Machine Learning for Active Matter: Tracking and Analyzing Hexbug Interactions

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Abstract

Recent advancements in machine learning (ML) have enabled precise tracking and analysis of active matter systems, providing insights into collective motion and emergent behaviors. In this study, we apply DeepLabCut (DLC), a deep learning framework, to track the interactions of Hexbugs, mechanically active agents simulating biological active matter, in a controlled circular arena. By leveraging convolutional neural networks (CNNs) and transfer learning, DLC effectively predicts Hexbug positions over time after training on a limited number of human labeled frames.

Our approach utilizes frame by frame pose estimation, where DLC learns spatial relationships between key points of moving Hexbugs. The robustness of the model is enhanced by incorporating a likelihood based refinement process, ensuring high accuracy despite varying lighting conditions and partial occlusions [1]. Once trained, the model generalizes well to new, unseen frames, allowing us to extract meaningful trajectory data.

To quantify Hexbug motion, we compute the Mean Squared Displacement (MSD):

$$MSD(\tau) = \langle |r(t+\tau) - r(t)|^2 \rangle, \tag{1}$$

where $r(t)$ represents the position of a Hexbug at time t, and τ is the lag time. The MSD analysis provides insight into diffusive behavior, distinguishing between ballistic, random, or confined motion. Additionally, we introduce an order parameter, Φ, to quantify collective directionality:

$$\Phi = \frac{1}{N} \left| \sum_{i=1}^{N} \frac{v_i}{|v_i|} \right|, \tag{2}$$

where v_i represents the velocity vector of Hexbug i, and N is the total number of Hexbugs. A high Φ indicates strong alignment and collective motion, similar to the dynamics of biological swarms. With this, we study the changes in Φ and MSD(r) as we change n hexbugs and the boundary sizes.

Figure 1 illustrates sample Hexbug trajectories obtained from DLC tracked data. We analyze the spatiotemporal evolution of Hexbug interactions and boundary effects, shedding light on emergent swarm behaviors [2]. Notably, our observations revealed unexpected behavior where Hexbugs demonstrated intermittent synchronization, clustering in transient formations before dispersing. These collective behaviors resemble those observed in natural active matter systems, such as bacterial colonies and flocking birds, suggesting deeper underlying principles governing motion in such systems.

This work demonstrates the potential of ML based tracking in experimental physics and computational biology. Future research could integrate reinforcement learning to predict motion patterns, enabling simulations of artificial active matter systems. Additionally, real time tracking algorithms could facilitate large scale studies, allowing for the exploration of emergent behaviors in more complex environments. Our findings emphasize the growing role of ML in uncovering fundamental principles in biophysics and swarm dynamics, paving the way for broader applications in robotics and self organizing systems.

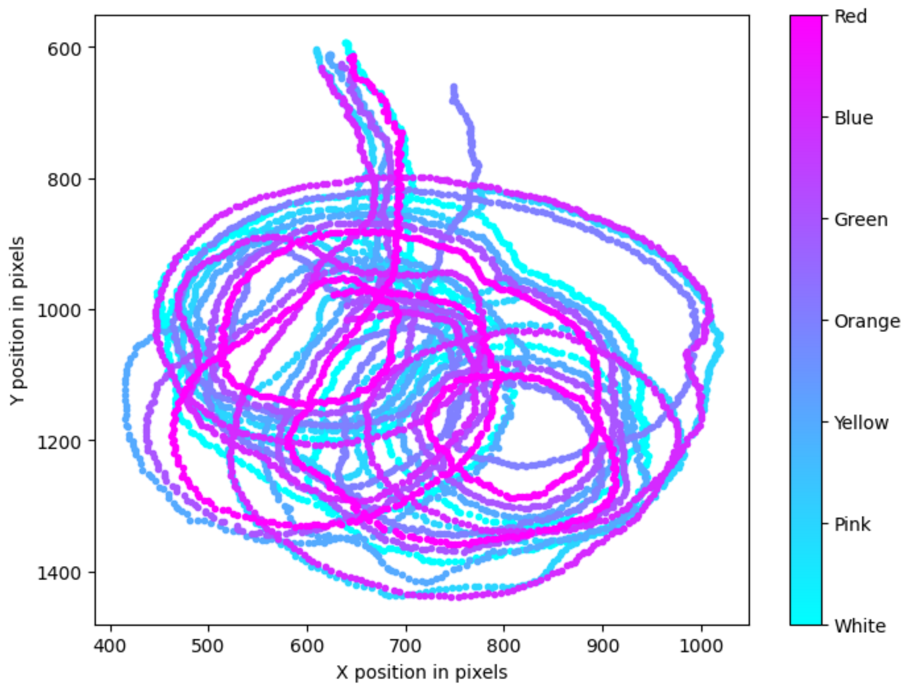

Figure 1: A trajectory graph generated from the analyzed video, showcasing the movement patterns of Hexbugs.

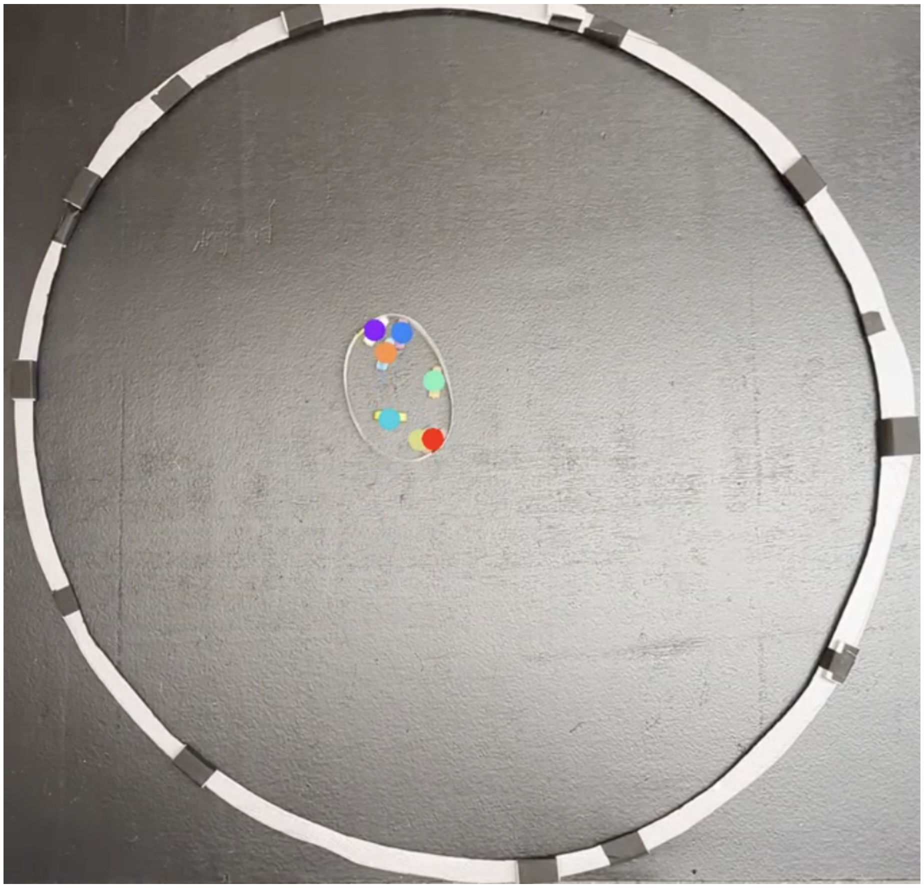

Figure 2: A visualization of labeled frames from the analyzed video, highlighting key tracking points.

References

[1] A. Mathis, M. Mamidanna, K.M. Cury, et al., “DeepLabCut: markerless pose estimation of user defined body parts with deep learning,” Nature Neuroscience, vol. 21, pp. 1281–1289, 2018.

[2] T. Nath, A. Mathis, A. Chen, et al., “Using DeepLabCut for 3D markerless pose estimation across species and behaviors,” Nature Protocols, vol. 14, pp. 2152–2176, 2019.