Supporting Animal Welfare with Automatic Tracking of Giraffes with Thermal Cameras

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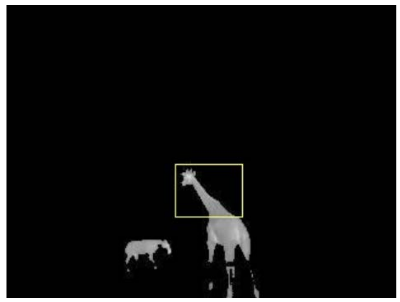


Figure 1: Unprocessed Thermal Camera vision of Giraffes. Figure 2: Sample image demonstrating giraffe neck detection, distinguishing Giraffes from Zebras. Figure 3: Location data visualisation over Giraffe enclosure

ABSTRACT

Externally observing of animal behaviour is an essential method for understanding and improving captive animal welfare, but is limited by observer subjectivity and high-labour costs, and is not embedded in day-to-day care. In this paper, we present a solution via a system that utilizes a single thermal camera to automatically locate giraffes within their enclosure, matching human estimation accuracy. We present an account of the development of this system, our approach, and an evaluation through focus-group interviews with zoo-keepers which provide insight into the most appropriate visualisation methods, and the future opportunities for automatic tracking technologies to support husbandry practices, zoo visitor experiences, and conservation education.

KEYWORDS

Digital ethogram, giraffes, animal-computer interaction, visualisation, zoos, husbandry

CCS CONCEPTS

•**Human Centred Computing → Interaction Design**.

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1 INTRODUCTION

Observation of captive animal behaviour using *ethograms* (libraries of animal behaviours) and *activity budget assessments* (how much time an animal spends doing different activities) provides essential information regarding animals' preferences and wellbeing [20], and are widely used by zoos to provide information on animal welfare. However, as these are done manually they are costly, labour-intensive, subjective, limited to daytime observation, and typically reactive to welfare concerns.

In this work-in-progress paper, we present the development of *GiraffeTrack* which utilizes a single thermal camera to locate giraffes within their enclosure, matching visual human-estimation. Similar to Gan et al. [8] we employ infrared thermal cameras as we are interested in monitoring both daytime and nocturnal behaviour. We describe how the principal components of the system work; namely, background segmentation, animal detection via Viola-Jones algorithm, tracking across frames, and how we interpret location data.

Based on focus-group interviews with giraffe zoo keepers at Melbourne Zoo, we identify the key opportunities for this system and digitised animal observation more broadly, principally; (1) the opportunity for 24/7 active monitoring, with the capacity to automatically flag potentially problematic changes in behaviour, (2) the ability to evaluate the impact of changes in husbandry practices, enclosure features, or zoo visitor behaviour, and (3) the potential for these systems to connect zoo visitors with animal welfare research and motivate pro-environmental behavioural change. We situate this work within the emerging field of animal-computer interaction and its goals of (a) providing methods for animal welfare enhancement with interaction design in mind, and (b) breaking the boundaries of technology and animal science by merging interaction design methods and computer science [18].

2 RELATED WORK

2.1 Technologies for Animal Detection

A breadth of research and commercial work utilizes invasive and animal-attached technologies to monitor animal behaviour and welfare, typically using GPS [13], accelerometers [3] or RFID systems [14, 35]. However, zoos are often reluctant to utilize animal-attached technologies that may negatively impact zoo visitor experience and perceptions of care, despite potential welfare and research benefits (e.g., [9]).

Various works have proposed and demonstrated methods that monitor animals remotely via images and videos, with computer vision algorithms [1, 22, 29, 31], but rarely with zoo animals. The majority of work focuses on either animal-attached device (typically in meat-production industries) or applying computer vision algorithms to studying lab animals in highly artificial and constrained environments. Remotely monitoring animals in zoos is far less controllable [23]. One notable exception is the work by Gan, Carr and Soltis [8] which uses computer-vision techniques to identify the *presence* of giraffes in video footage, to assist human-classification of behaviour and location by compressing video footage, but does not classify the giraffe behaviour.

2.2 Animal-Computer Interaction

This work is situated within the emerging field of animal-computer interaction [18], and its goals of providing methods for animal welfare enhancement with interaction design in mind, as well as merging computer science and interaction design with animal welfare science. Prior work in ACI has explored the use of remote animal tracking as an interface for providing enrichment for domestic pets [29], or as a method to evaluate the welfare of horses [23], though that system is currently only proposed and in-development.

A substantial body of work is now situating ACI research in the zoo context (e.g. see [4, 28, 36, 37]). This work recognises that the goals of ACI align with the goals of the contemporary zoo, namely; "*supporting animal welfare, respect for other species, and positive human-animal interactions*" [4]. Examples include the development of novel technologies for zoo-animal use [6, 11, 28, 30, 36]; studies of how technology impacts zoo visitor experience [24, 37] and how technology can support keeper decision making and welfare monitoring [15, 17]. Like our work, this interpretation of ACI draws on computer-science and animal welfare to explore how technologies can support human-animal relationships, rejecting a limited view of ACI as being only systems directly interacted with by animals.

3 SYSTEM DESIGN

3.1 Preliminary Work

We consequently set out to develop a tool to automatically track zoo animals within their enclosure to further investigate how technology can better support animal welfare monitoring in the zoo context, alongside the other aims of the contemporary zoo. Preliminary discussions with animal welfare staff at the zoo identified the giraffe as being a suitable case due to a staff need (a requirement to understand the giraffe's use of their enclosure during the night, where their activity is currently poorly understood) and ease of implementation (large-size, slow movement, and relevance of their location and activity to assessing their welfare). Building on the work by Gan, Carr and Soltis [8] we elected to use a single thermal vision camera (FLIR E60, 18mm FOL lens) which supported night-vision, as well as relatively simple background segmentation.

3.2 Background Segmentation

The collected thermal file from FLIR cameras is an image sequence file with each image containing a matrix of 240x320 temperature values, and other properties such as date and time. Here, we present the temperature values in grayscale to transform them into visual images (Fig 1). The body temperature of giraffes is 38.5 ± 0.5°C [21], but skin temperature varies depending on the daily temperature [12]. Fortunately, giraffes (and zebras in the same enclosure) are almost always the hottest objects in the frame. Consequently, the system dynamically detects the regions with the top 20% grayscale values in the whole frame as animals and segments the background. Most regions of the giraffe bodies are preserved except for lower parts of the legs due to low skin temperature.

3.3 Animal Detection

As zebras share the same enclosure as the Giraffes, the system also needed to distinguish between the two. We proposed three features that could be applied to distinguish them; skin temperature, body size and body shape. However, only body shape was applicable as the skin temperature of the zebras overlaps with the skin temperature of the giraffes, and the size of the animals in the frame vary greatly due to the depth of the animal enclosure. In terms of body shape, it's obvious that the most significant dissimilarity is the giraffes' distinctive necks, therefore, the distinction is made by neck detection. The animal tracking component is divided into two sub-tasks, neck detection and giraffe tracking.

Unfortunately, there is no algorithm described in prior work specifically for detecting and tracking Giraffe necks, so we examined several generic methods that could potentially be assembled or applied to solve this problem. While ***motion estimation*** is commonly used in surveillance systems [2, 10], and was able to track Giraffes across frames with tolerance for occlusion (such as by trees), this approach is unable to distinguish between Zebra-motion and Giraffe-motion. While frequently used in ACI (with dogs [27]; with rats [31]; and with sea turtles [25]) ***template matching*** does not perform well with occlusions or deformable objects (such as a Giraffe bending its neck). In the long term, ***deep learning*** may be an ideal method but it was beyond the scope of this work to prepare a sufficiently large training dataset.

Ultimately, we determined that ***machine learning*** was the appropriate approach. While Gan, Carr and Soltis [8] utilized support vector machines (SVM) to detect giraffe heads and bodies, they noted that it was not feasible to process all detections simultaneously as SVM exhaustively searches through every sub-window of each frame, requiring the video to be divided and processed one frame per second. Rather, Viola-Jones algorithm [34] using learning algorithms based on AdaBoost [7] is more capable at selecting a smaller set of critical features from a large data set. SVM and Viola-Jones were trained with 1000 training images (labelled manually with giraffe neck regions), as well as 2000 negative training images from the segmented frames with no giraffe present for Viola-Jones. SVM classifier took 5 iterations of mining with an non-overlap threshold of 0.3; Viola-Jones was trained with a 5-layer cascade and for each layer, the false positive and false negative rate were set as 0.5 and 0.995 respectively. The algorithms were then tested with 1000 images, in which there were 746 positive images and 254 negative images. Recall, precision and accuracy are calculated based on the confusion matrix of the detection results (See Table 1). Although the SVM classifier could outperform the Viola-Jones algorithm in some occasions (for example, high aspect ratio variation) the slow detection speed and loss of information between frames are unacceptable in a long-time tracking system. The detection time of SVM in our experiment was 10+ times slower than Viola-Jones algorithm.

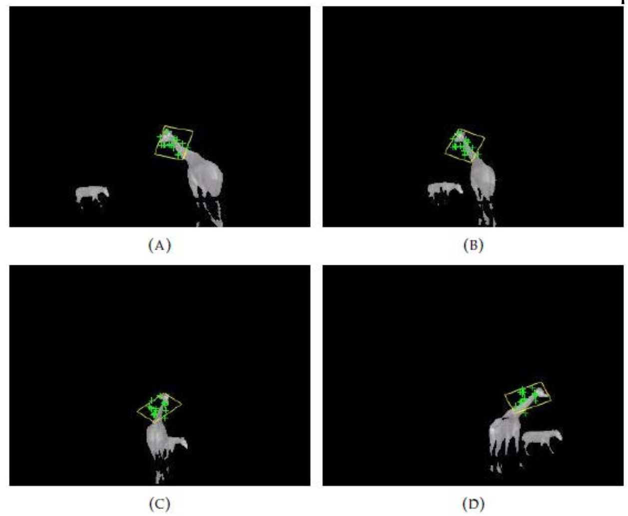
Table 1: Experiment results of object detection algorithms

	Recall	Precision	Accuracy
Template Matching	84.0%	51.9%	53.0%
SVM	83.5%	87.0%	78.6%
Viola-Jones	81.5%	83.4%	74.1%

In our implementation, we trained 1000 positive images with one or more giraffes present. The images are frames from videos with background segmented. Viola-Jones uses Haar Feature selections (*two-rectangle, three-rectangle* and *four-rectangle*, [26]) to detect possible neck regions, select features from all potential features as a strong classifier with AdaBoost, and discard background regions through a 5-layer Cascade Architecture. The training and detection was implemented with *vision.CascadeObjectDetector* in MATLAB Computer Vision System Toolbox. A sample frame demonstrating the result of giraffe neck detection, distinguishing Giraffes from Zebras, is shown in Figure 2.

3.4 Animal Tracking across Frames

Neck detection returns the location of the Giraffes, but applying object detection method on every frame slows it down. To accelerate the efficiency of the system, for each frame similarity values of the feature points are calculated to determine if the current feature points are the same object from the previous frame, otherwise the system reapplies neck detection on this frame, repeating the above operation. Prior work on feature point selection and different definitions of a "good feature" have been proposed [5, 16, 19, 33]. This project detects corners in the



2-D grayscale images as feature points with eigenvalues and monitors the quality of feature points with similarity as proposed in *Good Feature to Track* [32] (see Figure 4).

3.5 Interpreting Location Data

With background segmentation, neck detection and Giraffe tracking, we were able to retrieve the coordinates of detected animals within the frames. However, in order to display the location data in a meaningful way (projected onto a top-down map of the enclosure), the system uses perspective transformation calculation to calculate the distance between the Giraffe and the camera

based on the angle of the camera to the ground as the location

data on the y-axis. While robust when standing with necks raised, when Giraffes bend over the location output becomes closer to the camera. This problem was not solved in this study, but could be resolved by implementing some form of pose-detection. An alternate and potentially more reliable method (also overcoming occlusion issues) would be to utilize multiple cameras, but due to cost and lack of suitable locations for installing the cameras, this was not pursued in this study. The output of the system is a .CSV file with x,y location points for each tracked Giraffe, and a timestamp.

Table 2: Giraffe detection algorithm evaluation

		Prediction	
		Positive	Negative
Truth	Positive	762	238
	Negative	167	133

Recall = 76.2%
Precision = 82.0%
Accuracy = 68.8%

3.6 Evaluation of System Accuracy

To evaluate the accuracy of the Viola-Jones algorithm on Giraffe neck-detection, we tested it with 1,000 positive frames and 300 negative frames, from a variety of weather conditions (August ->

Figure 5: Location data map on a sunny day

December, with rainy and sunny days). Compared to the previous results (Table 1), the performance decreased where the weather conditions were different to the training data-set (see Table 2), but was sufficient for our purposes. The feature point selection is very robust; however, it does not guarantee correct tracking of all Giraffes. When an incorrect giraffe detection occurs, the method tracks the detected object until the similarity values drops below the threshold. The false detection could be a zebra, or a nonliving background object. The incorrect tracking could last for a long time for the latter, as the feature point similarity drops slowly for static objects. Moreover, the nature of the method design causes missing giraffe tracking; if a giraffe appears in the frame during the tracking of other giraffes, the location of this giraffe will not be recorded until a new round of giraffe detection is applied. In our experiments, the average time for a re-detection is within one minute, therefore, the loss of tracking is generally within an acceptable range.

The system outperforms many other studies on animal detection in terms of detection speed, thus is able to produce data of high density. The processing speed for the animal tracking component as a whole matches the thermal video frame rate (30 frames per second, vs. 1 frame per second in [8]) demonstrating the feasibility of the system to track animals in real-time. As we did not have a ground-truth for the locations of the Giraffes within the frames, we could only qualitatively evaluate the accuracy of the location data. Through manual review of sample frames by multiple researchers, we concluded that the location data accuracy level matches human estimation where the Giraffe neck posture is ideal. As the current method used by the zoo is by human-estimation, drawing approximate locations on a piece of paper, this demonstrates that useful automatic location data is achievable. We further note that the goal of location data for animal welfare studies is not necessarily to determine their precise location, but rather, their activity levels over different periods which our system can detect.

4 EVALUATION BY ZOO KEEPERS

Having developed and evaluated the accuracy of the system, we held focus groups with 11 Giraffe zoo-keepers to better understand the opportunities for automatic detection and the necessary interaction design requirements for achieving these opportunities. Focus groups involved a brief introduction of the tracking system, and keepers were presented with one of two location data visualisations from different days (one rainy day (Fig 3) and one dry sunny day (Fig 5)). Thematic analysis was utilized to identify potential usages of the system, as well as necessary and optional improvements to the technology.

4.1 Assisting Day-to-Day Care

Keepers unanimously felt that they "*would definitely use*" the location data and a display of average activity levels as a standard daily reference. The condensed display of sustained observation data could support their day-to-day provision of care. High levels of inactivity are a useful trigger that can indicate a health or welfare concern, and is recognizable from location data visualization but not a brief checkup. This suggests this system could be a useful tool for supporting early intervention on health issues. The keepers also commented that a system like this could support retaining consistent, durable information about 'standard' behavior when zoo-keepers change shifts to care for different animals or staff go on leave.

4.2 Evaluating Changes in Environment

In addition to assisting with day-to-day care, it was felt that *GiraffeTrack* could assist with evaluating the impact of changes in the animals' environment, which would further support decision making. Examples of environmental change that would be of benefit to evaluate includes the effects of adding in additional feeders, shaded areas, providing more access to indoor areas, or trialing new enrichment. Furthermore, this technique would also be particularly useful in evaluating more short-term, but seasonal changes in behaviour associated with fluctuations in visitor number and other events such as the Zoo Twilights concerts held during the evening in summer. There was also substantial interest in how night-time data could support their husbandry decision making to provide more direct insight into what the animals do at night.

5 DISCUSSION AND LIMITATIONS

While keepers felt that this system could be immediately useful if installed, a number of potential improvements were identified. Our system tracks an individual Giraffe across frames, but does not identify which Giraffe it is (of 3 in this enclosure). It was noted that tracking individual Giraffes would help detect issues easier, and would make welfare issues more visible. Keepers were excited about the potential for the system to take up a more active role in supporting care, such as by automatically recognizing deviations in behavior and demanding keeper attention, as a form of early warning system. They also felt that if *GiraffeTrack* could be installed at multiple zoos, the comparison of activity levels and use of the enclosure between zoos could be useful.

For the system to be of most use, the visualizations of the data needed to also include other relevant information such as temperature, rainfall, sunlight, numbers of visitors, and noise levels in the enclosure to assist keepers in interpreting changes in the data. Any implemented system should also provide keepers with the ability to compare multiple different time periods easily to make vertical comparisons of behavior patterns and explore the significance of any changes (such as visually comparing a day to all previous days at that temperature). Being able to do this remotely would also assist when visual checks are not possible. While there is a potential to independently make assessments of behavioral change, the primary use for monitoring welfare will be by visualizing data in an interpretable way so that domain experts can more effectively make decisions about Giraffe care. Consequently, future work should also explore the effectiveness of other visualization methods [20].

As noted by Carter, Webber and Sherwen [4], technologies in the zoo context have tandem opportunities to both improve the provision of animal welfare alongside improving the conservation and educational goals of the contemporary zoo. It was frequently speculated during the development process and during the focus groups that the data collected through this system could potentially be utilized in visitor-facing displays to educate visitors about the effect of noise on the Giraffes; involve them as citizen-scientists in the development or assessment of the system; or help them understand giraffe behavior in more detail. Future work should explore these opportunities.

6 CONTRIBUTIONS

This paper has provided an account of the design of a proof-of-concept system that utilizes computer vision and machine learning to identify the location of Giraffes from thermal video footage. This is the first system of its kind that is capable of locating Giraffes within their environment, with the potential for 24-hour monitoring. Expanding on this, we have presented the results of a focus-group evaluation by giraffe zoo keepers who identified the core opportunities of remote animal tracking in the zoo context and interaction design improvements.

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