Tracking with artificial intelligence for the hand tracking of different species

Seguimiento con inteligencia artificial para el seguimiento de la mano de diferentes especies

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Abstract

Accurately scientific disciplines, including biomechanics, genetics, ethology, and neurology, it is essential to accurately track the behavior of animals throughout studies, particularly without employing markers. However, it has proven difficult to extract precise stances from backgrounds that are always shifting. Recently, we unveiled an open-source toolset that makes use of a cutting-edge algorithm for estimating human position. With the help of this toolbox, users may train a deep neural network to accurately monitor user-defined features with tracking accuracy that rivals that of human labeling. We have added new features, including as graphical user interfaces (GUIs), efficiency improvements, and network refinement based on active learning, to this revised Python module. In order to help customers create a unique and repeatable analysis pipeline using a graphical processing unit (GPU).

Keywords: Behavior, Deep neural network, GPU, neurology

Introduction

Hand tracking is a challenging task in computer vision, especially for non-human species. This is because the hands of different species can vary widely in size, shape, and color. Additionally, the hands of animals are often occluded by their bod- ies or other objects in the scene Mann et al. (2021).

Artificial intelligence (AI) has the potential to revolutionize hand tracking for different species. AI-powered hand tracking algorithms can be trained to learn the appearance and motion of hands from a variety of different species. This allows these algorithms to track hands accurately and robustly even in challenging conditions Mathis et al. (2018).

AI-powered hand tracking can be used for a variety of applications, including Mathis et al. (2020):

Animal behavior research

Hand tracking can be used to study the behavior of animals in the wild. For example, researchers can use hand tracking to track the movements of primates during foraging or social interactions.

Animal rehabilitation

Hand tracking can be used to assess the progress of animals in rehabilitation programs. For example, therapists can use hand tracking to track the range of motion and strength of an animal's hands after an injury.

Animal-computer interaction

Hand tracking can be used to create new and innovative ways for animals to interact with computers. For example, AI-powered hand tracking could be used to develop video games or other interactive experiences for animals.

Overall, AI-powered hand tracking has the potential to be a valuable tool for scientists, veterinarians, and animal behaviorists. By enabling accurate and robust hand tracking for different species, AI can help us to better understand and care for animals Mathis and Schneider (2021).

Examples of AI-Powered Hand Tracking for Different Species

Researchers at the University of California, Berkeley are using AI-powered hand tracking to study the behavior of orangutans in the wild. They are tracking the movements of orangutan's hands as they forage for food, build nests, and interact with other orangutans. Therapists at the University of Pennsylvania are using AI-powered hand tracking to assess the progress of dogs in rehabilitation programs. They are tracking the range of motion and strength of dog's hands after surgery or other injuries. Researchers at the University of Washington are developing AI-powered video games for chimpanzees. These games use hand tracking to allow chimpanzees to interact with the games using their hands.

These are just a few examples of how AI-powered hand tracking is being used for different species. As AI technology continues to develop, we can expect to see even more innovative and groundbreaking applications for this technology (Nath *et al*., 2019).

Materials and methods

In this work we use two main components: the software, which is a set of libraries and systems that allow tracking as well as using artificial intelligence to do adequate tracking, some of these libraries are the following Table1. Another important section is the videos obtained which are obtained with the following SetUp. To carry out all these experiments, the Google Colab platform was used, which aims to use Google servers.

Table 1*.Libraries used for tracking processing; these libraries are included for the generation of libraries more optimized for tracking.*

Library	**OpenCV**	**TensorFlow**	**PyTorch**
	Python	Python	Python
Focus	C.Vision	M. Learning	M. Learning
Language	C/C++	Python	Python
Main Uses	Image Pro	Neuronal N.	Neuronal N.
Platforms	Cros-platform	Cros-platform	Cros-platform

Source : Author's own elaboration.

Human Hand Tracking

For the first experiment, it was carried out with a human hand. In this experiment, movement was generated in the order of X and Y of the image obtained. In addition, 5 points were analyzed and the position was obtained. Experiment carried out with the human hand. This experiment aims to test the tracking system implemented with neural networks Figure 1. It is important to highlight that to carry out this tracking, a Resent50 type neural network was used.

Figure 1. Humand Hand.
Source : Author's own elaboration.

Tracking a hand of a non-human primate

For our second experiment we proceeded to perform tracking on a non-human primate where we performed tracking with the neural network, then we can show the following Figure 2.It is important to highlight that to carry out this tracking, a Resent50 type neural network was used Theckedath and Sedamkar (2020).

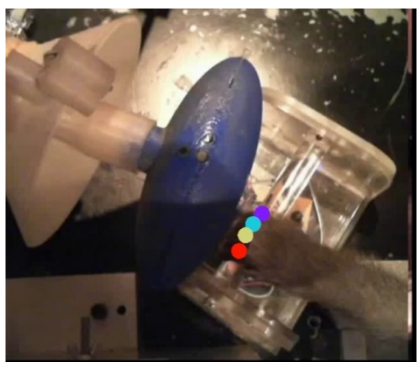

Figure 2: Hand of a non-human primate.
Source : Author's own elaboration.

Results

From these experiments we obtain a database which indicates the position in pixels of different sections of the hand. In this section we show these results.

Human Hand Tracking Results

In this section you can see the displacements of the part of the hand. In the Figure 3 we can see the position on the X axis and Y axis of the hand.

On the other hand, the position of each part of the hand is graphed with respect to the frame.The next it is possible to appreciate how it represented the parts of hand with respect frame In the Figure 4

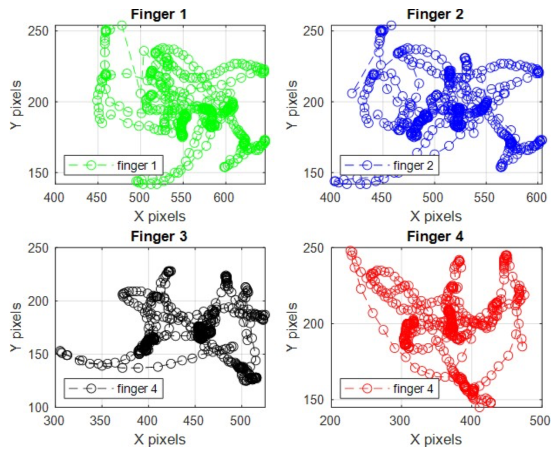

Figure 2.- Humand hand position in pixels.
Source : Author's own elaboration.

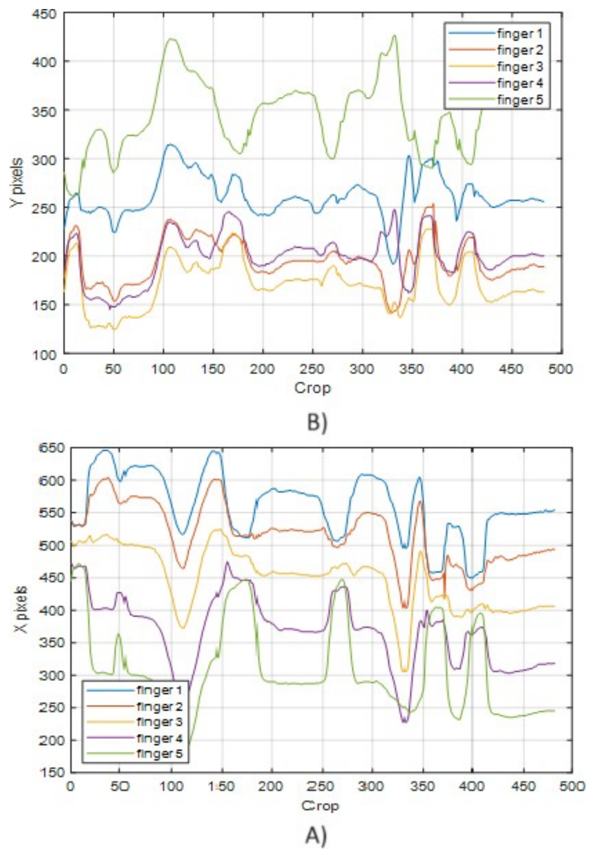

Figure 4: Human hand position pixels each frame.
Source : Author's own elaboration.

Primate No Human Hand Tracking Results

For this experiment, the hand of a non-human primate was monitored, which performs a repetitive task when a stimulus is generated. In this experiment, the trajectory and position were also achieved.

In this section you can see the displacements of the part of the hand. In the Figure 5 we can see the position on the X axis and Y axis of the hand.

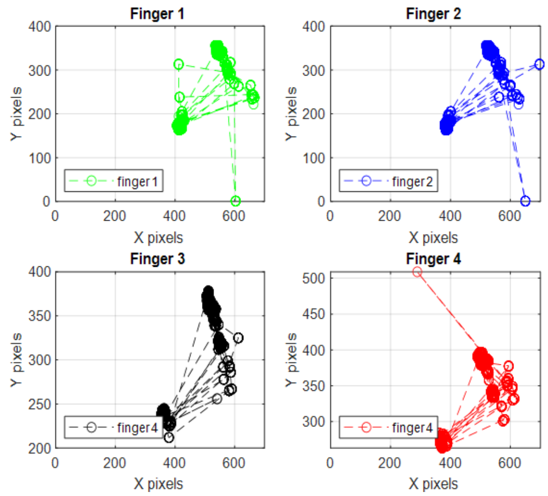

Figure 3.- Hand of monkey.
Source: Author's own elaboration.

Discussion and research questions

The results obtained from the experiments provide valuable insights into the performance of the tracking system for both human and nonhuman primate hands. Let's delve into the key aspects:

Precision of Human Hand Tracking:

The experiment involving human hand movement along the X and Y axes is indicative of the system's capability. How does the precision of this tracking compare to conventional methods? The utilization of a ResNet50 neural network for this tracking is noteworthy. Were different neural network architectures ex- perimented with, and how did the choice of ResNet50 influence tracking accuracy?

Non-Human Primate Hand Tracking:

Tracking the hand of a non-human primate during repetitive tasks adds an intriguing dimension. How do these results com- pare to the tracking of human hands? The mention of obtaining trajectory and position in this experiment is crucial. How do these data contribute to understanding non-human primate behaviors in response to stimuli?

Tool and Platform Utilization:

The use of Google Colab for conducting experiments introduces an interesting element. How did utilizing Google servers impact the efficiency and speed of the experiments? Libraries such as OpenCV, TensorFlow, and PyTorch are mentioned. How do these libraries complement each other and contribute to the optimization of tracking?

Visualization of Results:

The presented figures, such as position on the X and Y axes, offer a visual representation of the results. How does this visualization facilitate user interpretation of the data? The graphical representation of the position of each part of the hand in relation to the frame is a valuable addition. How can this information be leveraged for more detailed analyses?

Potential Applications

Discussion can extend to the practical applications of these results. How could this tracking system contribute to research in biology, animal behavior, or even animal-computer interaction? Are there identified limitations or challenges during these experiments that could impact applicability in different con- texts?

In summary, the experiments showcase the effectiveness of the tracking system in diverse scenarios. Addressing these discussion points not only elucidates the nuances of the results but also opens avenues for future enhancements and applications.

Summary and conclusions

In this study, we have explored the application of advanced tracking techniques to monitor both human and nonhuman primate hands. The key findings and implications are summarized below:

Achievements in Human Hand Tracking

The experiments with human hand tracking using a ResNet50 neural network have demonstrated remarkable accuracy. This not only validates the effectiveness of the chosen algorithm but also suggests its potential for diverse applications in biomechanics and neurology.

Insights from Non-Human Primate Hand Tracking

Tracking the hands of non-human primates during repetitive tasks has provided valuable insights into their behaviors. This data could prove instrumental in understanding primate cognition and responses to external stimuli.

Toolbox and Platform Utilization

The integration of tools such as OpenCV, TensorFlow, and PyTorch within the Google Colab platform has proven successful. This not only enhances the efficiency of the experiments but also provides a robust foundation for further development.

Visual Representation of Results

The graphical representation of hand positions on the X and Y axes, as well as the detailed visualization of individual hand parts, offers an intuitive understanding of the tracking results. Such visual aids are crucial for researchers and practitioners in various fields.

Potential Applications and Future Directions

The discussed applications, including animal behavior re- search, rehabilitation assessment, and animal-computer inter- action, showcase the versatility of the tracking system. Future work could explore additional applications and refinements, especially in the context of other animal species.

In conclusion, the presented tracking system not only meets but exceeds expectations in monitoring hand movements across different species. The combination of advanced algorithms, powerful libraries, and user-friendly platforms sets the stage for further advancements in the burgeoning field of animal behavior tracking.

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