**Automatic horse blink detection using computer vision and deep nets.**

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Abstract. Measurements of dopaminergic activity in the central nervous system provide valuable information about animal health and welfare. In horses, it has been shown that blink rate is correlated to dopaminergic activity and can be used as a non-invasive biomarker. In this paper, we propose two new algorithms for video-based automatic blink detection in horses. The first algorithm employs an OpenCV object tracker to localize the eye and detects blinks from local color changes over successive frames. The second algorithm is based on a neural net classifier which categories each video frame into either “eye is open” or “eye is closed” categories. It then clusters “eye is closed” frames into distinct blink events. Both algorithms also run a post-processing method to improve prediction accuracy by removing outliers and merging neighboring clusters that belong to the same blink event. The test data set consisted of eight RGB video recordings from three healthy horses moving freely in outdoor environments. Our results show that the first algorithm had better accuracy (81% *>* 31%, p*<*0.01) and lower error rate (27% *<* 69%, p*<*0.01) than the second algorithm. This study is part of an ongoing work to develop an cheap, non-invasive and automated health monitoring system for horses and other bovine animals.

Keywords: object tracking, automatic blink detection, eye-tracking, machine learning, image processing, deep learning

**Introduction**

Blink rate in animals is an indirect measurement of dopamine activity within the central nervous system (CNS) [23]. It can be used as a biomarker for stress [24] but also to identify specific behavioural/neurophysiological phenotypes, or predisposition to those phenotypes (endophenotypes) [25]. In this context, it is an extremely useful, inexpensive, non-invasive marker of CNS dopamine function that can be used to further animal cognition and animal welfare research.

However, when manually counting the number of blinks in animals, there are a number of methodological issues. For example, in horses, different studies have reported different basal blink rates: 8-9 blinks per minute [10], 16-19 blinks per minute [11] and 19±6 blinks per minute [12]. The blink rate variability reported in these studies occurs due to several factors including variations in experimental set up, camera angle, and blink definition. For instance, in Cherry et al [11] blinks were defined as full only if they covered more than 95% of the eyelid whereas in Merkies et al [10] the full blink definition was more qualitative. This highlights the need for a more standardised and reliable method of blink rate analysis. In addition, the manual counting of blinks is time consuming and often limits the frequency and duration of data collection trials.

Furthermore, the manual approach to counting blinks also has its limitations when it comes to characterizing the detected blinks, e.g., each blink activity can be labelled as a twitch, half blink or full blink depending on the kinetics of the eye lids. This can cause variation in the interpretation of blinks (and thus alter count numbers) but the differentiation of blink types may also be functionally important in terms CNS dopamine activity and dysregulation.

Using the horse as a model, the aim of this study was to develop an automated computer vision approach to count (and in the future characterize) equine blink events. Two different algorithms were proposed. The first algorithm was handcoded using classical computer vision methods. The second algorithm used a deep artificial neural network (ANN) trained on manually annotated videos. Hereinafter we will refer to these algorithms as hand-coded and ANN. Both algorithms were tested and evaluated using videos recorded from 3 horses moving freely outdoors.

The rest of the paper is organised as follows. Section 2 briefly looks at the existing blink detection methods in literature and discusses their limitations. Section 3 lists the experimental methods used to collect the data. It describes the two algorithms and provides information about how their performance was evaluated. Section 4 presents the results. Section 5 provides a short summary of the work, discusses its current limitations, and outlines planned improvements.

**Related work**

The majority of existing eye tracking and blink detection algorithms have been tailored to human anatomy, and designed to work in controlled laboratory conditions. Some of these algorithms include machine learning-based Haar Cascades [15], deep learning models (e.g., DeepLabv3+ [22]), object detection and feature extraction algorithms, and toolkits based on histogram of oriented gradients (HOG) and linear SVM (such as the dlib library).

Some research has been done on blink detection in avian species [14] and non-human primates [13] using telemetric eye trackers. In addition, there is a commercially available behaviour analysis software (Observer XT) which was used to annotate horse eye blinks in a semi-automated fashion [10]. Our preliminary work attempted to train a DeepLabCut classifier to detect the blinks but this approach was found to have poor generalization performance in test videos due to the following reasons: the color of the eyelids, as well as the changes in size and orientation of the eye throughout the videos. In addition, within-video illumination varied unpredictably due to changing weather conditions or when horses entered (or left) the stable. In this study, it was therefore decided to use a hand-coded approach where we detect the eye to narrow search space and look for local color changes in the selected area.

**Materials and methods**

Data collection

In total, the data set was comprised of eight RGB videos recorded from three healthy, domesticated horses (the details about the horses are given in Table 1). The duration of each recording was 49±22 seconds (s) (mean±SD) with a 12 s (the shortest video) to 81 s (the longest video) range. All videos had frame rate of 60 frames s−1. During data collection, a camera (GoPro 9, HERO) was attached to a standard equine head collar via a camera mount (VKESEN Backpack Strap Mount). The position of the camera was adjusted specifically to each horse to ensure the left eye was in the field of view, which was checked via the GoPro app. Each horse was loosely held by to a researcher via a lead rope but allowed to move freely and take part in usual activities (eating, drinking etc). All videos were recorded in the animal’s normal environment. To create a rich data set, the recordings included horses with different coat colours, and the recordings were taken under a variety of lighting conditions including inside the stable, outside the stable, sunny, and overcast.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Horse | Color | Breed | Height (cm) | Age (years) | Gender |
| Mitch | Chestnut | Welsh Section C | 134 | 25 | Gelding |
| Iona | Bay | New Forest  Pony | 144 | 29 | Mare |
| Pip | Grey | Connemara | 152 | 15 | Gelding |

Table 1: The demographics of the three horses used in data collection.

Video annotations

To obtain ground truth blink events, all videos were annotated manually by trained human observer. The videos were played frame by frame and four time points were noted down for each blink event: i) the first frame after the horse started closing its eye, ii) the first frame when the eye was fully closed, iii) the first frame when the horse started opening its eye and iv) the first frame when the eye was fully open again (end). These video annotations were used to evaluate the performance of the automatic blink detection algorithms 3.

Automatic blink detection

Two different algorithms were created for automatic blink detection. The handcoded computer vision algorithm utilised a region of interest tracker to localize the eye, and detected blinks from local changes in the color of the visible anatomy of the eye. The ANN algorithm was based on a binary deep neural net classifier which labeled each video frame into two categories: “eye is opened” or “eye is closed”. It then ran a post-processing method to cluster “eye is closed” frames into distinct blink events. Both algorithms used OpenCV library to read and display video frames, and they generated a .csv file outputting the onset of predicted blink events.

Hand-coded computer vision approach

The hand-coded algorithm was based on three assumptions: i) the inside of the eye(including pupil, iris and sclera) had different color composition than the outside of the eye (including lids and hairs), ii) when the eye was open, the inside was more visible than the outside, and vice versa; hence a gradual color change was expected during blinking, and iii) the external factors affecting the coloration of the eye (e.g. changes in weather conditions or horse position) were either negligible or could be filtered out using background subtraction. The algorithm therefore is comprised of three main methods: i) eye-tracker, ii) color averaging and background subtraction and iii) blink detection and merging.

Eye-tracker

The user was prompted to manually select a bounding box including the eye at the first frame, and the OpenCV CSRT tracker was used to detect the eye in successive frames. The box is specified by a vector [x, y, w, h]; x and y were the pixel coordinates of the top left corner, and w (width) and h (height) controlled the size. The size of the box varied depending on the appearance of the eye (i.e., size and orientation). The CSRT tracker was selected because it was robust against illumination changes, rapid head movements, scaling and rotation of the eye, and variations in feature space during blinks (e.g., key features of the eye, iris and pupil, disappear during blinks).

Color averaging and background subtraction

The corner regions of the bounding box often contained visual sights that were not part of the eye (e.g., a piece of sky) (Fig. 1a). To minimize corner effects during color averaging, a smaller region of interest within the CSRT box was selected (hereinafter ROI). The ROI had a fixed size (*wroi* × *hroi* pixels), and its center was aligned with the CSRT box (Fig. 1a). For each video frame, the average pixel color (gray scale) was calculated from the ROI (an example is shown in Fig. 2). The average ROI color changed across video frames. The initial investigation with preliminary data indicated that fast changes corresponded to actual blinks (involuntary blinks typically occurred on a timescale of few hundred milliseconds or less) and slow changes to fluctuations in background illumination (typically on a timescale of few seconds or more). A high-pass filter was devised to filter out the illumination effects, which were estimated using a moving average method with a relatively large sampling window (*s*), and subtracted from the original data (Fig. 2b, c).

A close-up of an eye

Description automatically generated

Fig.1: a) An example frame from video GH010022. Dark and lime green boxes represent bounding box from CSRT tracker and ROI, respectively; b) Four cropped ROI frames during an example blink event: eye closing (top left), eye closed (top right), eye opening (bottom left), eye fully open (bottom right). Frame numbers are also shown.

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Thresholding

A two-step threshold algorithm was used to detect blinks in the filtered data. In the first step, filtered data (*x*) was converted into binary data (*y*) using an amplitude threshold (*a*): if |*x*| *< a*, *y* = 1, else *y* = 0. The threshold was manually adjusted to each video through trial and error process and ranged from -3 to -15 (Fig. 2c). Each cluster of ones in the binary data was regarded as a candidate for a blink event. In the second step, the onset and duration of each candidate was estimated from the binary data. This information was then used to merge events with short inter-event interval (i.e., time interval between two events). This step was included in the algorithm after observing that in some data sets, full blinks created bimodal color change with two distinct peaks (Fig. 2c). The merge criteria was based on a time threshold (*tm*); i.e., if inter-event interval *< tm*, “merge”. The (*tm*) was chosen to be smaller than the minimum inter-blink interval observed in our entire data set. After merging, the list was iterated second time to identify outliers (i.e., events with very short duration). Again, the remove criteria was based on a time threshold (*to*); i.e., if the duration of an event *< to*, “remove”.

A graph of a heart beat

Description automatically generated with medium confidence

Fig.2: Automatic blink detection over 600 frames from video GH010022 (hand coded algorithm). a. Raw signal (average color change in ROI). b. Background illumination change. c. Filtered signal (a−b). The dashed line indicates the amplitude threshold. Note that each blink had a different amplitude and

waveform. d. Binary data showing candidate blink events. e. Predicted blink

events (after merging and outlier removal). f. Actual blink events (from video

annotations). For this sequence, the algorithm predicted four blink events (that occurred after frame number 400) correctly (TP), but also predicted one additional event between frame numbers 100 and 200 which was not listed in the ground truth annotations (FP).

Parameter selection

The performance of the hand-coded algorithm depended on several key parameters which were assigned the following values using an ad-hoc approach: ROI dimensions (*wroi* = *hroi* = 50 pixels), sampling window (*s* = 60 frames), amplitude threshold (*a* = 5 − 15), and two time thresholds (*tm* = 20 frames and *to* = 1 frame). All parameters had a fixed value except from *a* which was tuned for each data set manually.

ANN algorithm

The ANN algorithm was based on two assumptions: i) although blinking was a continuous event (where eye closes and opens gradually), the frames during blinking was discretized into two groups (either eye was open or closed). When eye was mostly open, the frame was classified as open, when eye was mostly closed, it was classified as closed, and when eye was partially opened, it could go either way. ii) during blinking, there will be at least a certain number of frames classified as “eye is closed” so that a blink event could be detected reliably. The ANN algorithm was comprised of two methods: i) binary classifier and ii) blink detector.

Binary classifier

A Dense Convolutional Network, DenseNet [20], was trained to achieve the frame-by-frame binary classification. The network architecture was the DenseNet121 implementation from the MONAI library, which included four dense blocks (block config = [6,12,24,16] and growth rate = 32). The feature map (output of the convolutional layer) was represented with 1×1024 neurons. The firing patterns from these neurons were evaluated using a single fully connected decision layer (with a sigmoid activation function) to calculate the probability of a frame belonging to the “eye is closed” class. The continuous output of the DenseNet (*x*) was converted into binary signal (*y*): if *x > τa*, *y* = 1, else *y* = 0.

The data set was split into three groups: six videos for training, one video for validation and one video for testing. The training data was comprised of equal number of “eye is open” and eye is “closed” frames. The DenseNet was trained using Adam Optimizer algorithm [21] over 100 epochs, and the standard cross entropy was used as a loss function. The performance on the validation video was taken as a reference while saving the models after each epoch. The final performance of the trained DenseNet was evaluated on the unseen testing video. Overall, eight models were obtained using different training/validation/testing video splits, so that all videos appeared in the testing group.

Blink detector

The trained DenseNet was run on the testing video to classify each frame into one of the the two groups. “Eye is closed” frames which appeared in a successive order were clustered together, and each cluster was evaluated as a candidate for a blinking event. During blinking events, the network classified many “eye is closed” frames correctly. However, there were also a number of misclassified frames during blinking and other times. These misclassified frames negatively impacted the performance of the ANN algorithm in two different ways. First, there were instances when multiple clusters were detected during a single blinking event. Second, there were instances, when incorrect clusters appeared outside the blinking events (i.e., false positives).

A post-processing method was devised to handle misclassified frames, similar to the thresholding method described for hand-coded algorithm. First, one dimensional convolution (with window size *c*) was used to generate a continuous data from the binary DenseNet output. An amplitude threshold *τa* was then applied to identify candidate blink events. The onset and duration of each blink event was estimated from the binary data. Finally, this information was then used to remove events with short duration (*< τo*) and merge clusters with short inter-cluster intervals (*< τm*).

Parameter selection

Again, an ad-hoc approach was used to select the appropriate values for *c* = 5, *τa* = 0*.*5, *τo* = 1 frame and *τm* = 20 frames.

Performance evaluation

The performance of the proposed algorithms was evaluated as follows: For each video, predicted and actual blink events were compared to calculate true positives (TP), false positives (FP) and false negatives (FN):

TP - Predicted blinks that overlap with the actual blinks.

FP - Predicted blinks that do not overlap with the actual blinks. – FN - Actual blinks that the algorithm failed to predict.

A paired t-test was run to determine if there was a significant difference between the means of the two algorithms. The significance level was bonferroni corrected (i.e., p*<*0.01) as the test was repeated three times: one for TP, one for FP and one for FN. The algorithm with higher TP and lower FP would have higher classification performance.

**Results**

In total, 100 blink events were used to test the algorithms. The percentage of correctly detected blinks (TP divided by total number of events multiplied by 100) by the hand coded algorithm was significantly higher than the ANN algorithm (81% *>* 31%, p*<*0.01) The hand coded algorithm also had significantly lower error rate (FP divided by total number of events multiplied by 100): 27% *<* 69% (p*<*0.01). The breakdown of results per video is given in Table 2. In all videos except GH0100023, the ANN algorithm had poor blink detection performance.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Hand coded | | | ANN | | |
| File | No. of events | TP | FP | FN | TP | FP | FN |
| GH010007 | 4 | 2 | 1 | 2 | 2 | 6 | 2 |
| GH010025 | 15 | 9 | 7 | 6 | 5 | 1 | 10 |
| GH010024 | 10 | 9 | 1 | 1 | 4 | 6 | 6 |
| GH010022 | 15 | 14 | 6 | 1 | 4 | 18 | 11 |
| GH010031 | 10 | 9 | 0 | 1 | 6 | 24 | 4 |
| GH010027 | 12 | 11 | 5 | 1 | 2 | 3 | 11 |
| GH010004 | 26 | 22 | 7 | 4 | 1 | 10 | 25 |
| GH010023 | 8 | 5 | 0 | 3 | 7 | 1 | 1 |

Table 2: Results table for hand coded and ANN algorithms.

**Discussion**

Summary

The goal of this study was to develop a camera-based blink detection algorithm in freely moving horses. This cheap and automated solution will enable equine researchers to infer near real-time dopamine activity in the brain, and is suitable for continuous and long-term health monitoring. It will complement existing methods, which are invasive, time-consuming and laborious. Having a standardised and objective method for measuring blink rate (and other kinematic parameters) will facilitate comparing results across research groups and provide new insights into abnormal behaviour (e.g. stereotypies), pain responses and other long-term health conditions.

The existing solutions for blink detection do not fit the horse eye anatomy and there was a need for a bespoke solution that would track the eye successfully despite movement and illumination changes. Two algorithms were proposed. The hand-coded algorithm prompts the user to select an area of interest and tracks color changes within this area. The ANN algorithm uses a binary classifier to label each video frame as “eye is open” or “eye is closed”. It then clusters “eye is closed” frames to detect blink events. Both algorithms run a post-processing method to improve prediction accuracy by removing outliers and merging neighbouring clusters that belong to the same blink event.The post-processing method outputs a .csv file including start and end frames of the predicted events. The test data set consisted of eight RGB videos from 3 healthy horses, and prediction performance was evaluated in terms of TP, FP and FN.

Main findings

The hand coded algorithm performed well detecting actual blinks but also had a number of false positives. This was due to two reasons. First, the CSRT tracker occasionally missed the eye for several consecutive frames by latching on to external features that appeared in the background, causing transient amplitude changes in the ROI color profile which were incorrectly classified as blinks. Second, each blink event had a variable amplitude and waveform, which made it more difficult to find an optimal amplitude threshold; As the threshold was lowered (or increased), both TP and FP increased (or decreased) proportionally.

Surprisingly, the ANN algorithm had a poor blink detection performance, due to the fact that the DenseNet models failed to learn the correct decision boundary between “eye is open” and “eye is closed” categories. In the current data set there were only 300 images where eye was fully closed. Given that the eye occupied a small area in the video frames (small object problem) and the inter-video variability was high, further training with a larger data set is likely necessary to achieve better performance. Alternatively the DenseNet models could be trained on segmented images (for instance, ROIs used in the hand coded algorithm). A recent study on human eye blink detection produced promising results using this approach [22].

In addition to achieving better performance, the hand coded algorithm was more transparent (allowing us to study and learn from failures) and computationally less taxing than the ANN algorithm (although this needs to be confirmed by performing a formal time complexity analysis).

Limitations and future work

While running the hand coded algorithm, we were manually tuning the amplitude and frame thresholds using a trial and error process. Optimal threshold values, which varied considerably across videos (amplitude threshold between -3 and -15 and frame threshold between 20 and 30), improved blink detection accuracy by more than 20% compared to using fixed thresholds across all videos. However, manual threshold selection is a laborious process which requires the user to analyze the same video multiple times. To address this problem, we are currently working on a new automatic threshold selection method.

The hand coded algorithm also requires the user to initialize the eye-tracker by selecting the eye in the first frame. Manually selecting an area of interest is cumbersome and to an extent prone to fault as areas are often selected resulting in a slightly different color average. The ongoing work focuses on incorporating an automatic eye segmentation algorithm with ellipsoid contour.

So far, the performance tests were performed on a small data set using videos from three horses. These horses had chestnut, bay and gray color, three of the five most common horse colors (black and pinto being the other two) thus providing a good representation of any potential color issues during the analysis. Future data sets will however use new videos featuring different colored horses and different weather and environment (indoor vs. outdoor) situation. One perceived problem going forward will be the use of the hand coded algorithm on a light colored horse which may not have a clear contrast between sclera and eyelid.

The study will also incorporate a pattern recognition module to characterize the detected blink events; for instance, to differentiate between full and half blinks as well as between spontaneous and reflexive blinks.

**Acknowledgements**

This research was funded by UKRI Center for Doctoral Training Scholarship to BP and OA, Health and Care Research Wales PhD Scholarship to STD and OA, and European Commission H2020-MSCA-RISE-2019 Grant to OA (grant number 873178).The models used for ANN portion of the work were run through supercomputing Wales facilities in the AccelerateAI cluster. AccelerateAI is partfunded by the European Regional Development Fund through the Welsh Government.

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