Generative Models for Incremental Learning to Advance Autonomous Agent Evolution: A 3D Perspective

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***Abstract*—Unmanned Aerial Vehicles (UAVs) are increasingly used for surveillance, inspection, and autonomous exploration. However, ensuring precise trajectory mapping remains challenging due to sensor noise and environmental uncertainty. This work introduces a novel approach to UAV trajectory analysis that integrates adaptive filtering with sequential clustering techniques. Using a 3D synthetic dataset, we project it onto 2D planes and apply the proposed steps to obtain final 2D clusters (i.e., our vocabulary) for each plane. Knowing the model that generated our data, we assume the data follow 3D Gaussian PDFs, which remain Gaussian when projected onto 2D planes. This allows us to compare the data-driven clusters with model-based ground-truth clusters on each 2D plane. Preliminary results show that our data-driven clusters effectively approximate the model-driven ones in the 2D space. This research advances UAV trajectory analysis in scenarios where only 2D data can be processed. It also provides insights into the effectiveness of different 2D projections, evaluating whether some perform better than others and how well they approximate a 3D model. Future work will focus on fusing 2D clusters from different planes into a 3D model and comparing it with the 3D ground-truth model.**

***Index Terms*—Artificial Intelligence (AI), Cognitive Computing, Generative Models, Machine Learning (ML), Self-Aware Autonomous Navigation**

I. Introduction

In recent years, various papers in the literature have highlighted the importance of embodied perception as a basis for self-awareness in intelligent agents. These agents are indeed equipped with both proprioceptive and exteroceptive sensors, allowing them to sense their own state and the surroundings for developing self-awareness and adaptive capabilities [1]–[3]. In this context, Unmanned Aerial Vehicles (UAVs) have become an essential component in various applications, ranging from surveillance and environmental monitoring to autonomous navigation and logistics. The increasing complexity of UAV operations demands robust trajectory analysis techniques that enhance precision, adaptability, and real-time decision-making capabilities. Traditional trajectory analysis methods often rely on predefined motion models, which may struggle to adapt to dynamic environments and unforeseen disturbances.

To address this, federated learning frameworks have been proposed, enabling UAVs to collaboratively update trajectory models while mitigating data heterogeneity issues [4]. In addition, the fusion of AI and defense technologies has demonstrated significant improvements in UAV situational awareness and decision-making, leveraging real-time data processing for enhanced autonomous operations [5], [6].

To further improve UAV trajectory analysis, generative models have been explored, offering adaptive learning through reinforcement learning and Bayesian inference. Extended reality (XR) simulations, combined with AI, have been employed to construct realistic trajectory models, facilitating predictive analysis and training scenarios [7], [8]. Meanwhile, breakthroughs in AI architectures, such as eliminating matrix multiplications in large-scale models, promise computational efficiency, paving the way for real-time UAV trajectory learning [9].

Furthermore, clustering techniques play a critical role in extracting meaningful motion patterns from UAV trajectory data. Dynamic Bayesian models, which are widely used for predicting time-series data, have been adapted to UAV motion forecasting by capturing sequential dependencies and decision-making processes [6], [9]. Additionally, cloud-edge-end federated learning has been utilized to aggregate multi-agent UAV trajectories, improving robustness in real-world deployments [8], [9]. These recent contributions [10]–[12] align with our research objectives by leveraging clustering techniques, hierarchical Bayesian modeling, and generative trajectory representations to enhance UAV navigation and self-awareness [13].

With this research, we employ a novel adaptive filtering followed by a two-stage clustering technique to improve state estimation and refine trajectory predictions, thereby enhancing 3D UAV trajectory modeling. Clustering is performed sequentially and operates on the hidden generalized state variables of the filter, identifying regions in the data (including positions and velocities) with similar characteristics. Each cluster acts as a switching variable, associated with a different dynamic model in distinct regions of the state space.

By combining these approaches, we aim indeed to develop a comprehensive framework that strengthens UAV self-awareness and decision-making in complex operational environments. This investigative exploration focuses on generating and analyzing 3D trajectories. Furthermore, we also explore the integration of multi-plane trajectory decomposition, where individual 2D projections are analyzed and could then be used to reconstruct a 3D representation.

The key contributions of this work are as follows:

- We advance UAV trajectory analysis by introducing an advanced approach that integrates adaptive filtering with sequential clustering techniques.
- We develop a methodology for projecting 3D data onto 2D planes, enabling the generation of 2D clusters (data-driven clusters) for each plane and comparison with ground-truth clusters derived from the 3D model (model-driven clusters).
- We evaluate the fidelity of 2D projections in representing 3D motion by comparing cluster formations from projected data with ground-truth clusters using Kullback-Leibler Divergence (KLD).

II. Methodology

The block scheme of our approach is depicted in Fig. 1. The following subsections detail each individual block.

A. 3D trajectory generation and its projection onto 2D planes

The 3D trajectory generation and projection onto the individual 2D planes process began with simulating UAV movements in 3D space using a dynamic model, incorporating Gaussian probability density functions (PDFs) to account for environmental uncertainties and sensor noise. These 3D trajectories were projected onto XY, XZ, and YZ planes, maintaining Gaussian consistency during projection.

B. Filtering

We are now considering the noisy 2D odometric observations obtained by projecting 3D noisy observations coming from an expert agent. A null force filter [1] is used to obtain a set of probabilistic errors called generalized state (GS) describing deviations from the null force assumption. A GS gs_t can be represented as a vector:

$$gs_t = [\mathrm{x}_t, \mathrm{y}_t, \mathrm{v}_{x_t}, \mathrm{v}_{y_t}]. \tag{1}$$

The state changes v_{x_t} and v_{y_t} correspond to the estimated velocity resulting from local forces in our environment that are not considered in the null force filtering process.

C. Clustering

The application of unsupervised clustering to the temporal sequence of GSs seeks to develop a simplified generative model with minimal parameters, enabling the prediction of new data sequences that adhere to the same principles and forces that shaped the expert-generated instance. Indeed, each gs_t can be modeled as a normal (or Gaussian) random variable with a certain mean $\mu_t \in \mathbb{R}^4$ and a covariance matrix $C_t \in \mathbb{R}^{4\times 4}$. The clustering step consists of two distinct stages.

1) First-stage clustering: First-level clustering mainly aims at providing an initial clustering of GSs based on the free energy minimization principle. It is a sequential clustering approach producing a series of discrete random variables that represent clusters. Each cluster group is generated by considering similar deviations from the null force hypothesis, forming structured random data useful for generative model learning. The initial clustering process ensures that GSs from different local forces have a low probability of being aggregated while minimizing false alarms. The sequence is processed sequentially, deciding at each step whether to create a new cluster or merge with an existing one. This process functions as a discrete filter or Hidden Markov Model (HMM), where merging decisions are based on free energy minimization.

2) Second-stage clustering: After the first-stage clustering, a second phase prunes noise-associated Gaussian modes (single-element clusters) and refines cluster grouping through hierarchical clustering. A merging technique based on KLD minimization at a lower spatial scale is applied, thus ensuring cluster alignment. Small clusters are merged if sufficiently aligned, maintaining accurate trajectory representation. This iterative approach will eventually result in a Gaussian Mixture Model (GMM), where each cluster is represented by mean position, velocity, and transition probabilities. The final model allows efficient UAV trajectory prediction and adaptation in dynamic environments, which is the focus of our case.

D. 3D modeling and projection on 2D planes

We describe the formulation for enhancing UAV trajectory analysis by integrating 3D modeling techniques and their corresponding projections onto 2D planes.

In our scenario, we assume a drone trajectory starting from $(0, 0, 0)$ in the (x, y, z) plane, flying up to a certain elevation and making a rectangular movement (see Fig. 2.a). These movement is generated using a dynamic model, considering a unit of time, which can be defined as:

$$\begin{pmatrix} \hat{x}_{t+1} \\ \hat{y}_{t+1} \\ \hat{z}_{t+1} \\ \hat{\dot{x}}_{t+1} \\ \hat{\dot{y}}_{t+1} \\ \hat{\dot{z}}_{t+1} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & \triangle & 0 & 0 \\ 0 & 1 & 0 & 0 & \triangle & 0 \\ 0 & 0 & 1 & 0 & 0 & \triangle \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_t \\ y_t \\ z_t \\ \dot{x}_t \\ \dot{y}_t \\ \dot{z}_t \end{pmatrix} + v_t, \tag{2}$$

where $\triangle$ represents the sampling period, $v_t \sim \mathcal{N}(0, Q)$ the noise, and Q the covariance matrix.

The objective of this trajectory could be, as an example, to examine a warehouse or a ship for inspection purposes. To enable a UAV to design its own trajectory according to the elevation of the warehouse, or the entity being inspected, it needs to generate a dynamical model that relates the internal commands to external odometry or GPS information. To

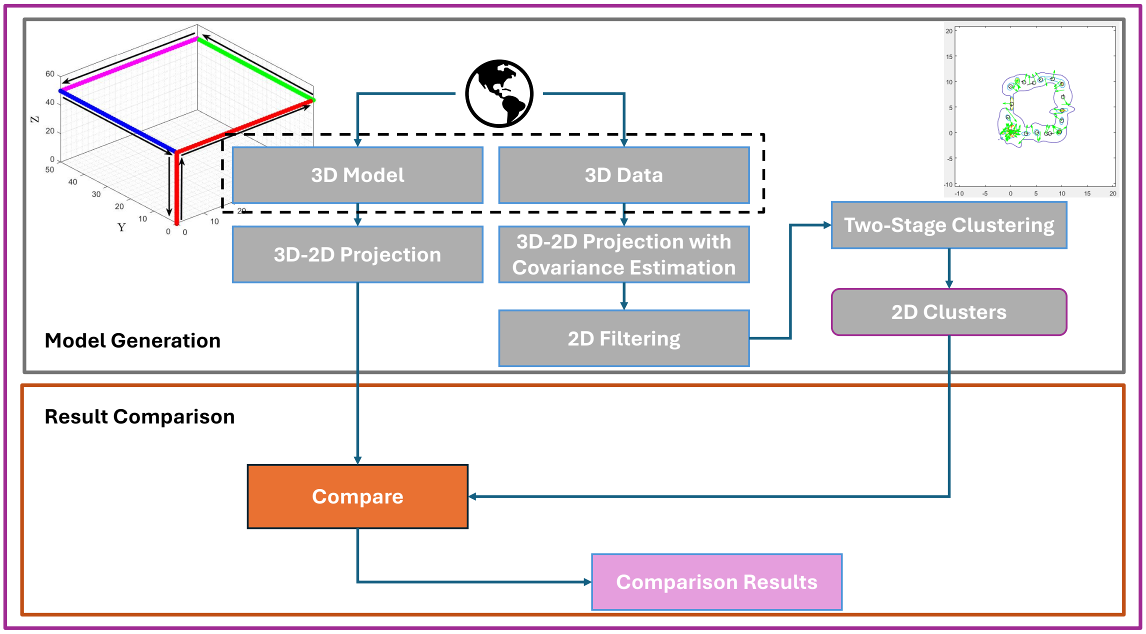


Fig. 1: The block diagram of our system.

predict the 3D coordinates from the prediction model in (2), an observation model, or a projection model, is used:

$$\begin{pmatrix} x_{t+1} \\ y_{t+1} \\ z_{t+1} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \hat{x}_{t+1} \\ \hat{y}_{t+1} \\ \hat{z}_{t+1} \\ \hat{\dot{x}}_{t+1} \\ \hat{\dot{y}}_{t+1} \\ \hat{\dot{z}}_{t+1} \end{pmatrix} + w_{t+1} \quad (3)$$

where $w_{t+1} \sim \mathcal{N}(0, R)$, with covariance matrix R.

We consider both the dynamic (2) and observation (3) models as a ground-truth trajectory generator of 3D trajectories. From this ground-truth 3D model, we can project it to obtain 2D ground-truth models. Finally, we compare the 2D clusters obtained from the two-stage clustering described above (data-driven clusters) with the 2D ground-truth models (model-driven clusters).

To compare the results, we employ the Kullback–Leibler Divergence (KLD) to measure the similarity between these Gaussian distributions.Re-projecting the 3D model onto 2D planes offers both computational efficiency and improved precision. Moreover, by considering each 2D plane combination, it is possible to reconstruct the original 3D information. It is self-explanatory that the changes in each plane can be modeled in 2D by projecting the (x, y, z) plane onto (x, y), (x, z), and (y, z) planes, providing a comprehensive combined view.

E. Comparative 2D Projection Analysis

To evaluate the fidelity of 2D projections in representing the original 3D motion, we compare cluster formations obtained from the projected data with ground-truth clusters derived from the 3D model. Given that each 2D projection retains Gaussian characteristics, we utilize KLD to quantify the discrepancy between projected and original distributions:

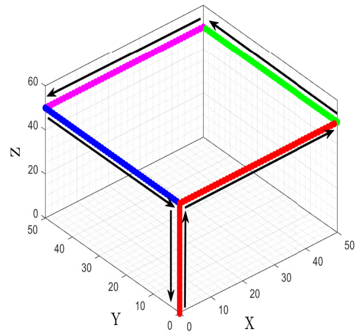
$$D_{KL}(F||G) = \sum F(x) log \frac{F(x)}{G(x)} \quad (4)$$

where F represents the projected data distribution, and G denotes the ground-truth 3D distribution projected onto the same 2D plane. This comparative analysis provides insights into the effectiveness of different 2D projections, guiding optimal feature selection for UAV trajectory modeling and incremental learning purposes.

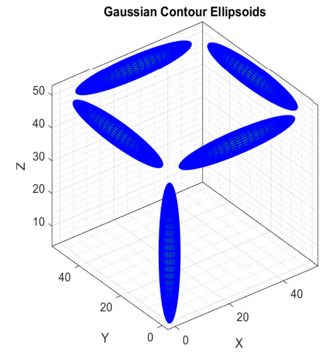
III. Results

In our research exploration, we consider the six 3D ellipsoids representing our model-driven clusters (see Fig. 2.b) and we project them onto the 2D planes (XY, XZ, YZ), thus incorporating their associated directions to represent forces and velocities.

Figure 3 highlights the alignment between the data-driven clusters and the ground-truth clusters for each 2D plane (XY, XZ, YZ). These findings demonstrate that the 2D projections effectively captured the underlying 3D motion patterns, with minimal divergence from the ground-truth model. The comparative analysis revealed that certain 2D planes (e.g., XY) provided better approximations of the motion compared to others, as evidenced by lower KLD values (see Fig. 4). This suggests that the choice of 2D projection can significantly impact the overall accuracy of trajectory modeling and reconstruction. In addition, by re-projecting the clusters, we could obtain a computational advantage in achieving better precision.

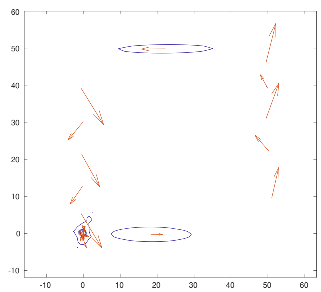


(a)

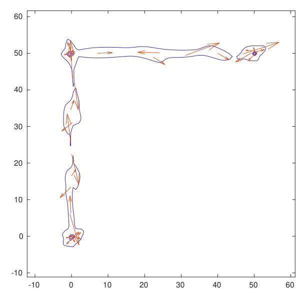


(b)

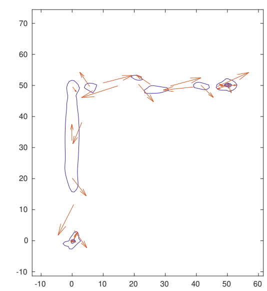
Fig. 2: (a) 3D ground-truth drone trajectory. (b) Set of six 3D Gaussian distributions (two overlap along the z-axis).



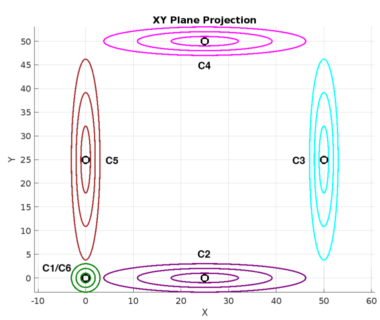
(a) Data model for the XY Plane



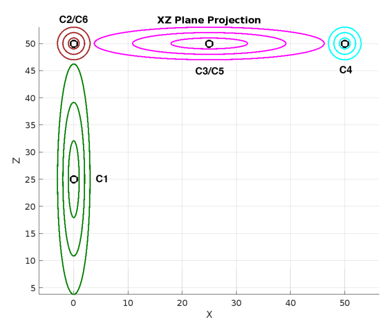
(b) Data model for the XZ Plane



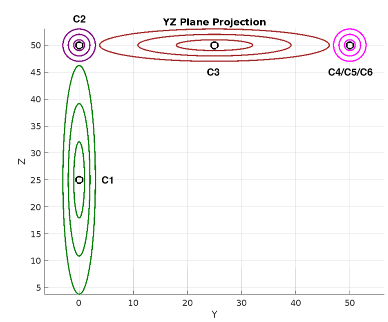
(c) Data model for the YZ Plane



(d) Generative model for the XY plane.



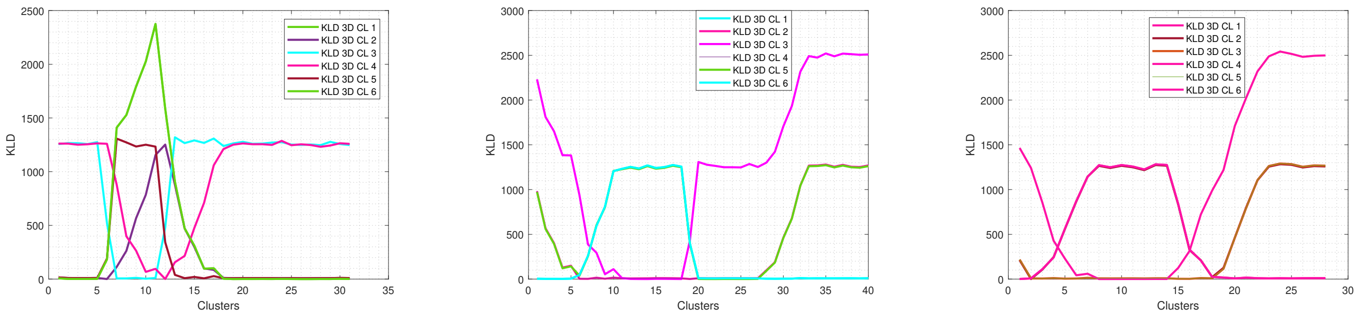
(e) Generative model for the XZ plane.



(f) Generative model for the YZ plane.

Fig. 3: (a-c) The data model for each plane represents our model-driven clusters. (d-f) The different colors represent the different formations obtained from the projected data with ground-truth clusters derived from the 3D model.

Along with that, by taking each 2D plane combinations from the clusters, it is also very much possible to reconstruct back the 3D information, which is our main goal and one of the key directions for future work. The proposed framework successfully integrates adaptive filtering and sequential clustering to improve UAV trajectory analysis. 2D projections provide a reliable approximation of 3D motion, with certain planes offering higher fidelity than others. The use of KLD as a metric for evaluating projection fidelity offers valuable insights for optimizing 2D feature selection in UAV trajectory modeling. In further detail, the six clusters in Fig. 4 represent the ground-truth models, numbered 1 to 6 and distinguished by different colors. As an example, in Fig. 4(a) the data-driven clusters correspond to 31 predictors, used as x-axis labels. The KLD, shown on the y-axis, measures how closely the distributions of the ground-truth models align with the data-driven models. Since we are using sequential clustering, the first five consecutive clusters are predictable from cluster 1. This is evident in Fig. 4(a), for the XY projection of cluster 1 and the first five data-driven clusters. Moreover, since the drone flight starts and ends at the same position, the first cluster and the sixth cluster overlap. Cluster 2 shows higher KLD values among the first five clusters compared to cluster 1, but reaches its minimum at the sixth cluster in the data-driven



(a) (b) (c)

Fig. 4: (a) KLD divergence for the XY plane. (b) KLD divergence for the XZ plane. (c) KLD divergence for the YZ plane

models. Cluster 3 exhibits minimum KLD values from data-driven clusters 7 to 11, indicating a good approximation in the corresponding positions. Cluster 4 shows its minimum KLD at data-driven cluster 12. Cluster 5 has its minimum KLD between clusters 13 and 18. Finally, from cluster 18 to 31, cluster 6 displays the lowest KLD values.

Generalizing the approach to more complex and non-linear paths requires a more complex vocabulary, with more clusters and dynamic models, to achieve a reasonable approximation. This increases computational complexity, mainly due to larger transition matrices. While hierarchical extensions of the proposed DBNs may mitigate this, their investigation lies beyond the scope of this study.

IV. Conclusions

This research work presents a UAV trajectory modeling framework that integrates generative models, adaptive filtering, and sequential clustering. By analyzing 3D trajectories through their 2D projections, we demonstrate the potential for accurate motion representation and reconstruction. The results confirm that certain 2D projections can effectively approximate 3D motion, supporting more efficient and interpretable trajectory analysis. Future work will focus on fusing multi-plane information into a unified 3D model using hierarchical Bayesian approaches to further enhance UAV autonomy and learning in complex environments.

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