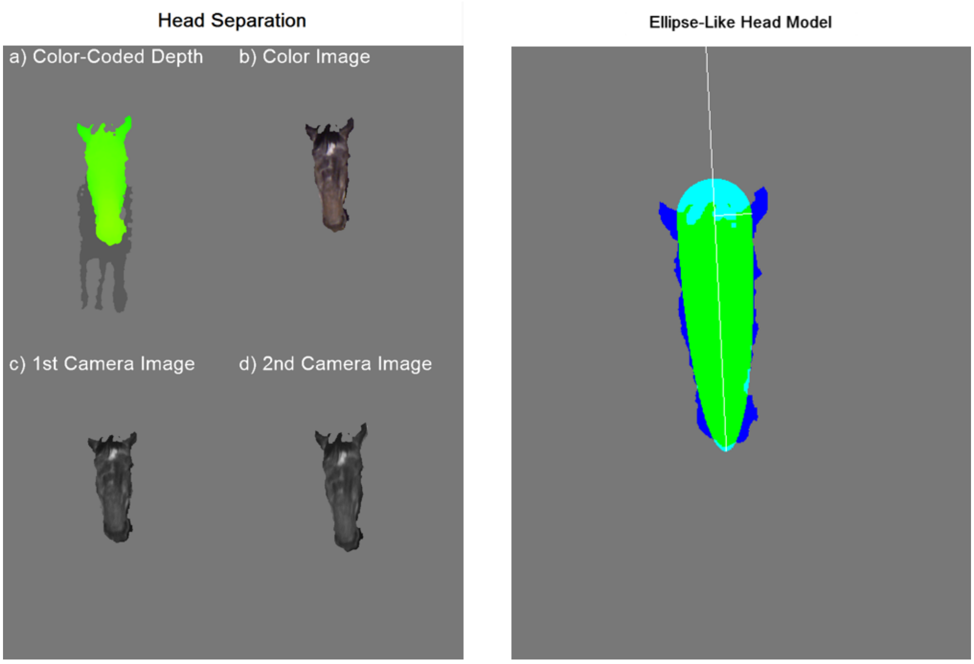


Figure 2: Left: Head Separation; Right: Fitting of the Ellipse-Like Head Model *(a,b,c,d: see fig.1)*

## 3. Results and discussion

### 3.1 Results

The device presented in section 2.1 was used to capture sequences of different horses under practical conditions on a livestock farm. Eight sequences of individual horses with around 3800 frames have been hand-labeled as good (showing the animal's head in a pose suitable for further processing) and bad (useless for identification) frames. Parameters for the goodness of the model fitting have been estimated in order to find the best discriminant between good and bad frames. The main goal was to remove most of the useless image frames and finding a sufficient number of good frames for further processing. The parameter were set for each individual horse by optimizing the F1 score (Van Rijsbergen, 1979). Cross-comparing these parameter sets to the remaining sequences more than 70% of all good frames are found, with only 4.5% of the bad frames wrongly identified as good ones. Since the frame rate of the device is quite high the number of exploitable images for the identification purpose is highly sufficient, even if the rejection rate of useful images is slightly higher. In figure 3 the true positive rates of the features selected are plotted against the false positive rates.

Due to the small computational load, this first processing step can even be done in real time during capturing.

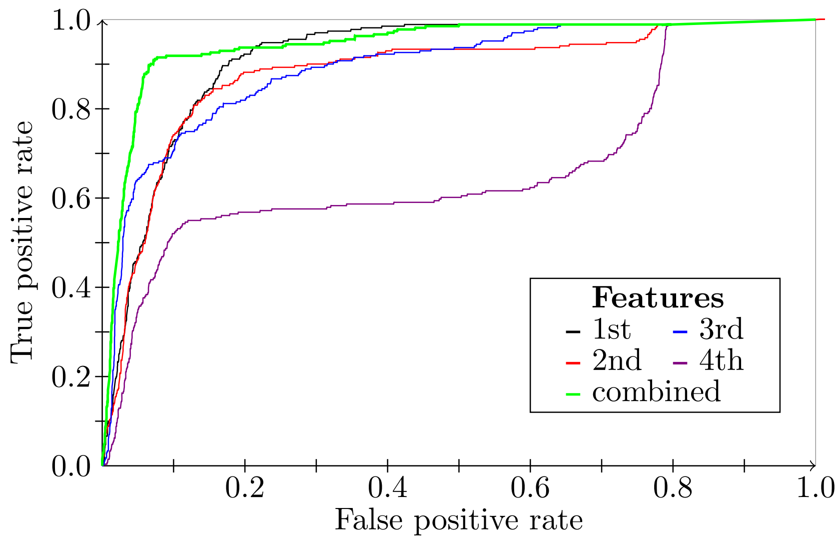


Figure 3: Feature characteristic rates (receiver operating characteristic curve)

### 3.2 Discussion

A noninvasive identification device is introduced, which automatically captures a video like sequence of frames, containing the depth, color and a set of high-resolution images, as soon as an animal approaches to the device. Further we presented a method to reject frames with less informational content for a face recognition system. The method also locates the image region with the facial biometric data, which can be processed in further steps to complete the queue of tasks in a facial recognition system.

The device and adapted methods are also applicable for the acquisition of other biometric features, for instance ankle flexion of horses or udder shape of cows.

## 4. Outlook

A first approximation of the heads pose is given by the main axis of our model's ellipse. But due to their influence on the approximation, the ears should be excluded from measurement. Investigations in finding the nose-back of the animals face in the depth image are scheduled, which allows for more accurate head pose detection. This can be used for normalization of the 3D, color and gray-level images. The normalized images can then be used for animal measuring and identification.

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