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A Deep Mixture of Experts Network for Drone Trajectory Intent Classification and Prediction using Non-Cooperative Radar Data

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***Abstract*—The intent prediction of unmanned aerial vehicles (UAVs) also known as drones is a challenging task due to the different mission profiles and tasks that the drone can perform. To alleviate this issue, this paper proposes a deep mixture of experts network to classify and predict drones trajectories measured from non-cooperative radars. Telemetry data of open-access datasets are converted to simulated radar tracks to generate a pool of heterogeneous trajectories and construct three independent datasets to train, validate, and test the proposed architecture. The network is composed of two main components: i) a deep network that predicts the class associated to the input trajectories and ii) a set of deep experts models that learns the extreme bounds of the trajectories in different future time steps. The proposed approach is tested and compared with different deep models to verify its effectiveness under different flight profiles and time-windows.**

I. Introduction

Predicting the intention of drones is becoming a trending topic due to the potential malicious use of drones that can disrupt national facilities and cause severe economic damage. Here, drone trajectory prediction [1]–[3] is one of the most challenging tasks due to the high diversity of possible intentions that the drone can perform. In addition, the use of non-cooperative radar poses some difficulties in the tracking procedure due to their high-level of noise.

Traditional prediction techniques are based on model-based approaches to estimate the future trajectory [4]–[7]. These models have the advantage that they do not require training data since they exploit physical laws and state estimation algorithms [8], [9] such as Kalman filters and their variants. These models are effective for short-term predictions but are usually ineffective for long-term predictions [10]. The hidden drone objective function [11], [12] specifies the set of actions that the drone might apply to achieve a desired goal in the long term. In consequence, short-term predictions of model-based methods will not be suitable to model these complex behaviours.

The limitations of model-based approaches can be improved through the development of intent-driven dynamical models [4], [6] that predicts both the future kinematics and the intended destination. In these approaches, the intent is modelled as a discrete set of destined locations [6] or as a continuous space over a designated region. Here, the intent is defined as whether the drone intends to enter to an unauthorized region during the flight [6]. However, these approaches do not leverage existing patterns and insights derived from past data, e.g., nearby routes, manoeuvres or flight profile characteristics. In consequence, many false positives may arise due to normal behaviours predicted as anomalous ones which can compromise the smooth operation of national infrastructures.

Another point that needs to take into account is that previous approaches [4] do not exploit the drone contextual information, e.g., its size, model characteristics and type of drone [13]. These features could provide useful situation awareness about the tracked drone and infer its hidden intent. For example, drones used by expert pilots for surveying may pose less risk than hobbyist drones that can enter to restricted areas and alert counter-drone technologies of a potential malicious activity. Furthermore, previous approaches use Kalman filter for state estimation which cannot model adequately the high nonlinear dynamics of the drone coupled with the nonlinear characteristics of the non-cooperative radar measurements [14].

In [5] it was designed a trajectory model conditioned on the inferred intent and the aircraft operating mode. This specific approach relies on complete knowledge of the aircraft dynamics, well-defined flight manoeuvres, ADS-B messages, and aircraft regulations. As outcome the model gives a robust solution for intent prediction and opportune conflict detection. Here, the intents are modelled as the pilot actions which consider regulations and specific flight actions associated to the intended destination. These ideas were adopted in [3] for drone intent inference in geofenced regions. The intents are modelled as regulation-based intents (e.g., avoiding other drones or geofenced areas, or remain within a geofenced area) and flight-based intents (e.g., forward and backward waypoint movements). However, the main issue of these approaches is that they depend on complete knowledge of the flight plan, along with having cooperative ADS-B transmissions. Furthermore, complete knowledge of the drone dynamic model poses a sensitive problem due to the drones' high nonlinear dynamics, high manoeuvrability, and different model structure.

Data-driven approaches have been used for inference of human behaviour [15]–[20]. Here, the approaches are based on classification tasks using image sequences to predict pedestrian trajectories. Deep generative models [21], [22] have been applied to predict the long-term human trajectory conditioned

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on the long-term objective of the task. In terms of drone intent prediction, genetic algorithms have been adopted to model dangerous drone intents using a support vector regressor (SVR) model of the drone kinematics based on ADS-B flight data [2]. In [23], it has been demonstrated that the drone trajectories can be modelled using recurrent neural networks (RNNs) [24] trained on GPS data. This idea is exploited in the proposed research to capture high-dimensional features and time-dependencies of the drone trajectories.

The aforementioned data-driven methods are promising but require a large amount of labelled data which is hindered by the small amount of open-access datasets of drones trajectories. Moreover, radar measurements are usually not openly shared with the research community due to commercial or security constraints. This problem has been alleviated in recent years with radar datasets provided by the Open Radar Initiative [25], Science Data Bank measurements [26], and Real Doppler RAD-DAR [27]. However, these datasets do not contain the information of the radar track features and target trajectories which are the main inputs of the proposed approach.

So, drone trajectories pose high heterogeneity due to its strong nonlinear dynamics dependent of the model structure, flight type, and intended operation. In consequence, it is hard or even impossible for any trajectory prediction algorithm to obtain a model that can generalize to all possible scenarios. Therefore, trajectory prediction algorithms can be enhanced by knowing beforehand the high-level intent [1] class associated to each input trajectory or input sequences. Several research [28]–[30] have been carried out to classify drones using trajectory features, including classification of clutter versus drones and discrimination of fixed-wing versus quadcopter flights. All of these works use extracted point-features from time series trajectories, such as feature means and standard deviations over time. However, to best of our knowledge, there is currently no work that aims to predict the trajectory intent by considering the high-level intent class.

In view of the above, this paper proposes a trajectory intent prediction and classification architecture to: i) classify the high-level intent class from simulated radar input trajectories, and ii) predict the future location of the drone by obtaining the extreme bounds of the possible future trajectory in t time steps. First, a framework is established to generate simulated-radar measurements and tracks from open-access telemetry data to construct three independent datasets. The proposed architecture is given by a deep mixture of models that combines the merits of a deep high-level intent classifier with m deep expert regression models. The final model enhance the prediction capabilities compared with other deep models of the state-of-the-art. Different high-level intent trajectories are tested under the proposed approach with satisfactory results.

II. Data Preparation and Radar Simulation

In [28] is proposed a radar-track generator using ground-truth telemetry. This strategy is by incorporating a variety of mission profiles to produce different drone radar-based simulations for different high-level intents.

The data used in this paper is obtained from open-access telemetry data [31] measured from GPS and inertial navigation system (INS) which define four high-level intent classes [32]–[35]. The four classes are: 1) perimeter flight, 2) point-to-point flights, 3) package delivery and 4) area mapping. These data are converted into simulated radar data and track estimations to model raw radar measurements and the inferred trajectory [36]. This step is helpful to increase the impact of the approach and future integration in current detection systems based on non-cooperative radar.

The proposed radar modelling architecture is based on two main elements: i) the radar location relative to the drone trajectory and ii) the noise distribution. The combination of these elements generate different simulated radar trajectories from one single trajectory. This is helpful to increase the richness of the dataset to train and test the proposed trajectory regression modelling algorithm. The telemetry data covers 400 flights with their associated high-level intent class that contains the longitude, latitude and altitude of the drone trajectory in the GNSS. These data are transformed into Cartesian coordinates [36] to ignore the global location of the drone. In addition, we apply up-sampling and down-sampling methods to homogenize the sampling time of each trajectory within the dataset to 1 Hz.

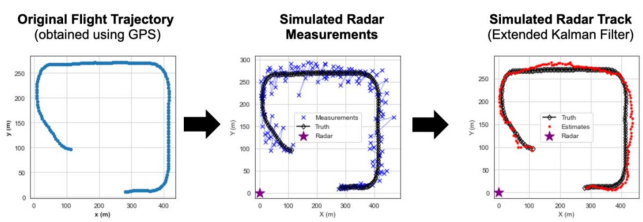


Fig. 1. Simulated radar data and trajectory inference

The noise intensity and location of the radar are iterated to generate heterogeneous radar trajectories [28]. The noise values are tested in the interval $q \in [1, 3]$ with seven arbitrary locations that produce different radar simulated data. The simulated radar data are used to feed an extended Kalman filter (EKF) algorithm to infer the associated trajectory. Here, a linear-time variant (LTV) Gaussian model with near constant velocity [37] is used per dimension to infer the trajectory. For the x-axis we have the following model

$$\boldsymbol{x}_t = \boldsymbol{F}_t \boldsymbol{x}_{t-1} + \boldsymbol{w}_t, \quad \boldsymbol{w}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{Q}_t), \tag{1}$$

with

$$\boldsymbol{x} = \begin{bmatrix} x_{pos} \\ x_{vel} \end{bmatrix}, \quad \boldsymbol{F}_t = \begin{bmatrix} 1 & d_t \\ 0 & 1 \end{bmatrix}, \quad \boldsymbol{Q}_t = \begin{bmatrix} \frac{dt^3}{3} & \frac{dt^3}{2} \\ \frac{dt^3}{2} & dt \end{bmatrix} q, \tag{2}$$

where x_{pos} and x_{vel} are the Cartesian position and linear velocity in the x-axis, d_t is the sampling time, and q is the velocity noise diffusion constant. Fig. 1 shows the inferred

[1]High-level intent defines the purpose of use of the drone

trajectory obtained from the simulated radar measurements under a specific radar location of a random trajectory profile.

Each simulated radar track are divided in different sub-trajectories $\boldsymbol{X}_{traj_t}$ to test the prediction capabilities of the proposed approach under different window length. The proposed window lengths are set to 8, 16, 32, and 64. In addition, we compute the summary features $\boldsymbol{x}_{sum_t}$ associated to each trajectory defined by the mean and the standard deviation.

III. Proposed Methodology

Fig. 2 depicts the general block scheme of the proposed deep mixture of experts (DMoE) network. The network consists in two complementary deep models: 1) a high-level intent classification network that predicts the class associated to an input trajectory, and 2) a deep regression model composed of M expert models that have as input the simulated radar trajectories and their respective summary features. Both the classifier and regression models are related by means of a linear combination of each regression model output $\boldsymbol{y}_{t,i}$ and the softmax output probabilities $\boldsymbol{z}_t$. The outputs of the proposed approach are the class $\arg\max(\boldsymbol{z}_t)$ and extreme bounds $\boldsymbol{y}_t$ of the current flight composed of the minimum and maximum bounds for each coordinate in a three-dimensional Cartesian space for a proposed number of future time steps t

$$\boldsymbol{y}_t = \left[x_{\min}, x_{\max}, y_{\min}, y_{\max}, z_{\min}, z_{\max}\right]^\top. \tag{3}$$

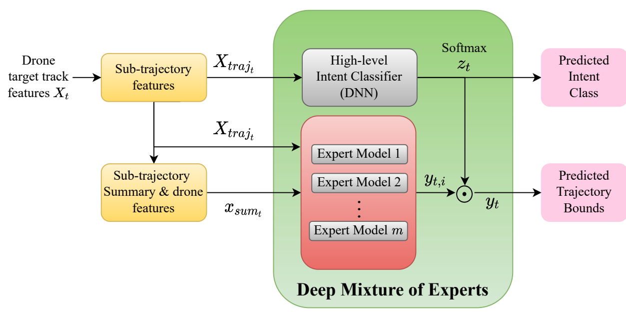


Fig. 2. Deep Mixture of Experts Network for Drone Intent Classification and Regression Prediction

The objective of the high-level intent classifier of Fig. 2 is evident: to predict the class of the input trajectories with high accuracy. However, the output of the regression part is not completely clear since it is not a common output for regression models. The extreme bounds are predicted instead of the future trajectory due to the extremely noisy and short-term uncertainty of the simulated radar tracks. Here, the extreme bounds help to estimate the future localization of the drone and to model potential airspace conflicts and violations.

The bounds are computed by obtaining the associated future (lookahead) trajectories of length t for each sub-trajectory. For each future trajectory, the minimum and maximum bounds across the entire sequence are computed relative to the last time step in the input sub-trajectory. Rather than predicting just one set of bounds, the framework is flexible to predict any number of sets of bounds at different times. In this paper, two sets of future time steps bounds are used: 15 and 30 seconds. Therefore, the final output bounds $\boldsymbol{y}_t$ are represented by a vector of 12 components that covers the minimum and maximum bounds of each dimension in 15 and 30 seconds of future time.

Notice that there exists different high-level intents or flight types of drones which can vary notably from each other or behave similarly. The assumption is that the long-term trajectory of the drone is dependent of the high-level intent associated to the purpose of use. Then, we hypothesize that the trajectory prediction algorithm will be enhanced by providing the information of the flight purpose. Therefore, we propose to use the predicted probabilities of the high-level intent classifier to increase the prediction capabilities of the regression model.

A. Model design

In the proposed approach, we use a bidirectional convolutional long-short-term-memory with attention (BCLSTM-A) network [38] to classify the high-level intent and a Deep Mixture of Experts (DMoE) as the regression model. The BCLSTM-A network is chosen due to its high capabilities to detect spatial patterns and time-dependencies which are suitable properties when we deal with time-series data. The DMoE model includes M unique multi-input convolutional models that are trained specifically on each high-level intent class. Each expert model serves as a specialist for predicting the future bounds of a particular high-level intent flight. The M experts are linearly combined with the outputs of the softmax probabilities of the high-level intent classifier. This means that a high probability of a softmax output will weight more a specific expert model than the others such that the extreme bounds will depend mainly of this specific expert.

Each simulated radar track $\boldsymbol{X}_t$ is decomposed into sub-trajectory features $\boldsymbol{X}_{traj_t}$ and summary features $\boldsymbol{x}_{traj_t}$ that feed the proposed DMoE. These complementary features enhance the trajectory prediction in comparison to using only the sub-trajectory features $\boldsymbol{X}_{traj_t}$. Four experts are trained for each of the high-level intent classes used in this paper. The outputs of the four experts are the extreme bounds of each class denoted as $\boldsymbol{y}_{t,1}$, $\boldsymbol{y}_{t,2}$, $\boldsymbol{y}_{t,3}$, and $\boldsymbol{y}_{t,4}$. Each extreme bound is weighted by the softmax probabilities of the high-level classifier $\boldsymbol{z}_t$ to determine the expert model with highest priority in the prediction. The final output is an ensembled vector $\boldsymbol{y}_t$ that is computed as

$$\boldsymbol{y}_t = \sum_{i=1}^{m} z_{t,i} \odot \boldsymbol{y}_{t,i}, \tag{4}$$

where $\odot$ represents the Hadamard product.

B. Comparison models and metrics

We compare the proposed DMoE architecture with other deep neural models to evaluate its performance. First, we design a multiple-output linear regression model as a baseline to gauge performance with the neural models. Three deep models are used to evaluate the proposed model, which include: 1) multi-input LSTM, 2) multi-input CNN, and 3) multi-input convolutional LSTM with attention (CLSTM-A). Each model has the same learning objective of the DMoE.

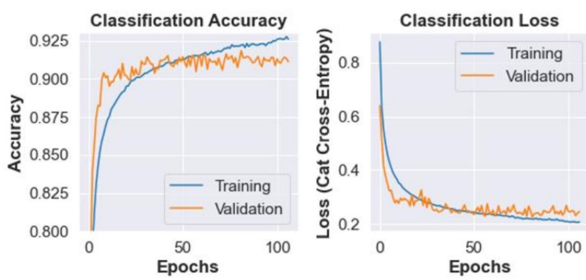
The proposed performance metrics for the classifier are: a) accuracy, b) precision, c) recall, and d) F1-score. For the regression models the metrics are: i) the root mean-squared error (RMSE), ii) mean absolute error (MAE), and the R^2 statistical measure.

IV. Model training and evaluation

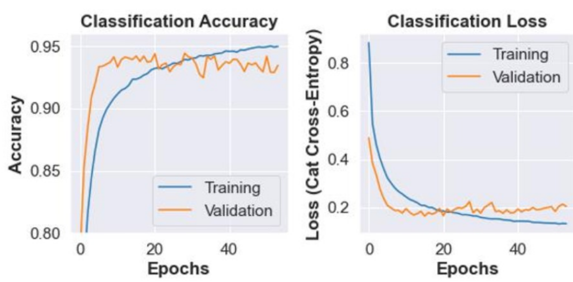
We apply dropout and early stopping regularization techniques to avoid overfitting problems in the model training phase. We monitor carefully the training and validation curves to obtain the best models that best generalize for both the classifier and regression tasks. Here, we stop the learning model if the learning curves do not exhibit improvement after 20 epochs. The hyperparameters are optimised using a grid search across a range of settings and maximising the performance on the validation data.

A. *High-level intent classification results*

The accuracy curves of the BCLSTM-A model for time-windows 8 and 32 are given in Fig. 3.



(a) Window length 8s



(b) Window length 32 s

Fig. 3. Accuracy of the BCLSTM-A under the training set

TABLE I
CLASSIFICATION PERFORMANCE AVERAGED ACROSS ALL TIME-WINDOWS

Model	Validation				Test			
	Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score
BCLSTM-A	**0.9467**	**0.9205**	**0.9230**	**0.9213**	**0.9795**	**0.9761**	**0.9844**	**0.9801**

Here, the accuracy results show that after certain number of epochs the BCLSTM-A tends to the overfitting problem which is solved by applying the early stopping regularization technique. Notice that the results are notably good for a small number of epochs. The final results of the BCLSTM-A under the validation and test dataset are averaged for all time-windows and summarized in Table I. The results demonstrate the high performance of the classifier to predict the class associated to the input trajectories which is highly beneficial for the DMoE.

TABLE II
REGRESSION MODELS RESULTS

Model	Input Window Length (s)	Validation			Test		
		RMSE	MAE	R^2	RMSE	MAE	R^2
Multiple Linear Regressor	8	160.1633	78.2503	-0.3420	132.5540	77.3753	-0.5326
Multi-Input LSTM	8	110.1799	41.7504	0.3842	85.4451	40.2597	0.5218
Multi-Input CNN	8	103.5907	39.0094	0.4657	85.3480	39.3726	0.3619
Multi-Input CLSTM-A	8	111.5730	41.5846	0.3653	87.3944	40.8109	0.2604
DMoE	8	**101.3812**	**31.3710**	**0.4863**	**68.6532**	**28.1353**	**0.7056**
Multiple Linear Regressor	16	153.6455	77.1540	-0.3620	132.7385	77.6763	-0.5332
Multi-Input LSTM	16	112.2328	42.1724	0.2797	86.8703	39.9684	0.6193
Multi-Input CNN	16	101.3007	39.2357	0.4251	86.9849	40.5390	0.2960
Multi-Input CLSTM-A	16	106.4226	40.2257	0.3550	91.1821	41.0788	0.0145
DMoE	16	**93.7063**	**29.3688**	**0.5005**	**66.3241**	**27.1486**	**0.7996**
Multiple Linear Regressor	32	141.9160	75.2715	-0.4356	133.8516	78.9101	-0.5807
Multi-Input LSTM	32	99.8031	38.2608	0.2939	96.5178	42.0042	0.4052
Multi-Input CNN	32	83.8012	35.1835	0.5015	82.2166	38.4593	0.3680
Multi-Input CLSTM-A	32	103.1382	40.0585	0.2450	88.9015	41.3739	0.1340
DMoE	32	**82.1361**	**25.7226**	**0.5235**	**65.8922**	**26.4180**	**0.8286**
Multiple Linear Regressor	64	118.1680	70.8340	-0.8352	150.1881	84.2064	-1.3223
Multi-Input LSTM	64	74.7022	37.1499	0.2205	113.5891	50.7256	0.2842
Multi-Input CNN	64	69.8620	35.8270	0.3235	86.8546	43.0635	0.2564
Multi-Input CLSTM-A	64	65.0951	33.9712	0.4254	98.7680	45.2943	0.3227
DMoE	64	**59.2363**	**22.5724**	**0.5318**	**80.1402**	**30.3676**	**0.6589**

B. *Trajectory intent regression results*

The numerical results of each regression model under the validation and test datasets are given in Table II and the averaged results over all time-windows are given in Table III.

TABLE III
REGRESSION MODELS PERFORMANCE AVERAGED ACROSS ALL TIME-WINDOWS

Model	Validation			Test		
	RMSE	MAE	R^2	RMSE	MAE	R^2
Multiple Linear Regressor	143.4732	75.3775	-0.4937	137.3331	79.542	-0.7422
Multi-Input LSTM	99.2295	39.8334	0.2946	95.6056	43.2395	0.4576
Multi-Input CNN	89.6387	37.3139	0.4290	85.3510	40.3586	0.3206
Multi-Input CLSTM-A	96.5572	38.9600	0.3477	91.5615	42.1395	0.1829
DMoE	**84.1150**	**27.2587**	**0.5105**	**70.2524**	**28.0174**	**0.7482**

The deep regression models outperform the baseline linear regressor across all metrics as it was expected. The proposed DMoE exhibits better results in both the validation and test datasets in comparison to the other deep models. This fact is clearly visualized in the R^2 results that demonstrates the DMoE fits better each high-level class across all the time-windows. The RMSE and MAE scores are useful for relative comparisons between each model, however they do not provide an indicator of how good is a model. The R^2 measure gives this indicator and is crucial in the model adjustment. Here, an R^2 score that tends towards to 1.0 represents a model that predicts exactly the desired outputs. The DMoE has the best R^2 score of 0.7842, whilst the second best model is the multi-input LSTM with 0.4576. These results show a large drop in performance compared with the DMoE. One relative minor disadvantage of the DMoE is the training and inference times caused by the number of expert models. In this case, a large number of experts may cause large learning time which can be mitigated by using different processor units.

Table IV shows the average times overall time-windows of each regression model.

TABLE IV
AVERAGE TIMES FOR TRAINING AND INFERENCE

Model	Training Time (s)	Average Prediction Time(s)
Multiple Linear Regressor (Baseline)	**0.95**	**3.57e-7**
Multi-Input LSTM	148.31	2.31e-5
Multi-Input CNN	171.37	1.48e-5
Multi-Input CLSTM-A	1092.22	3.10e-5
Deep MoE	655.25	6.19e-5

We can observe from the results of Table IV that, whilst the DMoE needs more time to train in comparison to the LSTM and CNN regression models, it is faster than the CLSTM-A. In terms of the average prediction time, the proposed DMoE require more computation time since it has to evaluate 4 experts. In terms of the specific implementation of this paper, the increased computation time is not a meaningful factor that influence in the final implementation of the algorithm. However, in a general case of m expert models the computation time can be an issue and it will require processing allocation between different units.

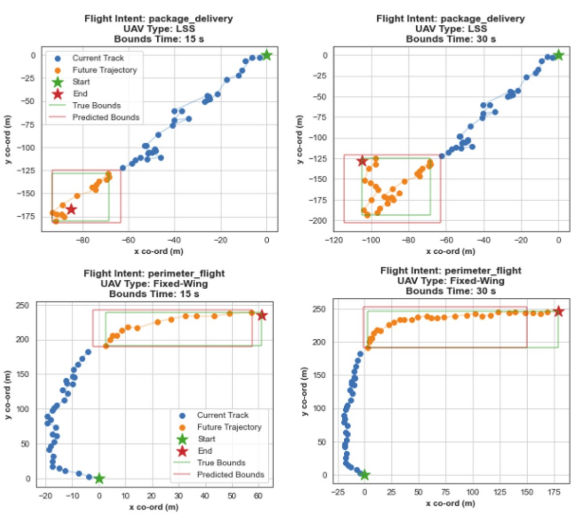
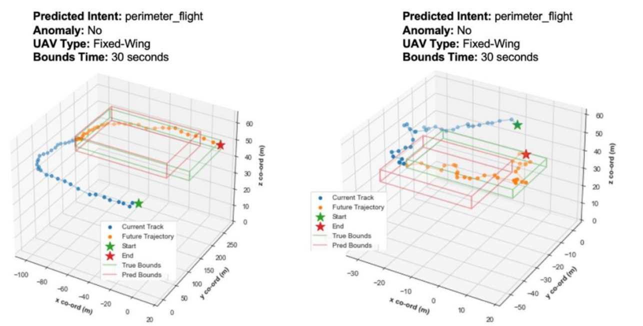


Fig. 4. Predicted extreme bounds examples

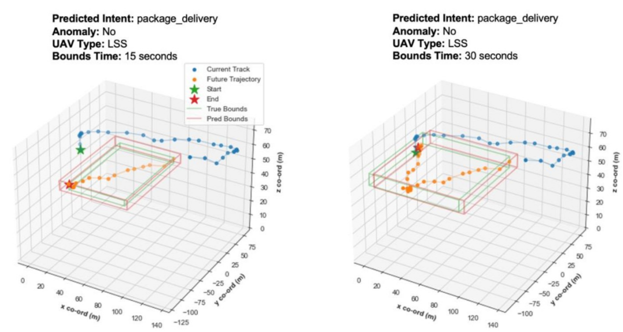
The overall results, show that applying the DMoE architecture yields to better predictive performance rather than using only a single model for all the trajectories associated to specific high-level classes. This suggests that individual expert models have more power to learn specific pattern representations and time-dependencies of the associated class, rather than obtaining an expert model that generalizes to all classes. This fact is more evident if we have more classes. In this scenario, a single expert model would fail to generalize to all the possible classes and hence the prediction performance will be poor. On the other hand, the DMoE solves this problem by creating a set of experts associated to each class. This as outcome will enhance the prediction performance but it will increase the computation time and the model complexity.

C. Prediction under unseen test trajectories

The trained DMoE is tested under unseen test trajectories to evaluate its performance. Fig. 4 shows some examples of the predicted extreme bounds in a future time of 15 and 30 seconds.



(a) Perimeter flight examples



(b) Package delivery examples

Fig. 5. Predicted extreme bounds in a three-dimensional Cartesian space

Furthermore, the approach can also visualize the extreme bounds in the three-dimensional Cartesian space. Figure 5 shows some examples of the predicted extreme bounds.

V. CONCLUSIONS

This paper proposes a deep mixture of experts architecture for both classification and trajectory prediction of simulated radar tracks of drones. Telemetry data of open access datasets are transformed into a wide variety of radar measurements by combining different locations of the radar and assumptions of the noise distribution. The radar tracks are obtained from an extended Kalman filter implementation based on a linear-time-variant Gaussian model. The classifier is designed as a bidirectional convolutional LSTM with attention that predicts the high-level class of the associated trajectory. The regression model is constructed from a set of experts models based on a multi-input CNN that learns the extreme bounds of specific tasks in t time steps in the future. These experts models are linearly combined by the output probabilities of the high-level intent classifier. The extreme bounds are determined by the expert model with highest softmax probability. The final model is tested, compared and verified under two independent datasets and different deep models to ensure good classification accuracy and trajectory prediction results. The obtained results show that the proposed DMoE achieves good classification and regression results by combining the merits of the high-level intent classifier with a set of expert models.

Future work will address the incorporation of additional features provided by the radar measurements to increase the capabilities of the proposed approach.

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