Can a Machine Learn to See Horse Pain? An Interdisciplinary Approach Towards Automated Decoding of Facial Expressions of Pain in the Horse

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Abstract

Because pain is a manifestation of disease, effective pain evaluation is of cardinal importance. Behavioural standardized scales have become key tools for pain evaluation in animals. However, prey animals are challenging as the may display subtle to no visible behaviours during direct observation. Consequently, Machine Learning has the promise of being a useful clinical as well as educational tool for many reasons. It can offer pain surveillance 24-7 without disturbing animals; it can generate real-time analysis and warning signals instanteously; and it can transfer valuable expert pain knowledge to novices through illustrative visuals for a better consensus. We have focused on the coding of the equine facial expression of pain - an important spontaneous component of pain behaviour - as the primary basis of Machine Learning input metrics. First, specific anatomy points of key interest are registered as "keypoints." As there are currently no large animal databases that can be used as reference material for training the machines to recognize these key points, members of our team have created an ingenious solution. They have created a method for transferring human database recognition of facial keypoints to the facial expression of horses and sheep, with an impressive low failure rate. The next step is to move from detection of still to moving images for better accuracy. The strength of our team is the interdisciplinary approach to address pain, with potentially translational implications for better health and well-being for human and non-human animals.

Introduction

Pain is an important subject of study since it decreases animal welfare. Much controversy exists about the nature of pain and the exact differences between nociception and the experience of pain. The International Association for the Study of Pain (1) defines human pain as "an unpleasant sensory and emotional experience associated with actual or potential tissue damage or described in terms of such damage." Without entering into the details of pain per se, the emotional component, the assessment of pain in animals poses a number of unmet challenges. Animals cannot verbalize their pain as humans can. The subsequent use of standardized behavioural pain scales is challenged by the fact that prey animals, such as horses and cattle, display subtle and less obvious pain behaviours (2).

Moreover, pain is a manifestation of disease. Examples are found in Swedish horse insurance databases where most Swedish horses are registered and disease data have been collected for decades (2). Such data show that the average lifespan of a Swedish warmblood horse is below half of the natural life expectancy (3). The most common specific diagnosis is fetlock arthritis, followed by lameness of undefined origin, other locomotor problems, traumatic injuries to the skin, arthritis in several joints, and colic. In Swedish riding school horses, the overall yearly incidence rate was 1584 events of veterinary care and the total mortalities were 790 deaths per 10,000 horse years at risk (4). These rates are considerably higher than for the general population of insured horses. Nevertheless, there is a large variation in “horse wastage” among riding schools: some riding establishments have strategies that positively effect the risk of injury and death (5). The large variation in veterinary claims made, in number of days-lost per horse-days-at-risk, for various diseases, indicate that large differences exist in the basic recognition and/or the management of health-related findings, including pain. The number of pain incidents a horse may experience during its life is thus co-dependent on the caretaker’s ability to monitor its health and wellbeing.

Pain recognition (as performed by a human observing the animal) is not only challenging but also takes significant training and experience. In addition, certain pain behaviours may only be displayed in the absence of human observers. Consequently, teaching recognition of pain to machines may not only increase the chance of recognizing and monitoring pain: Machine Learning also has the potential of becoming an important and needed two-way educational conduit-learning from expert experience and teaching novices.

Assessment of Pain in Horses

Despite its importance, the identification and management of pain in horses is surprisingly sparsely described in the literature, although different principles of pain quantification have been applied in equine medicine, reviewed by Ashley et al. 2005 (6). It is generally accepted and proven that no currently known single physiological or biochemical parameter is pathognomonic for pain. Because pain is an emotional experience and the use of pain scales is not yet common, there is little general consensus: on the amount of pain accompanying specific diseases or surgical procedures; whether a particular horse is in pain or not; or whether some pain may be “good” for the horse or not. As an example of lacking consensus, practicing veterinarians scored their assumption of pain in horses with the same diagnoses in a range from non-painful to very painful (7). Another consequence of the nature of pain is that there is no “gold standard” that can be used in pain studies. Therefore “analgesic testing” may be used where appropriate. If an effective pain medication reverses the abnormal behaviour suspected to be caused by pain towards normal behaviour of the horse, there is reason to believe that the horse was in pain.

Modern horse pain scales are primarily based on behavioural parameters that are more pain-specific than physiological measures (8-13). These scales were developed for use in hospital environments and the first scales were built on comprehensive registrations of activity budgets for healthy and painful horses.

Equine Pain Behaviour

Horses are flight-fight animals preferring to flee from threatening situations, including pain. If hindered in their natural escape behaviour, they might turn aggressive towards owners and caretakers. Consequently, pain should always be suspected when a horse shows a sudden and/or inexplicable aggressive change in behaviour. In their own surroundings, horses in pain are typically depressed with decreased physical activity, decreased appetite and a diminished interest in socialization. In foreign environments that can be perceived as threatening, this behaviour is often concealed, especially if the horse feels watched. Threatening environments could be new stables, hospitals, or the presence of unknown people, as veterinarians or new caretakers. These are the exact same condition for example for a hospitalized, sold, or riding school horse. Horse specific ethograms derived from careful observation of non-painful and painful horses in their own environment is central in the development of a valid pain-scale (6, 14, 15). Also, the observation of the undisturbed horse is a prerequisite for the specificity and sensitivity of the scale.

Composite Measure Pain Scales

The current most valid pain scales contain scorings of combinations of behavioural and physiological indicators of pain, so called composite measure pain-scales (CMP-scales) (13). CMP-scales for the evaluation of abdominal and/or orthopaedic pain in horses, with subsequent initial attempts at validation and determination of intra- and/or inter-observer agreement have been proposed by a number of research groups (11, 14-16). These CMP-scales have been used successfully in experimental pain models. One CMP-scale has been applied in a clinical setting where it discriminated well between horses with and without pain and had good inter-observer reliability (16). Recently, the performance and robustness of a CMP scale in horses with and without pain, developed by our group, was evaluated among veterinary students with little clinical experience. The scale was robust and had good inter-observer agreement for horses with and without pain (17) .

The CMP-scale used in this study contained a range of simple descriptive scales which score pre-selected behavioural and/or physiological features. Scale categories that are simple to understand and score would be, for example: the assignment of the location and position of the horse in box and the scoring of the height of the head of the horse in relation to the withers. Also, the interaction between the horse and the caretaker can be scored quite objectively. However, the CMP-scale also contains subjective scorings, which are derived from human medicine, the Visual Analogue Scale of Pain Intensity (VASPI) and the Numerical Rating Scale (NRS). The VASPI scale is defined only by its two endpoints - “no pain” and “worst imaginable pain.” There are no marks or definitions between these. While the human patient scores his/her own perceived pain intensity, the subjective elements in the CMP scale are scored by the observers of the horse. The VASPI scale accounts for information that potentially could fall outside the rigidly defined and very simple scoring criteria in a painful horse. This VASPI continued to score high in painful horses: we later defined that the facial expressions were key to high VASPI scores. Therefore, the concept of facial expressions of pain were developed to be included in the CMP. Horse owners and horse practitioners have over the years intuitively used the “worried” look as an un-specific indicator of disease. Yet no studies exist on the reliability of these signs (18).

Facial Expressions of Pain

Facial expressions of pain are known to be part of a communication system in humans. They are considered necessary to interact with other people (19). Spontaneous facial expressions of pain are believed to be innate responses that reflect activation of the nociceptive system. Contrary to this innate response, “stoicism” is considered an active suppression of the pain expression.

During 2014, two independent research groups published, for the first time, investigations on the facial expressions of pain in horses (20, 21), showing that horses exhibit a range of facial expressions when experiencing episodes of acute pain. In (20), pain was induced in otherwise healthy horses using known pain models, whereas the horses in (21) were postsurgical hospitalized patients, where the effects of residual anesthetic drugs and fatigue were present together with the postoperative pain from castration. Nevertheless, a range of facial cues appeared to be similar, namely “low or asymmetrical ears,” “angled appearance of the eyes,” “withdrawn/tense stare of the eyes,” ”medio laterally dilated nostrils,” and “visibly increased tension of the muscles of the mouth, lips and chin.” Interestingly, these features correspond to the more formalized ontology (22) described below.

Can People “See” Pain in Horses?

It is widely accepted that humans have a neural apparatus for processing facial cues to recognize emotions, including pain (23, 24). This has proven useful as a tool in pain assessment in non-verbalizing humans such as infants (25). Facial expression of durations less than 0.5 seconds may be interpreted and training may further improve this decoding ability (26). A pilot study was conducted to investigate if persons of different background could be trained to assess clinical pain in video films of horses (27). The study showed that at least some people can be trained to recognize moderate and severe pain with moderate rater agreement in video clips of horses when video clips were selected and trimmed by the research team. However, movement, stress, coat colour and nervous behaviour of the horse interfered with the correct interpretation. Other and less time consuming objective and automated methods are therefore necessary for correct decoding of the facial cues in a large number of horses. Sensitivity and specificity could not be calculated due to the pilot nature of the study and the lack of gold standard for pain.

Computer Assessment of Equine Pain Expressions

As discussed above, there is significant evidence that horses communicate their experiences of pain in a rich manner to other horses and humans, not least through their repertoire of facial expressions. Moreover, it has been shown that humans can learn to recognize these expressions of pain. However, as mentioned above, horses may hide these expression under conditions they perceive as threatening. Therefore, we argue that there are great benefits of training computers to recognize horse pain, using different types of Machine Learning methods.

Facial Action Coding System (FACS)

The Facial Action Coding System (FACS) (29) provides a method for identifying and recording facial expressions based on the movement of the underlying facial muscles. FACS exhaustively describes all observable facial behaviour in terms of the muscular actions that comprise it, using elements called action units (AUs) (28). Each AU, designated by an arbitrary numeric code, denotes the movements of an underlying facial muscle group. FACS coders rely on direct observation of facial muscle movement as well as changes in facial morphology (e.g., the position of the eyebrows, size/shape of mouth, lips, or eyelids, the appearance of various furrows, creases, bulges of skin, etc.) to determine which AU(s) occurred. Any interpretations made about the emotional meaning of the observed AUs occur post-coding. After appropriate training, human observers are able to use the FACS-system with high agreement between coders. FACS has been adapted to several animal species, for example orangutans (29), cats (30), mice (31) and dogs (33).

Although FACS may not always be sufficient to capture the emotional state of some animals (31), the objective nature of this coding scheme makes it highly suitable for automation. We will now review the adaption to horses.

EquiFACS

The adaption to horses, EquiFACS, is based on a thorough dissection of underlying facial musculature and filming of naturally occurring facial expressions of the horse (22). EquiFACS is strictly based on muscle anatomy while other ethograms may use concepts such as grimaces that may reflect changes in other adjacent tissues. This difference may be of importance when evaluating pain score scales based on different ethograms.

Facial expressions in horses are dynamic and often complex signals that can change rapidly in response to a range of environmental stimuli and internal affective states (32). The facial expressions of ridden horses may reflect responses to a range of stimuli, including responses to the signals from the rider, pressure from saddle and tack (33, 34), and interactions with the surroundings, in addition to pain. It is therefore imperative to take these complications into account when designing studies evaluating facial expressions in horses. A carefully prepared protocol must include control of exposure to external stimuli and factors so that demonstrated differences really can be ascribed to pain. The lack of a gold standard for pain is an issue that must be addressed when implementing computer recognition of pain.

One important consequence of the rapidly changing facial expressions across mammals is the use of still photographs which may pose limitations to the interpretation of facial expressions. Selected stills images are prone to selection bias. In addition, the use of a single frame carries an inevitably loss of information in temporal distribution, as shown previously in the work by Wathan (22). Wathan argues that certain facial movements can only be distinguished accurately from sequences. This is particularly true of facial movements around the muzzle and corresponds with Mullard et al.'s (35) results that show that indicators around the muzzle were poorly interpreted. Preparation of un-validated and "case-based" ethograms based on still images out of context – a situation known from for example blinded scorings - is therefore not advisable.

Can computers be trained to "see" pain in horses?

Computer Vision science has now advanced to the point where automatic facial expression recognition systems can be used in the investigation of behavioural research (36-39). During the past decade, fully-automated systems have been developed for recognition of basic human emotions (neutral, anger, disgust, fear, joy, sadness, and surprise) in video streams of human faces. For example, Littlewort et al. (39) achieve 100% accuracy on emotion classification for four of the seven expressions and are additionally able to code videos and images with action unit (AU) activations and intensities in real-time. Performance on pain identification in humans is similarly high, with Rodriguez et al. (40) reaching 91.3% accuracy. Figure 1 show a visualization of what a Machine Learning model has learnt to detect in face images.

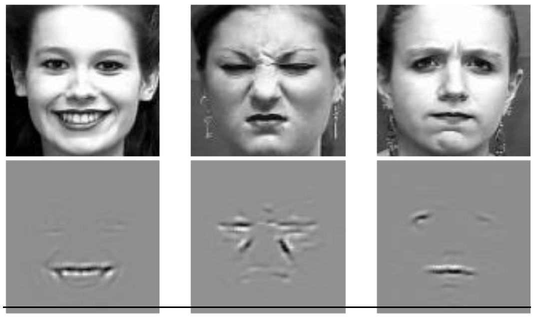

Figure 1. Top row: Images with happiness, disgust, and anger expressions. Bottom row: facial patterns that a Machine Learning model (CNN) has learnt to detect, as visualized in (48).

These systems learn to identify patterns of facial features that distinguish one expression from another, using a large set of "ground truth" examples provided by expert human observers. They not only give comparable performance to human experts but are also often able to produce real-time predictions for video data. Meanwhile, human experts can take up to 3 hours to code a 1-minute video by hand. There are no existing analogous systems for recognizing facial expressions or pain in videos of animals as there are for humans.

A rudimentary issue with animals is the need for registration of the facial image before expression recognition can be attempted. An approach to this is to detect facial keypoints, i.e. points in an image or video that indicate the location of an important part of the face. For example, Figure 2 (source?) shows the facial keypoints that indicate the location of the horse's nose, mouth and eye corners. The registration of the facial image, "face alignment," uses the keypoints to rotate, scale, or otherwise transform images so that the location of the keypoints are approximately the same across all images in the training data. This helps in extracting useful features during both training and testing. Keypoints are also used to extract features around parts that visually change with AU activations. Therefore, it is important to reliably detect facial keypoints so that high performing systems can be developed.

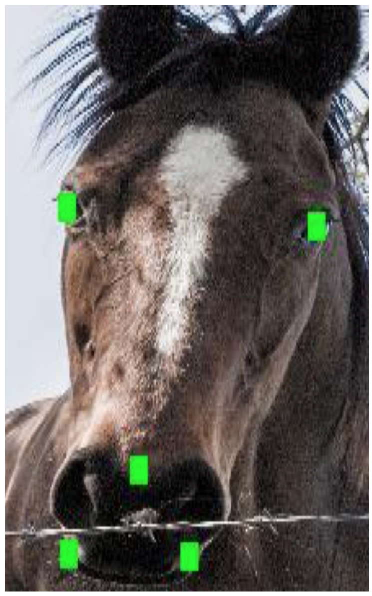

Figure 2. Example of facial keypoints on a horse face, from (47).

Keypoint detection, like other Machine Learning tasks, needs training data. While there are large datasets with human facial keypoint annotations, e.g. (41), there are unfortunately no large datasets of animal facial keypoints that could be used to train a Machine Learning method from scratch – for instance, the sheep dataset from (42) has only ~600 images. To address this limitation, Rashid et al. (47) developed a method to transfer information from human datasets for animal keypoint detection by training a Convolutional Neural Network (CNN) to reduce the structural face shape differences between human and animal faces (43). The method achieved state of the art performance on both horse and sheep facial keypoint detection with 8.36% and 0.87% failure rates, respectively.

In parallel, Bhatti (43) has developed a preliminary horse pain detection method based on feature extraction with Gabor filters and linear classification. Even with this standard method, they reached a classification accuracy of up to 78% accuracy in horses. Experiences with the performance improvement in human pain expression recognition with the introduction of Deep Neural Networks, e.g. (42), lead us to hope for massive improvements in automatic recognition of equine pain expressions using these kinds of methods. We are exploring two different traits, one where we focus on the face and register facial images using keypoint detection (47) and capsule networks (49,50) and another where the method learns more holistic cues about the entire horse pose, weight distribution, and spatial behaviour.

Moreover, the current methods for horse pain detection are based on still images. This means that temporal information has been ignored. As shown with both humans (42) and horses (24), temporal information is important when a human interprets signs of pain. We therefore focus the holistic behaviour study on temporal information, using a combination of Long-Short Term Memory (LSTM), a temporal Deep Neural Network, and CNN.

Concluding comments

The work described in this paper is part of a larger effort aimed at improving standards for recognizing and assessing pain in horses and other mammals. Also, we wanted to investigate the potential development of technology platforms that can monitor and detect pain automatically in real-time. During this process, we have learned that an interdisciplinary approach is needed from the outset, for example, to avoid differences in descriptions of AUs or collection of data that inadvertently teaches the machine inaccurate categories. The clinical implications of valid and reliable pain recognition, assessment and monitoring are critically significant for both animal welfare as well as human health and wellbeing. The technology platforms eventually could also support a productive research agenda to further our understanding of pain and related states such as fear, fatigue and stress.

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