Chameleo: walk like a chameleon detection with AI

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Extensive research over the last few years has revealed the potential of computational based models to understand animal behavior. However, computational ethology using reptiles as models is still under investigation. Chameleons are known to have slow arboreal locomotion and present a distinct movement of rocking back-and-forth in between periods of the traditional quadrupedal walk. This curious, and yet, under-investigated behavior known as "leaf movement", has been observed in different species of the genus Chamaeleo. Here we present our work-in-progress and propose the means to quantitatively examine plausible gaits of chameleons using an Artificial Neural Network system named Chameleo. We recorded and labeled around 8 hours of chameleons moving horizontally on a rope in an experimental setup and aim to use this data for training and further testing of the Neural Network. We expect that Chameleo will be an accurate and reliable model for the identification and classification of chameleon locomotion. Furthermore, our long-term goals are to 1) adapt Chameleo to a wider range of lizard behaviors, 2) make the model available for the scientific community through a website where researchers will be able to add additional models and datasets to further explore reptile behavior, 3) contribute to the welfare of pet chameleons, and finally 4) encourage citizen science and thus conservation and environmental protection of the species.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**.

Additional Key Words and Phrases: animal-centered computing, behavior, lizard, machine learning, neural network

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1 INTRODUCTION

This poster showcases the initial work done for the Chameleo system as identified during the 2021 Summer School on Animal-Centered Computing (SSACC). Chameleons present a species-specific locomotion pattern where their body rocks back and forth while standing in the same place or slowly moving forward. This phenomenon is referred to interchangeably as "leaf movement", "jerky walk" or "rocking". From hereon we will refer to it as leaf-movement. The leaf-movement is likely to be important for camouflage via matching environmental motion. Observation, description and characterization of an animal behavior is crucial for the understanding of the plethora of information provided by an individual species. The perks of the chameleon arboreal locomotion, its anatomic features and kinematic parameters have long been discussed. The leaf-movement, however, remains unexplored in natural and experimental conditions.

Behavioral research often requires manual labeling of images and videos, demanding a great investment of time and effort from the observers. This time-consuming task takes at least three times the length of the footage [1]. An automated solution would be beneficial not only by reducing the time of evaluation, but also decreasing human annotation bias and fatigue-related errors. Here we propose the use of a Convoluted Neural Network to identify and quantify the different classes of locomotion in chameleons. In addition, we aim to analyze the relative time spent in each activity and check for differences between males and females. The design proposal was developed at the SSACC in July 2021 through discussion between researchers, including an expert panel from multiple backgrounds. Initially, we aim to investigate the use of neural networks (NN) to describe chameleon locomotion. The idea being that, in the future, this system can be modified and adapted to other lizard behavior, depending on the context of the research. The purpose and motivation of the "leaf-movement" are beyond the scope of this study. Yet, our results may contribute to future research on the functional mechanism underlying this behavior.

2 BACKGROUND AND RELATED WORK

2.1 Chameleon movement and anti-predator behavior

Chameleons are known to be the only truly arboreal reptiles [6] navigating extremely well through challenging arrays of perches. They are occasionally seen on tree trunks [25], but mostly prefer perches of small to moderate diameter in the bush [22], with the average branch diameter for adults being approximately 7mm. Chameleons are highly adapted to arboreal locomotion and camouflage displaying cryptic coloration, lateral compression of the body, a prehensile tail, tong-like zygodactylus feet, highly independent eye movement, and a protrusile tongue feeding mechanism [17, 22]. They developed behavioral strategies to travel on narrow perches and inclined surfaces [10], and to bridge gaps between branches without jumping. The habitat-driven specialized morphology leads to different performance in different tasks such as clinging and sprinting speed depending on the species [9, 13]. Chameleons are extremely slow compared to other lizards, moving at speeds similar to chelonians. Detailed information on the chameleon locomotion system can be found elsewhere [6, 9].

Several behavioral strategies employed by these animals are well described considering the social and evolutionary context (e.g. mating, anti-predation, feeding) such as head-bobbing, gaping, biting, and changing color. These animals are able to almost instantly improve camouflage by hiding, tuning their body position and appearance to the background, and also modify their manner of moving [26]. Herrel et al. [9] noted that chameleons often display a movement exhibiting a back and forward rocking motion, naming it "jerky walk" rather than leaf-movement. A common, but not well described or proven explanation is that they are mimicking leaves or vegetation swaying in a breeze, potentially for anti-predator purposes. On the other hand, this movement is often reported outside the context of threatening (prey/predator) and spotted in open areas as well as in places with challenging and closed vegetation. Another hypothesis is that the movement is required for body balance. Despite being known for many years [4], the overall significance of these motor patterns associated or not with concealment has not been largely explored. Furthermore, the frequency, motivation and triggering conditions that cause the movement to happen are also unknown.

2.2 Computational animal behavior analysis

Anderson and Persona [1] introduced the notion of 'computational ethology', also subsequently conceptualized as 'computational analysis of behavior' [3]. The use of computational means to (semi-)automatically assess animal behavior has been increasingly explored within ACI contexts (cf. Menaker et al. [14]) as a push to design and build AI-driven systems that support and part-automate ethological analysis in order to facilitate and improve human annotation. Deep learning is a subfield of machine learning, which is, in turn, a subfield of artificial intelligence (AI). On one hand, we have the classic machine learning algorithms, such as SVM, random forest classifier, among others. On the other hand, we have Artificial Neural Networks (ANNs), which are a class of machine learning algorithms that learn from data and specialize in pattern recognition, inspired by the structure and function of the brain. In order to work with more challenging datasets we need both (1) nonlinear activation functions (such as the usage of activation function ReLU) and (2) multi-layer networks between the input and output layers (what we called Deep Neural Network). To train multi-layer networks we must use the backpropagation algorithm, which allows the computer to learn complicated concepts. We mainly deal with two types of ANN:

(1) CNN (Convolutional Neural Networks) are now considered the most powerful image classifier and are currently responsible for pushing the state-of-the-art forward in computer vision subfields that leverage machine learning.
(2) RNN (recurrent neural networks) is a class of ANNs where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. Derived from feedforward neural networks, RNNs can use their internal state (memory) to process variable length sequences of inputs. LSTM (Long short-term memory) [8] or GRU (Gated recurrent units) [2] are an RNN variant that was designed to store and access information in a long time sequence that persists in the network's internal state (GRU has fewer parameters than LSTM).

Recently, machine learning based techniques for identifying user-defined behaviors have been applied to several species and produced promising results for challenging classification problems [18]. Neural networks have been used for a numerous range of analysis, including gait and locomotion patterns in mammals and insects [11, 15, 21]. However, there are very few reports on technology and machine learning applied to reptile behavior outside the purpose of species identification [19, 23] and wildlife monitoring [16]. To the best of the authors' knowledge, this is the first AI-based tool being developed to quantify and compare lizard's patterns of locomotion.

3 DESCRIPTION OF THE CHAMELEO SYSTEM

3.1 Data collection

This study was approved by the Animal Welfare and Care Committee of Ben Gurion University (IL-05-01-2020(B)) and The Israel Nature and Parks Authority (2020/42435, 2021/42837). All work undertaken for this abstract was observational.

Twelve chameleons (*Chamaeleo chamaeleon musae*; 6 males, age range: 10-11 months old) were recorded (Panasonic Lumix DMC-FZ200) performing a fair range of locomotion movements. Chameleons were captured by hand at Negev Desert, Israel and transported to the University campus at Be'er-Sheva. Animals were temporarily housed in individual cages. Food (mealworm, locusts, crickets and cockroaches) and water were offered daily. In each cage, branches (*Tamarix*) and plants (*Epipremnum aureum*) were provided as environmental enrichment. Ultraviolet light (UV), essential for reptiles in captivity allowing the synthesis of vitamin D3 and appropriate calcium metabolism, was provided through UVB bulbs located above each cage. Note that as chameleons are known to present the leaf-movement behavior both in captivity (both when captured for limited time or held as pets) and in the wild, the use of videos of just captive chameleons should not pose any threat to external validity.

The animals were recorded moving on a 50 cm polypropylene 8mm rope. The rope was stretched, so that the animals moved horizontally. They moved at different speeds presenting different classes of locomotion. An example of the recorded movement is presented in Fig. 1. We recorded 90 videos, resulting in approximately 8h of footage. Each video duration was determined by the individual's response and varied between 2 to 15 minutes.

Fig. 1. Examples of different leg positions during chameleon movement.

3.2 Data labeling

In order to train the neural network to recognize the motion type, we manually labeled all movements in the videos using BORIS v.7.10.7 (Behavioral Observation Research Interactive Software) [7]. Labeling was performed by two observers with experience in chameleon behavior (S.G. and L.S.). Both observers annotated the dataset. Any disagreements in annotations were discussed and resolved between the authors in order to produce a final annotated dataset. The ethogram was built from scratch in BORIS and included only behaviors related to locomotion. The four behavior possibilities are shown below:

(1) Walking: chameleon moves continuously alternating movement of the right and left limbs – standard quadrupedal lizard movement
(2) Leaf-movement: chameleon rocks back and forth, slowly moving forward
(3) Falling: chameleon falls from the rope and/or is not visible on the video
(4) Stationary: chameleon is still

We performed a focal animal sampling and evaluated each individual continuously during the entire duration of the video. The actions were considered a "state event": the activity has a duration with a start and an end. When the animal begins, for example, the leaf-movement, the observer selects this activity from the list and presses START. Once the leaf-movement stops, the observer presses STOP. As a result, we have the individual time elapsed for each activity, but also a time budget from all of them.

The behaviors presented by the chameleons in the video recordings were labeled using one of the four classifiers above. With the labeled dataset in hand, we could then proceed with a supervised learning algorithm to train the NN. Labeled data from BORIS is stored in a detailed sheet with the exact time and duration of the action. Figure 2 represents the summary of activities by a male chameleon. As an example, the activities coded during the 10-minute observation were Stationary and Leaf-movement.

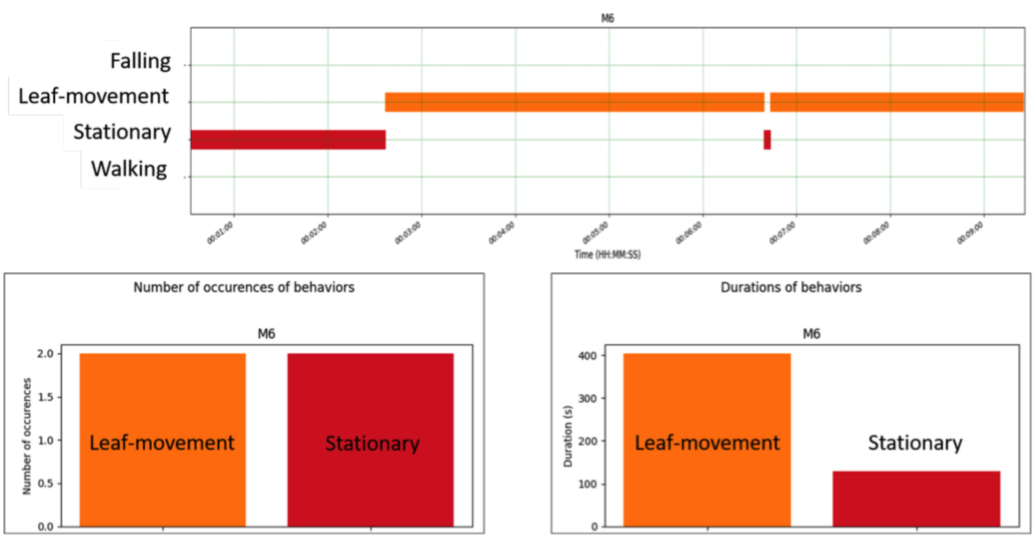

Fig. 2. Top: Summary of the activities performed by a male chameleon during a 10-minute observation and coding using BORIS. Bottom: Number of occurrences and total duration of each activity.

3.3 Proposed training of the neural network

Initially, we thought about applying video classification with a CNN-RNN Architecture, sketched out in Fig. 3. The idea being to classify the class of locomotion for each frame of the video: chameleon in stationary position, standard walking, leaf-movement or absent. The video structure consists of an ordered sequence of frames. Each frame contains spatial information, and the sequence of those frames contains temporal information. To model both aspects, we use a hybrid architecture that consists of convolutions (for spatial processing) as well as recurrent layers (for temporal processing). Specifically, we will use a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN) consisting of GRU or LSTM layers.

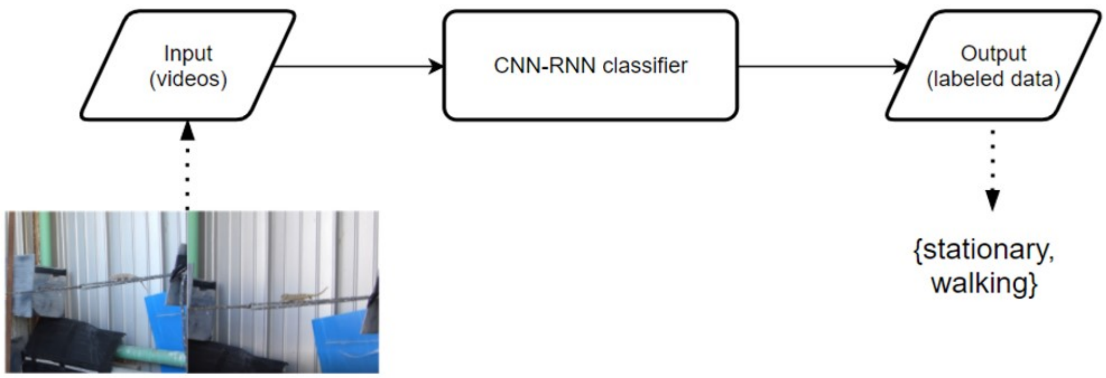

Fig. 3. Overview of the classifier's architecture: videos of chameleons are processed by the classifier, resulting in labeled data showing specific classifications per frame of each video.

As we train a video classifier and not images, we face the challenge of figuring out a way to feed the videos to a network. As aforementioned, our video is an ordered sequence of frames, thus, we could just extract the frames and put them in a 3D tensor. However, the number of frames differ from video to video which would prevent us from stacking them into batches (unless we use padding). As an alternative, we can save video frames at a fixed interval until a maximum frame count is reached. For example we can do as following:

(1) Capture the frames of a video
(2) Extract frames from the videos until a maximum frame count is reached
(3) Pad the video with zeros in the case where the video frame count is lesser than the maximum frame count

It is worth mentioning that our implementation idea is based on Keras documentation of "Video Classification with a CNN-RNN Architecture" by Sayak Paul as the implementation will be in Python and Keras library. Next, for the detection of the Chameleon itself, if needed, there are some models that can be helpful for that task:

- EzTrack [20]: An open-source video analysis pipeline for tracking the location, motion, and freezing of animals.
- OpenCV Object Tracking: OpenCV includes eight separate object tracking implementations for computer vision applications, most of them used classic ML algorithm (except of GOTURN Tracker which used deep learning-based object detector)
- CSRT: when higher object tracking accuracy is needed and we can tolerate slower frames per second throughput.
- KCF: when faster frames per second throughput is needed but we can handle slightly lower object tracking accuracy.
- MOSSE: when pure speed is needed.

- You only look once (YOLO) [24]: when fast, robust object detection is needed, as YOLO is a state-of-the-art algorithm for real-time object detection using extremely fast architecture for object detection using single forward propagation that can be easily generalized to new domains.

4 DISCUSSION

Further research is needed to understand the social and evolutionary meaning of the leaf-movement. Chameleo can give an opportunity for deep research using high end technologies. We envision this system to become a generalized tool allowing for crowd-sourcing of other video-materials provided by experts as well as nature enthusiasts to engage in citizen-science efforts in building a large database of both raw material (i.e., videos) and behavioral models.

Chameleo can also be further exploited for the evaluation of reptiles in captivity. In the last few years, reptiles have risen in popularity as pets, with a population of over nine million only in Europe [5]. Owners are usually curious about the behavior of their pets and often record them performing daily tasks. The between owners, veterinarians and researchers can contribute to early detection of diseases and its monitoring, since the observation is focused on their behavior and does not rely on verbal communication [12, 27].

Moreover, we expect to use this tool to investigate locomotion patterns of different chameleon species, a wider range of habitats, during threat perception, and to explore a potential specific behaviors repertoire observed in free-ranging wild animals compared to pet chameleons. Chameleo can provide novel information about leaf-movement, including (but not limited to) its mechanism, its presentation in relation to other behaviors, or perhaps the reasons leading to it. Chameleo can also enable nature enthusiasts to investigate chameleon behavior at their own home, while traveling or while observing their own pet-chameleon. Understanding of leaf-movement might explain its causes and effects, and whether this behavior is affected by health conditions or habitat alteration. As a part of our model development, which uses several techniques to analyze chameleon movement, we wish to create a website and invite other researchers to add more models and more data (i.e., turn Chameleo into an open source), which will increase our project value. Hopefully, this can create an infrastructure for many more research projects to come, either for lizard researchers or other researchers who wish to use video movement analysis framework.

Even though we considered four different classes of locomotion, this system can potentially be adapted to any other combination of previously labeled movements observed in lizards. In this manner, the use of the system is not restricted only to locomotion, but to a wider range of behaviors depending on the context of the study, In summary, we present a method for identifying and quantifying chameleon locomotion, specifically leaf-movement. We hope that the Chameleo will be useful to further understand chameleon locomotion while reducing manual effort as well as the time of analysis.

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REFERENCES

[1] David J Anderson and Pietro Perona. 2014. Toward a science of computational ethology. *Neuron* 84, 1 (2014), 18–31.
[2] Rahul Dey and Fathi M Salem. 2017. Gate-variants of gated recurrent unit (GRU) neural networks. In *2017 IEEE 60th international midwest symposium on circuits and systems (MWSCAS)*. IEEE, 1597–1600.
[3] SE Roian Egnor and Kristin Branson. 2016. Computational analysis of behavior. *Annual review of neuroscience* 39 (2016), 217–236.

[4] Linda Evans, Fred Hardtke, Emily Corbin, and Wouter Claes. 2020. Camouflaged chameleons: a new discovery at the Egyptian site of el-Hosh. *Archaeological and Anthropological Sciences* 12, 8 (2020), 1–9.

[5] European Pet Food Industry Federation (FEDIAF). 2020. *Facts & Figures 2020*. https://www.fediaf.org/images/FEDIAF_Facts_and_Figures_2020.pdf

[6] Martin S Fischer, Cornelia Krause, and Karin E Lilje. 2010. Evolution of chameleon locomotion, or how to become arboreal as a reptile. *Zoology* 113, 2 (2010), 67–74.

[7] Olivier Friard and Marco Gamba. 2016. BORIS: a free, versatile open-source event-logging software for video/audio coding and live observations. *Methods in ecology and evolution* 7, 11 (2016), 1325–1330.

[8] Klaus Greff, Rupesh K Srivastava, Jan Koutník, Bas R Steunebrink, and Jürgen Schmidhuber. 2016. LSTM: A search space odyssey. *IEEE transactions on neural networks and learning systems* 28, 10 (2016), 2222–2232.

[9] Anthony Herrel, Krystal A Tolley, G John Measey, Jessica M da Silva, Daniel F Potgieter, Elodie Boller, Renaud Boistel, and Bieke Vanhooydonck. 2013. Slow but tenacious: an analysis of running and gripping performance in chameleons. *Journal of Experimental Biology* 216, 6 (2013), 1025–1030.

[10] Timothy E Higham and Bruce C Jayne. 2004. Locomotion of lizards on inclines and perches: hindlimb kinematics of an arboreal specialist and a terrestrial generalist. *Journal of experimental biology* 207, 2 (2004), 233–248.

[11] Mayank Kabra, Alice A Robie, Marta Rivera-Alba, Steven Branson, and Kristin Branson. 2013. JAABA: interactive machine learning for automatic annotation of animal behavior. *Nature methods* 10, 1 (2013), 64–67.

[12] Mary P Klinck, Margaret E Gruen, Jérôme RE del Castillo, Martin Guillot, Andrea E Thomson, Mark Heit, B Duncan X Lascelles, and Eric Troncy. 2018. Development and preliminary validity and reliability of the montreal instrument for cat arthritis testing, for use by caretaker/owner, MI-CAT (C), via a randomised clinical trial. *Applied animal behaviour science* 200 (2018), 96–105.

[13] JB Losos, BM Walton, and AF Bennett. 1993. Trade-offs between sprinting and clinging ability in Kenyan chameleons. *Functional Ecology* (1993), 281–286.

[14] Tom Menaker, Anna Zamansky, Dirk van der Linden, Dmitry Kaplun, Aleksandr Sinitica, Sabrina Karl, and Ludwig Huber. 2020. Towards a Methodology for Data-Driven Automatic Analysis of Animal Behavioral Patterns. In *Proceedings of the Seventh International Conference on Animal-Computer Interaction*. 1–6.

[15] Nikola Mijailovic, Marijana Gavrilovic, Stefan Rafajlovic, M Đuric-Jovicic, and D Popovic. 2009. Gait phases recognition from accelerations and ground reaction forces: Application of neural networks. *Telfor Journal* 1, 1 (2009), 34–36.

[16] Hung Nguyen, Sarah J Maclagan, Tu Dinh Nguyen, Thin Nguyen, Paul Flemons, Kylie Andrews, Euan G Ritchie, and Dinh Phung. 2017. Animal recognition and identification with deep convolutional neural networks for automated wildlife monitoring. In *2017 IEEE international conference on data science and advanced Analytics (DSAA)*. IEEE, 40–49.

[17] Matthias Ott. 2001. Chameleons have independent eye movements but synchronise both eyes during saccadic prey tracking. *Experimental Brain Research* 139, 2 (2001), 173–179.

[18] Veronica Panadeiro, Alvaro Rodriguez, Jason Henry, Donald Wlodkowic, and Magnus Andersson. 2021. A review of 28 free animal-tracking software applications: current features and limitations. *Lab Animal* (2021), 1–9.

[19] Anika Patel, Lisa Cheung, Nandini Khatod, Irina Matijosaitiene, Alejandro Arteaga, and Joseph W Gilkey. 2020. Revealing the unknown: real-time recognition of Galápagos snake species using deep learning. *Animals* 10, 5 (2020), 806.

[20] Zachary T Pennington, Zhe Dong, Yu Feng, Lauren M Vetere, Lucia Page-Harley, Tristan Shuman, and Denise J Cai. 2019. ezTrack: An open-source video analysis pipeline for the investigation of animal behavior. *Scientific reports* 9, 1 (2019), 1–11.

[21] Talmo D Pereira, Diego E Aldarondo, Lindsay Willmore, Mikhail Kislin, Samuel S-H Wang, Mala Murthy, and Joshua W Shaevitz. 2019. Fast animal pose estimation using deep neural networks. *Nature methods* 16, 1 (2019), 117–125.

[22] Jane A Peterson. 1984. The locomotion of Chamaeleo (Reptilia: Sauria) with particular reference to the forelimb. *Journal of Zoology* 202, 1 (1984), 1–42.

[23] Nagifa Ilma Progga, Noortaz Rezoana, Mohammad Shahadat Hossain, Raihan Ul Islam, and Karl Andersson. 2021. A CNN Based Model for Venomous and Non-venomous Snake Classification. In *International Conference on Applied Intelligence and Informatics*. Springer, 216–231.

[24] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. 2016. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 779–788.

[25] Karl Patterson Schmidt, Robert F Inger, and Roy Pinney. 1957. *Living reptiles of the world*. Hanover House Garden City, New York.

[26] Martin Stevens and Graeme D Ruxton. 2019. The key role of behaviour in animal camouflage. *Biological Reviews* 94, 1 (2019), 116–134.

[27] Atsushi Yamazaki, Kazuya Edamura, Koji Tanegashima, Yuma Tomo, Makoto Yamamoto, Hidehiro Hirao, Mamiko Seki, and Kazushi Asano. 2020. Utility of a novel activity monitor assessing physical activities and sleep quality in cats. *Plos one* 15, 7 (2020), e0236795.