# Machine Learning-Based Traffic Management Model for UAS Instantaneous Density Prediction in an Urban Area

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Abstract—The number of daily recreational and commercial sUAS operations in low altitude airspace is expected to reach into the millions in the near term. Therefore, UAS density prediction has become an emerging and challenging problem. In this paper, a machine learning-based UAS instantaneous density prediction model is presented. The model takes two types of data as input: 1) the historical density generated from the historical data, and 2) the future sUAS mission information. The architecture of our model contains four components: Historical Density Formulation module, UAS Mission Translation module, Mission Feature Extraction module, and Density Map Projection module. The training and testing data are generated by a python based simulator which is inspired by the multi-agent air traffic resource usage simulator (MATRUS) framework. The quality of prediction is measured by the correlation score and the Area Under the Receiver Operating Characteristics (AUROC) between the predicted value and simulated value. The experiment results demonstrate outstanding performance of the machine learning-based UAS density predictor. Compared to the baseline models, for simplified traffic scenario where no-fly zones and safe distance among sUASs are not considered, our model improves the prediction accuracy by up to 15.2% and its correlation score reaches 0.947. In a more realistic scenario, where the no-fly zone avoidance and the safe distance among sUASs are maintained using A\* routing algorithm, our model can still achieve 0.822 correlation score. Meanwhile, the AUROC can reach 0.951 for the hot spot prediction. Finally, we extend our UAS instantaneous density prediction model to a continuous prediction framework. By applying the continuous prediction framework, the UAS density prediction time horizon can be significantly increased from 60 simulation cycles to 360 simulation cycles (1 hour), with highest 0.892 correlation score on average. This feature grants us a chance to apply our density prediction model in real-word scenarios.

Index Terms—instantaneous density prediction, UAS, spatial-temporal model, continuous prediction framework

## I. INTRODUCTION

Recently, many companies devote themselves to develop small Unmanned Aircraft Systems (sUAS). Complicated and high density UAS traffic imposes significant burden on air traffic management, city planning and communication resource allocation. In this environment, the following critical questions are usually asked: Given the list of sUAS scheduled launches in an area, do we know in advance whether a feasible route in

terms of air space safety and energy efficiency can be found for a specific mission at a specific time? Do we need to delay the launch of some sUAS in advance to accommodate a mission with higher priority scheduled at a specific time? Answering such questions and being able to predict the traffic distribution ahead of time will provide an opportunity for more efficient planning and control.

UAS density prediction is a critical and challenging problem in the Unmanned Aircraft System Traffic Management (UTM) system. Most existing studies focus on simulation-based approaches. Although accurate, they usually take a long time to deliver results. Neural networks have been used to predict traffic density [1]. However, most such studies require the sampling of the traffic density from the past data and predict the future density using past density information. These models assume a static environment. For example, the source (i.e. the location where the sUAS enters the air space) and sink (i.e. the location where the sUAS leaves the air space) of the traffic flow are assumed to remain the same, and air space constraints, such as no-fly zones, are fixed. Based on these assumptions, the traffic in the future will exhibit a similar pattern as the traffic in the past, and can be predicted from the historical data. A constant environment may be reasonable for road traffic, however, the operational environment of sUAS features higher dynamics and flexibility. The model based on historical data will become obsolete as soon as the environment changes. New data must be collected and a new model needs to be trained, which can take days or weeks. Furthermore, most of the existing models consider traffic distribution as a stationary process, and focus on predicting the steady states. For resource provisioning or safety assurance, we need to know not only the steady state traffic but also the worst case traffic. Hence the ability to predict the transient behavior of air traffic distribution is highly desirable.

In this paper, a machine learning-based prediction model is presented for semi-transient traffic density distribution prediction. The model takes the air space environment and the prescheduled launch list in the next T time units as the inputs, and predicts the average traffic density of traffic distribution in this air space during time  $[T-\delta, T]$ . The parameter T controls

the prediction horizon and by reducing the value of parameter  $\delta$ , the focus of the model changes from the long-term average behavior to the transient behavior of the traffic. By taking the flight environment and detailed launch information as part of the inputs, the model is specialized only with respect to the type of trajectory planning algorithms. It can be generalized to different air space as long as the trajectory of each UAS is routed using the same algorithm. It will have no "down time" after the map or the launching/landing zone has changed.

Compared with other existing methods, our model has high prediction accuracy and can achieve a correlation score of 0.947 and can improve the prediction accuracy by up to 15.2%. In a realistic traffic scenario, where no-fly zone avoidance and safe distance between sUASs are considered by planning the trajectory using A\* routing algorithm [2], our model can still achieve a correlation score of 0.823. The following summarizes the major contributions of our work:

- A novel UAS traffic density prediction model is developed that captures the information from the historical data and the pre-scheduled sUAS launch list.
- A novel input representation of the future sUAS mission information is proposed. The pre-scheduled missions are categorized into 3 types according to their launching times. Our model is designed to extract features from all types of inputs simultaneously.
- Compared to the baseline models, our model improves the prediction accuracy by up to 15.2%. When doing hot spot prediction, our model can achieve an AUROC score of 0.951.
- The qualitative results demonstrate that our model can accurately predict hot spots (congestion) in the future traffic map and has the ability to predict the density of UAS with broad range of missions/trajectories.
- The UAS instantaneous density prediction model has been extended to a continuous prediction framework.
   By applying the proposed framework, the UAS density prediction time horizon can be significantly extended from 60 simulation cycles to 360 simulation cycles, with highest 0.892 correlation score on average.

#### II. RELATED WORKS

Over the past decade, unmanned aerial vehicles have played an increasingly essential role in many areas [3] [4] [5] [6]. With the rise in the popularity of sUAS, many notable issues related to UAS traffic management have been studied. However, the study of the UAS cluster behaviors such as forecasting the UAS traffic density has generally not been addressed. In our investigation, the density forecasting approaches can be categorized into simulation based methods and machinelearning based methods. In this section, we will analyze the pros and cons of recent works in these two categories.

Many existing works study issues such as sUAS navigation, obstacle avoidance or UAS traffic management, by developing a corresponding simulator with manageable time complexity. In [7], the authors presented an indoor algorithm to navigate a single sUAS to avoid collisions. [8] proposed a solution to

avoid collisions in a static environment by importing geometrical constraints. Other approaches considering a single sUAS included the application of rapidly-exploring random trees [9] and Voronoi graphs [10] [11]. Trajectory simulation with multiple sUASs has been studied as a multi-agent cooperative system and solved in a rolling horizon approach using dynamic programming [12] or mixed integer linear programming [13]. Other strategies [2] [14] involved real-time routing algorithms with communication and airspace safety considerations. Recently, a very strict and rigid airspace structure to handle dense operation in the urban low altitude environment was suggested by the work on UAS Traffic Management (UTM) at NASA in [15]. The authors explored UAS operations in nonsegregated air space and managed the risk of mid-air collision to a level deemed acceptable to regulators. In the paper, the airspace was divided into multiple layers, and the layers were further divided into orthogonal sky lanes. There are no current studies that solve the traffic prediction problem from a broad perspective within a small runtime.

In this work, instead of developing a simulator, we utilize machine learning for UAS traffic density prediction. The machine learning based approach has shown outstanding success in many domains [16] [17] [18] . Similar multi-agent frameworks are employed in other fields such as pedestrian density prediction [19] and autonomous driving [20]. In [21], authors proposed an LSTM based scene-aware model to predict trajectories for autonomous driving. However, the prediction errors grew exponentially as the time horizon increased. Another work addressed pedestrian traffic flow prediction by fusing historical information, but the prediction is limited by historical data regardless of the upcoming event information. Existing approaches on single-agent trajectory prediction concentrated on the behavior of a single sUAS and the impact of environment conditions, without any consideration of sUAS clusters. For example, [22] proposed an LSTM-based flight trajectory model with weather considerations taken into account. [23] [24] aimed to solve environment navigation problems, and developed a reinforcement learning model to plan energy efficient waypoint in a static environment.

Compared to the existing work, our model has the ability to learn and extract information from the historical data and the pre-scheduled sUAS mission launch list. And the error is restrained strictly via dynamic feature extraction. By adopting a novel channel segmentation approach, our mission feature extraction module can learn the density features accurately.

# III. METHODS

Our density prediction model is an end-to-end model. Each component module is fully differentiable. The mean square error (MSE) loss is calculated by measuring the difference between the predicted density map and the labeled density map. The architecture of our model contains four components: Historical Density Formulation module, UAS Mission Translation module, Mission Feature Extraction module, and Density Map Projection module. The model structure is depicted in

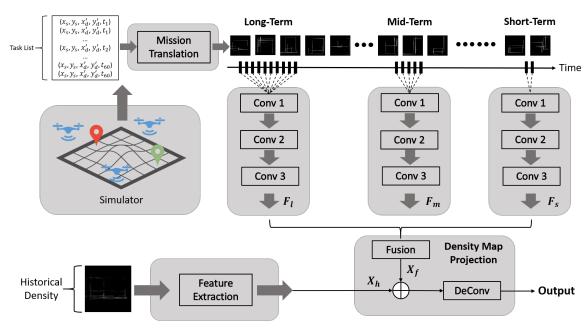


Fig. 1: Mission-Aware Spatio-Temporal Model Architecture

Figure 1. In this section, each component of the model will be elaborated.

#### A. Historical Density Formulation

The historical density describes the pre-existing air space environment. The size of the historical density map is  $100 \times 100$  grid unit which is the same as the simulation environment. The value at each pixel is between 0 and 1 and represents the average density in the past m simulation cycles. The value of m is set to be 10 in this paper. The historical density will also be called "initial density" in this paper. Given the historical density, we employ a convolutional neural network (CNN) to extract the relevant features. The model is composed of 3 convolution layers, 2 pooling layers and the ReLU activation layers. Finally, the  $C \times 32 \times 32$  feature maps are obtained from the feature extractor, where C is the number of feature channels. The feature extracted from the historical density is denoted as  $X_h$ .

#### B. UAS Mission Translation

This module is responsible for translating the trajectory of each sUAS mission to image representation. First, the UAS future missions are summarized into a mission list. The dimension of the mission list is  $n \times 5$  where n is the number of missions in the future. Each mission is defined by a 5 dimensional vector:  $\{X_s, Y_s, X_d', Y_d', T_n\}$ . The  $\{X_s, Y_s\}$  and the  $\{X_d', Y_d'\}$  represent the launching and landing locations of the mission. The launching time is indicated by  $T_n$ . Given the mission list, the model will first cluster the missions into different groups based on the mission launching time. Then, the mission translation module follows in the same manner as the breadth-first search (BFS) algorithm to map the trajectory of each mission into a 2D map. From each Origin-Destination

(O-D) pair, we draw a shortest path from the launching location to the landing location. For each individual mission, we assume that the horizontal direction movement has a higher priority than the vertical direction movement. The movement priority is the same as in the MATRUS simulator [25]. After the UAS mission translation procedure, a K channel output can be obtained. Each channel lumps the trajectory information of the sUAS that will be launched in the same simulation cycle. K is set to be 60 in this paper.

Moreover, we introduce a novel sUAS trajectory representation approach, which we refer to as the "Flow". The "Flow" input representation uses an ascending sequence to represent the sUAS movement from the launching location to the landing location. Therefore, in the visualization of the 2D map, the waypoints near the landing location are brighter than the waypoints near the launching location. If one location is occupied by more than one sUAS, we use the mean of all the overlapped values to represent this location. By using this input representation, the model can distinguish launching and landing locations. In addition, the order of the sUAS movement is also specified. Figure 2 shows two mission translation examples.

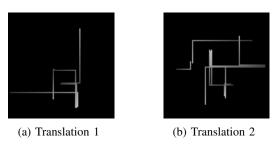


Fig. 2: UAS Mission Translation Examples

#### C. Mission Feature Extraction

The translated UAS missions are fed into the mission feature extraction module. This module is responsible for learning the density features from the pre-scheduled missions. Inspired by [1], we develop a novel channel segmentation model. First, according to the mission launching time, the translated missions are categorized into 3 groups: long-term, mid-term and short-term. In our case, the long-term group contains the launching missions from cycle 1 to cycle 30. The midterm group involves the launching missions from cycle 31 to cycle 50. The rest of the launching missions, cycle 51 to cycle 60, belong to the short-term group. Then, three types of models with different number of input channels are employed to extract the features from the inputs. The number of input channels for long-term, mid-term and short-term models are 10, 5 and 2, respectively. Each individual model has the same structure but the weight will be updated independently. The intuition behind the model architecture design is that the mission whose launching time is close to the end should have a larger impact on the final density. Then, three types of features (long-term feature, mid-term feature and short-term feature) can be obtained, which are denoted as  $\{F_l, F_m, F_s\}$ . In the fusion module, the learnable parameters are introduced to adjust the degrees affected by different features. Therefore, the mission from different times will contribute accordingly to the final density. The fusion equation is defined as follows:

$$X_f = \{W_1 \times F_{s_1} + \dots + W_k \times F_{m_1} + \dots + W_n \times F_{l_n}\}$$
 (1)

where W denotes the learnable parameters. The output density feature is denoted as  $X_f$ . And, the  $F_s$ ,  $F_m$  and  $F_l$  are the features extracted from short-term input, mid-term input and long-term input, respectively.

Consequently, a  $C \times 32 \times 32$  feature map is obtained from this module, where C stands for the number of feature channels.

# D. Density Map Projection

Finally, two features  $\{X_h, X_f\}$  are concatenated together to construct a fused density feature representation. Then, we apply a de-convolution module to project the density feature into a 2D density map that has the same width and height as the whole simulation environment. The de-convolution module is composed of four 2D-transpose layers, batch normalization layers and the ReLU activation layers. The value at each location stands for the average density at the given prediction time  $T_1$ . In this paper,  $T_1$  is set to be 10 simulation cycles.

## IV. EXPERIMENTS

# A. Data Generation

Inspired by the MATRUS framework [25], we implement a Python based sUAS flight simulator. For each traffic scenario tested in this paper, we ran the simulator to generate 3000 samples. All the data sets are divided into two subsets: training and testing. The split ratio is 90: 10. For each sample, the simulator randomly generates 5 launching areas and 5 landing

areas on a  $100 \times 100$  grid environment. Each area has the size  $3 \times 3$ . Any grid in this area can be considered as the launching location. The minimum distance between any two areas is 5 cells. For each launching area, the simulator uses uniform distribution to randomly generate a floating-point number as the launch probability. At every simulation cycle, the simulator randomly selects 15 launching locations from all launching areas. For each selected location, the simulator randomly decides whether a mission should be launched from current location at current cycle based on the launch probability.

For each sample, the simulation time horizon is defined as T. In this paper, T is set to be 60 simulation cycles, and each cycle lumps sUAS launching information in 10 seconds. The time period that generates the density map will be described as  $T_1$ . The data generation procedure is depicted in Figure 3.

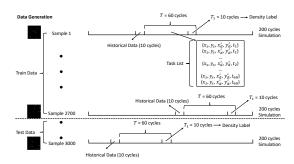


Fig. 3: Data Generation Procedure

# B. Evaluation Metrics

Two metrics are used to measure the quality of the prediction.

(1) Correlation: Correlation is calculated between the simulated traffic density (Y), which is considered as the ground truth, and the predicted traffic density  $(\hat{Y})$ . In our experiments, this shows whether and how strongly the predicted and labeled variables are related. The equation of the Correlation is as follows:

$$\rho(X,Y) = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} \tag{2}$$

where  $\rho(X,Y)$  is Pearson's correlation coefficient of X and Y,  $\sigma_X$  and  $\sigma_Y$  are the standard deviations of X and Y, respectively. Cov(X,Y) is the covariance of variables X and Y, which can be calculated by the following equation:

$$Cov(X,Y) = E[(X - E[X])(Y - E[Y])]$$
 (3)

where E[.] denotes the expected value.

(2) Area Under the Receiver Operating Characteristics (AUROC): The ROC curve is plotted by mapping the True Positive Rate (TPR) against the False Positive Rate (FPR) with different thresholds. Given a ROC curve, the AUROC evaluates the performance of the model by distinguishing between classes. The higher the AUROC score of a model, the better the performance is. For an uninformative model, the AUROC is close to 0.5. The maximum AUROC is 1.

# C. Comparison Models

To the best of our knowledge, there is no prior work considering exactly the same application as this paper. For comparison, we selected several existing models that are potentially promising for traffic prediction, and re-trained them using our data set. We also compared with a modified version of our own model to show the effectiveness of certain design decisions of our model. The following five models are tested and compared.

- Vanilla CNN (VCNN): This is a typical CNN based encoder-decoder model. The model assumes that, the location and action probability of each launching/landing area is static and can be represented in a 2D map. It tries to learn the relation between traffic density and the 2D map, and makes predictions based on the static information.
- Vanilla LSTM (VLSTM): This is a typical LSTM based encoder-decoder model. It takes the T-cycle scheduled launching information and predicts the density at the  $T+1^{th}$  cycle. Because the traffic density of cycle (t+1) is determined by the density at cycle t and the current launching information, it is expected that such temporal dependency can be captured by an LSTM model.
- RouteNet [26]: The RouteNet model is encouraged by the Fully Convolutional Network (FCN) architecture that predicts the congestion in VLSI placement and routing. The FCN allows the input to be any size and produces an output with exactly the same size as the input, indicating the density (or hotspot) at any location.
- Segmented Channel: This is our model as discussed in this paper. The inputs are categorized into 3 groups. Then, the designated models are assigned to each group for extracting the features. The model applies the 2D convolution with 2 × 2 and 4 × 4 kernel size. The max pooling is also used in the model.
- All Channel: This model has a similar structure as the one presented in this paper except that there is no input channel segmentation. The model treats all missions with different launching times equally.

# D. Experiment Setup

We run our experiments on a desktop server running Ubuntu 16.04 OS with 3.60GHz Intel Xeon W-2123 CPU, 256GB Memory and a NVIDIA 2080Ti GPU. During the training, the Adam optimizer is applied with a 0.005 learning rate. The weight decay is set to 0.0001. We use the ReLU to be the activation function. Batch normalization and dropout are also applied for preventing the overfitting. The training and testing framework are built in PyTorch.

#### V. RESULTS

# A. Predicted Density Accuracy Improvement

In the first experiment, we compare the accuracy of the density prediction between our model and the other baseline models mentioned in Section IV-C. The model which extracts

the trajectory features from all input channels is denoted as " $channel_{all}$ ". Our presented channel segmentation model is denoted as " $channel_{seg}$ ". Because the prediction model assumes a non-empty air space, we are interested to know how close the initial traffic density resembles the density at the target time of prediction. The column "init" gives the correlation between the initial density and the label density.

TABLE I: The Correlation Score of the Density Prediction

Init	VCNN	VLSTM	RouteNet	$Channel_{all}$	$Channel_{seg}$
0.822	0.863	0.803	0.889	0.944	0.947

Table I shows the correlation score for all the models. The LSTM model has the worst performance among all the models. The correlation score of the "VLSTM" model is even lower than the "init" correlation score. One reason for this is that the 60 cycle prediction period is too long for the "VLSTM" model. The error will accumulate and propagate from the first cycle to the last cycle. The "VCNN" model improves the correlation score by 5.0%. However, ignoring the information of exactly when and where each sUAS is going to be launched and where it is heading from now to the end of prediction window makes the prediction much less specific. Therefore, the "VCNN" model cannot achieve a higher accuracy. In the "RouteNet" model, each scheduled mission will be marked by a bounding box between the Origin-Destination (O-D) pair. This approach gives the model a more forthright indication of each mission and the relation between the launching and the landing locations. Consequently, the "RouteNet" model improves the correlation score by 8.2%. Finally, our presented model, "channelall" and "channelseg", outperforms all other models. Compared to the initial traffic density, the predicted density of these models clearly resembles the actual density at the end of prediction window better, with 14.8% and 15.2% improvement of the correlation score, respectively.

Between the two model architectures that we proposed, the "channel<sub>seg</sub>" model can achieve higher correlation score than the "channel<sub>all</sub>" model. However, the difference is very marginal. In the next, we will show that using segmented channel is important under the scenario in which the process of UAS launching is non-stationary.

# B. The Model Sensitivity to Missions

In the second experiment, we study the model's sensitivity to missions. In our assumption, the most recent missions should have a larger contribution to the predicted density than those that took place earlier in time. And the model should be able to capture the features from the non-stationary missions. In order to further analyze this conjecture, we use the normal mission list as the input in the model training phase. The normal mission list means that all the 60 cycles have the launching missions. However, in the testing phase, we remove the missions from either the first 30 cycles or last 30 cycles. Therefore, the experiments are broken down into 2 scenarios:

- No Task Before 30 (NTB\_30): No new launching mission from cycle 1 to cycle 30.
- No Task After 30 (NTA\_30): No new launching mission from cycle 31 to cycle 60.

TABLE II: Model Sensitivity to Missions Experiments

Scenario (2D)	NTB_30	NTA_30
init	0.699	0.647
$channel_{all}$	0.765 (+9.4%)	0.751 (+16.1%)
$channel_{seg}$	<b>0.836</b> (+19.6%)	<b>0.858</b> (+32.6%)

Table II shows the correlation score of the experiment. The "init" stands for the correlation score between the initial density and the label. We take the "channel\_{all}" and the "channel\_{seg}" to be two comparison models. The results show that the "channel\_{seg}" model always has a better prediction performance than the "channel\_{all}" model. With 2D convolution operation, compared to the "init", the "channel\_{seg}" model can achieve 19.6% and 32.6% improvement in the correlation score in NTB\_30 and NTA\_30, respectively. However, the "channel\_{all}" model can only achieve 9.4% and 16.1% improvement. This result is consistent with our hypothesis at the beginning of the section. In our "channel\_{seg}" model, the missions with different launching time can be distinguished. Our model is capable of learning the meaningful features from the non-stationary missions.

# C. Density Prediction with No-Fly Zone Avoidance and Routing Algorithm

In the third experiment, we introduce no-fly zones into the simulation environment. In each batch of the simulation, the ratio of grids which are occupied by a no-fly zone is varying from 5% to 45%. By applying the routing algorithm, the simulated sUAS is capable of avoiding the no-fly zone and other sUASs. Hence, the sUAS trajectory is more heuristic and that leads to a more challenging density prediction task. In order to reach a high prediction accuracy, we investigate three potential input representations at the same time. The "Flow" input representation has been presented in Section III-B, as shown in Figure 4(a). In the second input representation, we draw a bounding box to incorporate the launching and landing grids of each sUAS. The launching/landing grids are located at the two corners of the bounding box. The value in each grid represents the needed steps to move from the launching location, as shown in Figure 4(c). Therefore, we call it "Ones" input representation. For the "Probability" input representation, we use the same bounding box to incorporate the launching and landing grids. However, the value in each grid stands for the probability that the sUAS moves from its previous adjacent grid to the current grid, as shown in Figure 4(b).

Table III shows the correlation scores for the different representations. From the result, we can notice that both models can improve the correlation in all the input representation types. However, the performance of the "channel $_{seg}$ "

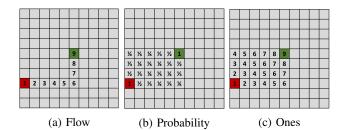


Fig. 4: Different Input Representation

TABLE III: Density Prediction with No-Fly Zone Avoidance and Routing Algorithm

Correlation	Flow	Probability	Ones
init	0.698	0.698	0.698
$channel_{all}$	0.795 (+13.9%)	0.818 (+17.2%)	<b>0.821</b> (+17.6%)
$channel_{seg}$	0.798 (+14.3%)	0.820 (+17.5%)	<b>0.822</b> (+17.8%)

model is slightly better than all-channel model. Compared to the correlation score of the initial density, our presented "channel<sub>seg</sub>" model can improve the correlation score up to 14.3% in "Flow" input representation, up to 17.5% in "Probability" input representation and up to 17.8% in the "Ones" input representation. The "Ones" input representation outperforms other two representations due to two reasons: 1) The routing algorithm is used in the simulation, therefore, the potential sUAS trajectories are more heuristic. Although the "flow" representation has the ability to indicate the sUAS movement, the flexibility of the model is also reduced by given only one possible path. 2) Compared to the "Probability" representation, the "Ones" representation does not only have all the possible trajectories, but also indicate the moving order of the sUAS.

Besides the correlation evaluation, we also apply the AU-ROC to evaluate the performance of the " $channel_{seg}$ " model. In this experiment, the pixel with a non-zero value label is considered to be the evaluation reference as we are more interested in the high dense area on the map. The P estimation is a popular method in financial risk assessment and internet congestion investigation. Hence, we employ the P50, P75, P90 and P99 to select the threshold. After the threshold is defined, the pixel in the label whose value is larger than the threshold is binarized to 1, and vice versa. Table IV shows the selected threshold for different P values. For the prediction, the threshold value is sampled progressively from 0.0 to 1.0, with 0.01 granularity.

TABLE IV: Threshold Selection in Different P Value

	P50	P75	P90	P99
Threshold	0.2	0.3	0.5	0.8

Figure 5 shows the AUROC in different thresholds. As we can see from the figure, the "Ones" input representation still outperforms other methods. The P50 means that half of the

UAS flight areas are considered as the hot spot. In this strict circumstance, the AUROC of the "Ones" representation can still achieve 0.803. However, in reality, the severity is often exaggerated by choosing the P50. For the P75, P90, and P99, the AUROC of the "Ones" representation are 0.836, 0.889 and 0.951, respectively. This result further proves that our model is capable of making an accurate hot spot prediction.

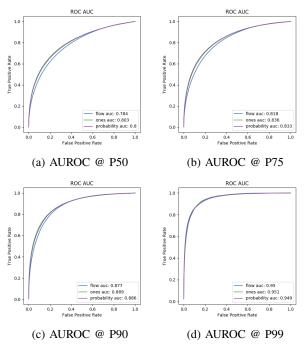


Fig. 5: AUROC at Different P Value

# D. Density Prediction Visualization

In the fourth experiment, we visualize several UAS density predictions to give a qualitative demonstration of our model. The model is extended to predict two types of UAS trajectories: 1) Manhattan trajectory type, and 2) point-to-point (p2p) trajectory type. For the Manhattan style trajectory, we select two typical scenarios to test the performance: a) dense traffic, b) sparse traffic. Both scenarios are tested with/without the routing algorithm. For the p2p style trajectory, the reactive "routing" that utilizes artificial potential field [27] to dynamically avoid potential conflicts is integrated.

Figure 6 shows the Manhattan style trajectory density prediction results without the routing algorithm. The figures on the left-hand side are the predictions and the figures on the right-hand side are the labels (i.e., the ground truth). The value of each pixel varies from 0 to 1, representing the average density in  $T_1$ . The brighter area indicates that there are more sUAS passing through this location. The Manhattan style trajectory density prediction with the routing algorithm is shown in Figure 7. Finally, the p2p trajectory density prediction with the artificial potential field collision avoidance algorithm is presented in Figure 8.

From Figure 6 we can notice that, our predicted densities are close to the label in both scenarios. In the dense traffic scenario, all 6 dense areas are predicted by our model, as shown in Figure 6(a) and Figure 6(b). Although some of the dense areas are close to each other, the model can still predict them clearly. In the sparse traffic scenario, there are only two horizontal dense areas. One is in the middle of the map, and the other is at the bottom of the map. Both of them are predicted accurately by our model.

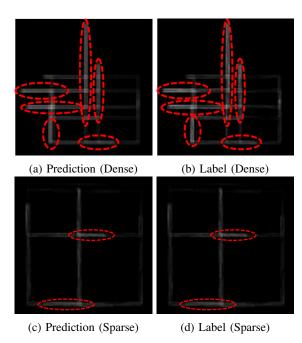


Fig. 6: Density Prediction without Routing Visualization

After the routing algorithm is introduced, the sUAS trajectory is heuristic which will lead to a more random density distribution. Both prediction and label become blurry in this situation. Under this circumstance, our presented model can still predict the most obvious dense areas. In Figure 7(b), there are four obvious dense areas which are marked by the red dashed circles. Figure 7(a) shows that all of the dense areas are predicted successfully by our model. In the sparse traffic scenario, there are three obvious dense areas in Figure 7(d). Although the model fails to predict the dense area at the top of the map, two other dense areas at the left bottom have been predicted successfully, as shown in Figure 7(c).

Figure 8 visualizes the p2p style trajectory density prediction results with the reactive routing algorithm. From the visualization, we can notice that some of the density paths are tangled, such as in the middle left area in Figure 8(b), the bottom left area in Figure 8(d), the top right area in Figure 8(f), and the bottom right area in Figure 8(h). The tangled paths, which are marked by the red dashed circles, lead to a more tough density prediction problem in our model. It requires our model to learn the clear and meaningful features from both historical density and future UAS missions. Figure 8(a) 8(c) 8(e) 8(g) show that our model can successfully predict the UAS density in p2p trajectory type. Almost all the

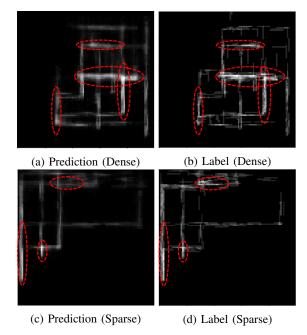


Fig. 7: Density Prediction with Routing Visualization

density paths can be predicted accurately. Furthermore, the density path in the tangled area can be easily distinguished by the observer (human). In conclusion, the above results demonstrate that our model can be used to predict the density of the UAS with a broad range of missions/trajectories.

# E. UAS Instantaneous Density Continuous Prediction Framework

In the last experiment, we extend our UAS instantaneous density prediction model to a continuous prediction framework. The framework architecture is depicted in Figure 9. The yellow box is the mission-aware spatial-temporal model, which was introduced in Section III. The model takes two types of input: 1) the historical density, and 2) the future sUAS mission information. For the continuous density prediction, the extended simulation time horizon is defined as  $T_{extend}$ . In this section,  $T_{extend}$  is set to be 360 simulation cycles, and each cycle lumps sUAS launching information in 10 seconds. The future sUAS launching information in  $T_{extend}$  is equally divided into N segments. Each segment contains 60 cycles of launching information. The continuous prediction framework consists of N UAS instantaneous density prediction models. Each model takes one segment of the future sUAS launching information as the input. The initial density will be given to the first model of the continuous prediction framework. The following models take the density map which is predicted by the previous model as the historical density input. Finally, the continuous density maps can be obtained by running the prediction framework.

Table V shows the correlation score of our UAS density continuous prediction framework in three scenarios:

 $\bullet$  Cont.-W. Init.-Random Start: In this scenario, the start time of the  $T_{extend}$  simulation cycles are randomly se-

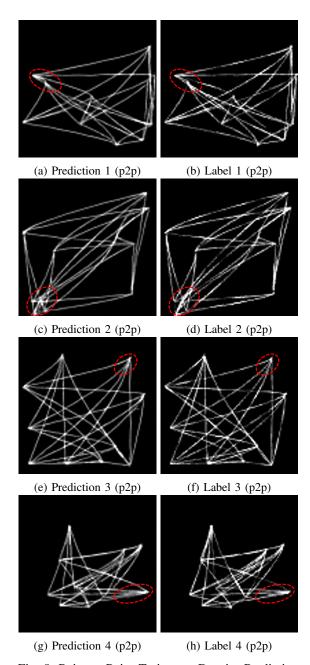


Fig. 8: Point-to-Point Trajectory Density Prediction

lected. When the start time is selected, the data will be generated by running the simulator for  $T_{extend}$  cycles.

- Cont.-W/O. Init.-Random Start: Compared to "Cont.-W. Init.-Random Start" scenario, the "Cont.-W/O. Init.-Random Start" scenario uses the same method to generate the data. However, the initial density will not be provided to the continuous density prediction framework.
- Cont.-W/O. Init.-Zero Start: Compared to "Cont.-W/O. Init.-Random Start" scenario, the "Cont.-W/O. Init.-Zero Start" scenario sets the start time of the  $T_{extend}$  simulation cycles as 0. Therefore, there is no initial density that can be provided to the prediction framework

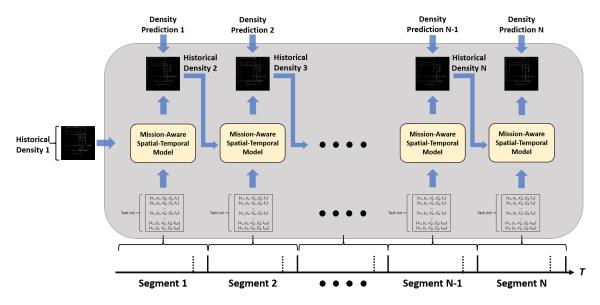


Fig. 9: The UAS Instantaneous Density Continuous Prediction Framework

TABLE V: The Correlation Score of the Continuous Prediction Results

	Init	Avg. Pred.	Pred. (seg. 1)	Pred. (seg. 2)	Pred. (seg. 3)	Pred. (seg. 4)	Pred. (seg. 5)	Pred. (seg. 6)
	ContW. InitRandom Start							
Correlation	0.767	0.892 (+16.30%)	0.891	0.892	0.892	0.892	0.892	0.893
ContW/O. InitRandom Start								
Correlation	0	0.891 (N/A)	0.888	0.892	0.892	0.892	0.892	0.893
ContW/O. InitZero Start								
Correlation	0	0.887 (N/A)	0.843	0.893	0.895	0.894	0.896	0.894

# as the input.

The Avg.Pred. evaluates the average correlation score of N segments. The  $Pred.(seg.\ n)$  indicates the correlation score of segment n. The Init. stands for the correlation score between the initial density and the label density of segment 1. In addition, the scenarios in this section are generated without the UAS collision avoidance algorithm. The evaluation of the continuous prediction framework with the UAS collision avoidance algorithm will be included in our future work.

First, we can observe from Table V that, for the "Cont.-W. Init.-Random Start" scenario, the continuous prediction framework achieves an average correlation of 0.892, which is the highest in all testing scenarios. Compared to the *Init.*, the prediction framework improves the correlation score by 16.30%. This result proves that the initial density map can help the model improve the prediction accuracy. Then, in "Cont.-W/O. Init.-Random Start" scenario and "Cont.-W/O. Init.-Zero Start" scenario, the average correlation scores are 0.891 and 0.887, respectively. This phenomenon shows that, even without the initial density map, each individual model in the continuous prediction framework can extract the meaningful features from each segment of pre-scheduled missions.

The second observation from the result is that, compared to the correlation score of the first segment, the correlation scores of the following segments have similar values. In "Cont.-W. Init.-Random Start" scenario and "Cont.-W/O. Init.-Random Start" scenario, the correlation scores from segment 2 to segment 5 are between 0.892 and 0.893. For the "Cont.-W/O. Init.-Zero Start" scenario, the minimum and maximum correlation score from segment 2 to segment 5 are 0.893 and 0.895, respectively. This result demonstrates that our framework can immediately achieve the most detailed result. Furthermore, even if the prediction error at the beginning is accumulated and propagated to the end of the prediction, our framework can still maintain an accurate density prediction.

In summary, the experiment results show that, by applying the continuous prediction framework, the prediction time horizon can be significantly extended, while maintaining the prediction accuracy. This feature grants us a chance to apply our density prediction model to real-word scenarios.

# VI. CONCLUSIONS

In this paper, we have proposed a novel machine learning-based model, which aims at predicting the UAS instantaneous density. The model has the ability to extract meaningful features from the given historical density and learn the information from the pre-scheduled sUAS missions. In the experiment section, we use the correlation score and the AUROC to evaluate the prediction accuracy of our model. Compared to the baseline models, in a simplified traffic scenario where nofly zones and safe distance requirements among sUASs are not

considered, our model improves the prediction accuracy by up to 15.2% and its correlation score reaches 0.947. The results in Section V-B show that our model is sensitive to the prescheduled missions and has the ability to predict the transient behavior of the traffic distribution. In a more realistic scenario, where the no-fly zone avoidance and the safe distance among sUASs are maintained using A\* routing algorithm, our model can still achieve a correlation score of 0.822. Moreover, the AUROC results demonstrate that the hot spot predictions by our model are accurate. The qualitative results also show that the presented model can generate a detailed prediction and can be generalized to broad range of UAS missions/trajectories. By designing the continuous prediction framework, the UAS density prediction time horizon can be extended from 60 simulation cycles to at least 360 simulation cycles (1 hour), with highest 0.892 correlation score on average.

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