Automated Detection of Equine Facial Action Units

Zhenghong Li,2 Sofia Broomé,1 Pia Haubro Andersen,4 Hedvig Kjellström,1,3
1 KTH Royal Institute of Technology, Sweden sbroome, hedvig@kth.se
2 Stony Brook University, USA zhenghong.li@stonybrook.edu
3 Silo AI, Sweden pia.haubro.andersen@slu.se

Abstract—The recently developed Equine Facial Coding System (EquiFACS) provides a precise and exhaustive, but laborious, manual labelling method of facial action units of the horse. To automate parts of this process, we propose a Deep Learning-based method to detect EquiFACS units automatically from images. We use a cascade framework; we firstly train several object detectors to detect the predefined Region-of-Interest (ROI), and secondly apply binary classifiers for each action unit in related regions. We experiment with both regular CNNs and a more tailored model transferred from human facial action unit recognition. Promising initial results are presented for nine action units in the eye and lower face regions. Code for the project is publicly available.

I. INTRODUCTION

The horse is a highly social species, and facial communication is of utmost importance for the function of the herd. In accordance, the horse has a remarkable repertoire of facial expressions which may be described by 17 degrees of freedom, so called actions units [20]. This repertoire is smaller than for humans which have 27 action units [5], but larger than for example the chimpanzee repertoire of 13 action units [3].

While the detailed analysis of the facial expressions of people to assess their emotions is mature [4], almost nothing is known about the association between facial activity and emotional states of animals. This is primarily due to the lack of self-report of emotions and other inner states in animals. Nevertheless, facial expressions are expected to convey important information of animal welfare [9], but methodologies for investigations are lacking.

In the past few years, great progress has been made in the field of Computer Vision. With the adoption of Deep Learning models, such as Convolutional Neural Networks (CNN), in Computer Vision, in some tasks such as image classification, the accuracies of computer models are even competitive with human capabilities. Related works for human facial action unit detection have also made progress in these years.

Therefore, in this work, we investigate the possibility of automatically recognizing horse facial action units. We currently focus on how to do this from still images. Even if the facial configurations of horses and humans are very different, a remarkably high number of action units are conserved across species [21]. We therefore transfer methods for human action unit detection to horses.

There are two main contributions of our project:

• We propose a cascade framework for the recognition of horse facial action units.
• We apply standard models for general image classification as well as for human facial action unit recognition to horses within our framework and compare their performance across multiple experimental settings.

II. RELATED WORK

Facial expressions can be described as combinations of different facial action units. A facial action unit is based on the visible movement of a facial muscle lying under the skin [18]. In 1978, Ekman and Friesen proposed the Facial Action Coding System (FACS) [5]. Through electrically stimulating individual muscles and learning to control them voluntarily, each action unit was associated with one or more facial muscles [2]. The recording of facial actions is entirely atheoretical; any inference of their meaning takes place during the later analysis. In 2002, Ekman et al. [6] proposed the final version of human FACS which since has been widely used for research in human emotion recognition.

Inspired by the progress of human FACS, Wathan et al. [20] created EquiFACS. As for FACS, EquiFACS consists of action units (AUs) and action descriptors (ADs). In addition, the movements of the ears of horses are specifically named as ear action descriptors (EADs). Until recently, EquiFACS has not been used for research in animal emotions, due to the very time consuming manual labelling. An initial study of facial expressions of pain in horses [14] showed that pain indeed is associated with increased frequencies of certain facial AUs. These AUs were anatomically located in the ear region, around the eyes, nostrils and muzzle. A major limitation of that study was the small sample size, which was attributed to the extremely resource demanding, but necessary, hand labelling of the videos. A prerequisite for more research in animal emotions using AUs is therefore development of methods that allow automated AU detection.

Pain recognition in animals via pre-defined facial features has previously been explored for sheep [12], [13] and for horses and donkeys [8]. Compared to our method, these works rely on more coarse-grained underlying facial expression representations, albeit using precise landmark extraction to extract regions of interest. The simpler structure increases robustness but limits the range and precision of expressions that can be represented. A third approach is to learn the underlying representation of pain expressions in horses from
raw data in an end-to-end manner [1], without imposing any designed network coding system. In [1], the authors used a recurrent neural network structure that exploited both temporal and spatial information from video of horses, and found that temporal information (video) is important for pain assessment. A future research direction is to study the interplay between data-driven learned emotion expression representations and EquiFACS.

Ever since Krizhevsky et al. proposed AlexNet [10], deep CNNs have been replacing the traditional methods in image classification fields with their outstanding performance. After AlexNet, deeper models such as VGG [19] and ResNet [7] have been proposed and applied as feature extractors in various fields. In our work, we chose CNNs as the classifiers of AUs.

CNNs are also widely used for object detection. In this work, an object detector network is employed to detect predefined regions of interest (ROI). Object detectors can be divided into two categories: one-stage methods and two-stage methods. One-stage methods such as YOLOv3 [15] and SSD [11] generate anchor proposals and perform detection in one stage and can be trained in an end-to-end manner. Two-stage methods such as Faster-RCNN [16] first generate anchor box proposals via a region proposal network and then use ROI-Pooling to crop the related features out for the final prediction.

Previous works in human facial AU recognition from still images usually employ regional learning. Zhao et al. [22] inserted a region layer into a classical CNN to learn the features of AUs on sparse facial regions, and trained the model via multi-label learning. Shao et al. [18] further cascaded region layers with different sizes of patches together and employed an attention mechanism for AU detection.

III. DATA

In total, the dataset used for this study contains 20180 labeled video clips across 31 AUs or ADs, with durations ranging from 0.05 seconds to 2 minutes. The data is recorded across eight horse subjects. We randomly sample one frame from each labeled clip to use as input for our classifier.

The class distribution is quite uneven. There are, e.g., 5280 labeled samples for EAD104 (ear rotator), but only one for AD160 (lower lip relax). For our experiments, we selected the 11 categories listed in Table I. Each contains more than 200 labeled crops, which we consider to be the minimal sufficient number of samples for the training, validation and test sets. However, we quickly found that the ear action descriptors were not suited to detect using still images, since they are defined by movement. For this reason, we chose to exclude EAD101 and EAD104 from our experiments.

We perform subject-exclusive eight-fold validation across the different horses, using six for training, one for validation and one for testing in each fold.

As for the sampled images, the original sizes are 1910 × 1080 or 1272 × 720. For the face, eye and lower face crops, we first zero-pad the detected regions, to then resize them. Face crops are resized to 512 × 512, as they are then fed into YOLOv3-tiny whose default input size is 416 × 416. Eye and lower face crops are resized to 64 × 64 for the modified DRML and modified AlexNet classifiers, which can run on smaller input sizes.

IV. METHODOLOGY

Considering the class imbalance, the dataset is not suited for multi-label classification. Initial tests were carried out in this fashion, but the model would get stuck in a local minimum where it predicted the dominant AUs to be true and the others to be false. Therefore, we use multiple binary classifiers for the nine classes. For each binary classifier set-up, we randomly sample negative samples to make the number of positive and negative samples equal. This was done for both the training, validation and test split of the data.

Further, binary classification for facial AUs is a highly fine-grained image classification task. As such, directly applying networks for common image classification tasks will fail to reach acceptable results. Noticing that the horse face is usually only a fraction of the raw frame (Fig. 1), and inspired by the framework for sheep pain estimation by Lu et al. [12], we propose our Deep Learning cascade framework (Fig. 2) for horse facial AU recognition. For each input image, we first detect the horse face and cut it out. Then, depending on the facial location of the action unit class, we extract either the eye region or the lower face region (including nostrils and mouth) from the detected face region. This is because the eye regions and the lower face regions naturally take up even smaller fractions of the raw frames, and the detector network is not able to detect these regions directly. Finally, two CNN-based models for image classification are used as binary classifiers for the respective classes belonging to these regions. Note that the classifiers are trained separately for each class.

A. ROI Detector

YOLOv3 [15] is a widely used object detector, with high performance with respect to both average precision and computation speed. For our task, we chose one of its light-weight implementations, YOLOv3-tiny for the ROI detection, since...
evaluate the performance of the DRML model and AlexNet relatively “easy” classes. Using eight-fold validation, we images and the class has more labeled samples than other shape of the inner brows) are relatively easy to recognize in brow raiser), because the key features of AU101 (the angular facial AU recognition. We evaluate these on AU101 (inner A. Model Exploration on AU101

11 kernels (instead of 5 convolutional layer in each model to use 64 the input to a resolution of 5 × 11 as in the original models).

V. EXPERIMENTAL RESULTS

A. Model Exploration on AU101

First, we explore which frameworks are suitable for horse facial AU recognition. We evaluate these on AU101 (inner brow raiser), because the key features of AU101 (the angular shape of the inner brows) are relatively easy to recognize in images and the class has more labeled samples than other relatively "easy" classes. Using eight-fold validation, we evaluate the performance of the DRML model and AlexNet on raw frames, detected face regions, and detected eye regions, in turn. Results are shown in Table II.

For both DRML and AlexNet, we observe that there is no large difference between classification on the raw frames and on face crops. The results are merely random. We further employed Grad-CAM [17] to visualize what the critical portions of the images were for these classifiers (Fig. 3). According to the visualization results, both classifiers failed to focus on the relevant regions, i.e., the inner brows, both for the raw frames and face crops.

Our hope was that if we forced the classifiers to focus only on the eye regions, they could learn something meaningful for the recognition of AU101. The last two columns in Fig. 3 show that although the classifiers sometimes still look everywhere in the eye regions, they become able to pay attention to the exact inner brows in some cases. Based on these results, we believe that for the task at hand, it is critical to give pre-defined ROIs as input to the classifiers.

B. Model Validation on Eight Other AUs

Based on the experiments on AU101, we carried out experiments on eight other AUs on the eye and lower face regions. The results are shown in Table III.

In these experiments, generally, the difference is not large between the performance of DRML and AlexNet, but the DRML typically showed a more stable performance across the different subject folds than AlexNet. For most AUs, the results lie close to the those on AU101, except for AU47 (half blink). Moreover, AU47 is sometimes confused with AU145 (blink). We believe that this is because the difference between the presence or absence of AU47 is too small in still images. Our framework would need to be extended to take sequences of images as input to to detect it, as in e.g. [1].
Similarly, we note that theoretically, we cannot distinguish AU145 (blink) from AU143 (eye closure) in still images because the sole difference between these is the duration of the time the eyes remain closed. However, since the AU143 class has too few samples in our dataset, we did not include it in our experiments. Therefore, the bias of our dataset causes this ”good” result of AU145.

To further validate our models, we visualized their saliency maps, shown in Fig. 4. Similar to AU101, the classifiers are in many cases able to pay attention to the correct regions, such as eyelid, nostril, corner of mouth, and tongue (the even columns in Fig. 4), if we crop the pre-defined related regions out before training for classification.

VI. CONCLUSIONS

In this project, we proposed a framework for automated detection of equine facial AUs and descriptors and showed that our framework could help the classifiers to focus on more relevant regions and to improve the classification accuracy.

There are many avenues to explore in the future. Firstly, because the dataset used in this article is quite small and unbalanced, deeper models such as VGG and ResNet cannot be trained well, and multi-label learning is not suitable. These techniques will be explored when we collect enough data. Secondly, we are aware that the attention of our model is not fully stable, and we would like to add an attention mechanism to the classification models to make our framework more effective. Finally, our framework currently does not work well for the EADs. This is probably due to the many possible positions of the ears, which are extremely mobile and rarely still in horses. EADs are therefore probably best determined from video. This is also the case for the blinking AUs (AU47 and AU145). A future direction is therefore to extend the method to the temporal domain.

ACKNOWLEDGMENTS

The authors would like to thank Elin Hernlund, Katrina Ask, and Maheen Rashid for valuable discussions. This work has been funded by Vetenskapsrådet and FORMAS.
REFERENCES

[1] S. Broome, K. B. Gleerup, P. H. Andersen, and H. Kjellström. Dynamics are important for the recognition of equine pain in video. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2019.

[2] J. F. Cohn, Z. Ambadar, and P. Ekman. Observer-based measurement of facial expression with the Facial Action Coding System. *The Handbook of Emotion Elicitation and Assessment*, 1(3):203–221, 2007.

[3] R. Diogo, B. A. Wood, M. A. Aziz, and A. Burrows. On the origin, homologies and evolution of primate facial muscles, with a particular focus on hominoids and a suggested unifying nomenclature for the facial muscles of the Mammalia. *J. Anatomy*, 215, 2009.

[4] P. Ekman. Facial expression and emotion. *American Psychologist*, 48(4):384–392, 1993.

[5] P. Ekman and W. V. Friesen. *Facial Action Coding System*. Consulting Psychologists Press, 1978.

[6] P. Ekman, W. V. Friesen, and J. C. Hager. *Facial action coding system [E-book]*. Research Nexus, 2002.

[7] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2016.

[8] H. I. Hummel, F. Pessanha, A. A. Salah, T. van Loon, and R. C. Veltkamp. Automatic pain detection on horse and donkey faces. In *IEEE International Conf. Automatic Face and Gesture Recognition*, 2020.

[9] K. A. Descovich, J. Wathan, M. C. Leach, H. M. Buchanan-Smith, P. Flecknell, et al. Facial expression: An under-utilized tool for the assessment of welfare in mammals. *ALTEX*, 34, 2017.

[10] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *Neural Information Processing Systems*, 2012.

[11] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg. SSD: Single shot multibox detector. In *European Conf. Computer Vision*, 2016.

[12] Y. Lu, M. Mahmoud, and P. Robinson. Estimating sheep pain level using facial action unit detection. In *IEEE Int. Conf. Automatic Face and Gesture Rec.*, 2017.

[13] F. Pessanha, K. McLennan, and M. Mahmoud. Towards automatic monitoring of disease progression in sheep: A hierarchical model for sheep facial expressions analysis from video. In *2020 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020)*, pages 387–393, 2020.

[14] M. Rashid, K. B. Gleerup, A. Silventoinen, and P. H. Andersen. Equine facial action coding system for determination of pain-related facial responses in videos of horses. *PLOS ONE*, accepted, 2020.

[15] J. Redmon and A. Farhadi. *YOLOv3: An Incremental Improvement*. arXiv preprint arXiv:1804.02767, 2018.

[16] S. Ren, K. He, R. Girshick, and J. Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Neural Information Proc. Syst.*, 2015.

[17] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. *International Journal of Computer Vision*, 128(2), 2019.

[18] Z. Shao, Z. Liu, J. Cai, Y. Wu, and L. Ma. Facial action unit detection using attention and relation learning. *IEEE Transactions on Affective Computing*, 2019.

[19] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. In *International Conf. Learning Representations*, 2015.

[20] J. Wathan, A. M. Burrows, B. M. Waller, and K. McComb. EquiFACS: the equine facial action coding system. *PLOS ONE*, 10(8), 2015.

[21] A. C. Williams. Facial expression of pain: An evolutionary account. *Behav. Brain Sciences*, 25, 2002.

[22] K. Zhao, W.-S. Chu, and H. Zhang. Deep region and multi-label learning for facial action unit detection. In *IEEE Conf. Computer Vision and Pattern Rec.*, 2016.