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Prediction of Air-to-Ground Communication Strength for Relay UAV Trajectory Planner in Urban Environments

Pawel Ladosz¹, Hyondong Oh² and Wen-Hua Chen¹

Abstract—This paper proposes the use of a learning approach to predict air-to-ground (A2G) communication strength in support of the communication relay mission using UAVs in an urban environment. To plan an efficient relay trajectory, A2G communication link quality needs to be predicted between the UAV and ground nodes. However, due to frequent occlusions by buildings in the urban environment, modelling and predicting communication strength is a difficult task. Thus, a need for learning techniques such as Gaussian Process (GP) arises to learn about inaccuracies in a pre-defined communication model and the effect of line-of-sight obstruction. Two ways of combining GP with a relay trajectory planner are presented: i) scanning the area of interest with the UAV to collect communication strength data first and then using learned data in the trajectory planner and ii) collecting data and running the trajectory planner simultaneously. The performance of both approaches is compared with Monte Carlo simulations. It is shown that the first implementation results in slightly better predictions, however the second one benefits from being able to start the relay mission immediately.

I. INTRODUCTION

Utilizing wireless communication in an urban environment is challenging due to obstructions and occlusions by buildings, resulting in significant delays and limited range and bandwidth [1]. To facilitate reliable communication between several ground nodes in an urban environment, this work proposes the use of small, low-altitude and low-power (in terms of communication) UAVs as communication relays. UAVs are beneficial for this mission as they can arrive at the mission area rapidly without reliance on roads and existing infrastructure and change their positions with ease in order to adapt to dynamic communication environments.

To plan an efficient UAV relay trajectory, air-to-ground (A2G) communication for arbitrary UAV positions needs to be available. In the past, several approaches were used for communication strength computation and relay trajectory planning. They can be largely divided into the model-based and measurement-based approaches [2]. In model-based approaches, communication strength between nodes is calculated by using a pre-defined model with communication parameters which are dependent on the mission environment. Model-based approaches can be further subdivided into

range-only and channel propagation methods. The range-only method was shown in [3], [4] where communication is assumed to be possible only within a certain radius away from the node. The channel propagation method is shown in [5]–[7] where the distance-dependent equation is used to model communication quality. Both range-only and channel propagation approaches suffer from being unadaptable to changes in the communication environment and inaccuracy due to errors in models and unknown noise sources.

To mitigate this issue, measurement-based methods try to use measured communication signal data. They rely on collecting communication data to either create or update the communication strength model in real time. They can be split into gradient following and the learning methods. In the gradient following method such as [8], [9], measurements (e.g. signal-to-noise ratio or received signal strength indication) are used to calculate and follow gradient to better communication strength positions gradually. However, the gradient following method might struggle in urban environments due to numerous and significant signal strength variations caused by buildings and interference. Learning approaches in [10], [11] can mitigate those issues where real communication data is collected and then used to create a correction to a priori communication model. In particular, Gaussian Process (GP) for predicting inaccuracies in a priori A2G communication model was used in [10] for the data ferry mission which was proven to be useful. The UAV collects the data from a fixed ground node and then transmits them to another node outside the normal communication range by physically flying towards it.

Similar to [10], this work uses GP to learn the A2G communication strength for the communication relay mission using UAVs (described in [12]). Unlike ferrying, the relay UAV is to be included in an existing network as a node to provide additional links with the higher bandwidth thus improving communication quality of a team of networked nodes. In this work, a priori communication model consists of a constant path loss and transmission power model, while the GP technique is used to predict the effect of building obstruction and noise sources in the environment on A2G communication strength. Communication strength at arbitrary positions can be predicted by GP and used to plan the efficient relay trajectory for UAVs which maximises communication quality of a team. Main contributions of this paper can be summarised as: i) use of GP to predict a communication map in a complex urban environment and ii) inclusion of GP in the nonlinear model predictive control-based relay trajectory planning in two different ways.

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II. PROBLEM DEFINITION

A. Scenario Overview

A sample scenario considered in this paper is shown in Fig. 1. There are four ground nodes (yellow dots) and one UAV. The trajectory of the UAV is represented with a cyan line. The red lines represent network connections with the minimum communication cost (which will be explained in detail later) and green areas are additional noise patches applied. 30 scenarios were randomly generated with changing the height of buildings, the position of ground nodes and the position and the size of noise patches. **The assumption of**

Fig. 1. A sample urban scenario used in this paper.

this work can be listed as follows: 1) Ground node position is known to UAV at all time 2) pathloss and transmitted power components of communication strength are known 3) Position, sizes and effects of buildings are unknown a priori to UAV 4) Position, sizes and effects of noise sources are unknown a priori to UAV

B. Considered Implementation

Learning approaches for predicting air-to-ground communication strength are implemented with the relay trajectory planner in two manners: i) scan+NMPC with GP and ii) NMPC with GP. Scan+NMPC with GP starts by performing a scan pattern (shown in Fig. 3) to collect communication strength data for the full environment. This data is used by GP to learn the effect of buildings and other noise sources not considered in a priori communication model. Such a communication map is then used by the relay trajectory planner to guide the UAV on the optimal path. Another implementation, NMPC with GP, takes a slightly different approach. Instead of scanning, the UAV first plans the relay trajectory with the best knowledge it has at that time (i.e. using a priori model initially). Every time it reaches a new position (or periodically), it collects the communication data locally to update its knowledge on the effect of buildings and noise sources using GP. In this way, the UAV saves time for the scan at the expense of the communication prediction quality. Both approaches are described in Fig. 2.

III. GP-BASED COMMUNICATION MAP BUILDING

A. Communication Model

The realistic communication model proposed by [13] is used in this work, which is designed explicitly for aerial platforms. It is based on extensive ray tracing simulations in

Fig. 2. Overview of the proposed algorithms for the communication relay mission.

Fig. 3. Pattern for UAV scan on a sample scenario.

four different types of urban environments: Suburban, Urban, Dense Urban and High-rise Urban. The general formulation is defined as [14]:

$$P_{r,ij} = \begin{cases} P_{t,i} - L_{dB,ij} - \Psi_{LoS}, & \text{if LOS exists} \\ P_{t,i} - L_{dB,ij} - \Psi_{NLoS}, & \text{otherwise} \end{cases} \quad (1)$$

where $P_{r,ij}$ is a received power strength by node j from node i , $P_{t,i}$ is transmitted power by node i , $L_{dB,ij}$ is a path loss between nodes i and j and Ψ_{LoS} and Ψ_{NLoS} are shadow fading for when there is line-of-sight (LOS) and NLOS between the UAV and the ground node, respectively. It is worth noting that shadow fading in the model accounts for diffractions and reflections (multipath propagation) only. Path loss can be represented as:

$$L_{dB,ij} = 10n \log_{10} \left(\frac{4\pi f_c d_{ij}}{c} \right) \quad (2)$$

where f_c is a frequency of transmission, n is a path loss exponent, d_{ij} is distance between ground node i and UAV j , and c is a speed of light. Shadow fading is represented with the normal distribution: $\Psi_{LoS} \sim N(\mu_{LoS}, \sigma_{LoS}^2)$ and $\Psi_{NLoS} \sim N(\mu_{NLoS}, \sigma_{NLoS}^2)$ in dB for LOS and NLOS situation respectively. In [13], it was shown that μ_{LoS} and μ_{NLoS} are constant for a given scenario type, whereas σ_{LoS}^2 and σ_{NLoS}^2 can be calculated as:

$$\sigma_{LoS}^2 = k_1 \exp(k_2 \theta_{ij}) \quad (3)$$

$$\sigma_{NLOS}^2 = g_1 \exp(g_2 \theta_{ij}) \quad (4)$$

where θ_{ij} is elevation angle between ground node i and UAV j and k_1, k_2, g_1, g_2 are a constant dependent on the environment type. In this work, GP will be used to predict shadow fading component of Eq. (1) as this is mostly dependant on the existence of an obstruction, while path loss and power component will be assumed to be a priori communication model. It is worth noting that other noise sources could also be considered and shadow fading is used as an example of such noises. Additionally, there are extra noise sources added to each scenario to simulate extra unknown interferences. In this work, noises take a very simple form of a rectangular patch. If UAV flies within the patch, the LOS and NLOS (depending on a case) are reduced by a certain amount.

B. Communication Performance Metric

In this work, global message connectivity (GMC) is used as the communication performance metric to indicate the performance of UAV relay. The GMC is defined as a probability of a message being successfully transmitted to all nodes within the minimum spanning tree (MST) [7]. The MST is defined as a subset of a graph where all nodes are connected to each other but there are no loops, having a minimum (or at least the same as a minimum, as there can be several minimum spanning trees in a single scenario) sum of edge weights [15]. When there are a number of nodes involved in a scenario, the number of possible connections between them in the network could increase significantly. MST solves this problem by considering the most efficient way of connecting all nodes in the network, which facilitate the efficient and reliable sharing of information.

With knowledge of positions of ground node and communication model (consisting of a priori model and GP estimation), the MST can be built. Let the adjacency matrix of the MST be represented as $A' \in \mathbb{R}^{(n+m) \times (n+m)}$, where n is the number of UAVs and m is the number of ground nodes, then $A'_{ij} = 1$ if the link from node i to node j is the part of the MST, and $A'_{ij} = 0$, otherwise. In the MST, a total communication strength to all nodes (i.e. GMC performance metric J_{GMC}) can be represented as the sum of all connections within the MST, and the problem is finally formulated to find the position of relay UAVs which maximises J_{GMC} :

$$\max_{\bar{\mathbf{x}}^{pos}} J_{GMC}(\bar{\mathbf{x}}^{pos}, \bar{\mathbf{x}}^{g,pos}) = \max_{\bar{\mathbf{x}}^{pos}} \sum_{i=1}^{n+m} \sum_{j=1}^{n+m} A'_{ij} P_{r,ij} \quad (5)$$

where $\bar{\mathbf{x}}^{pos} \in \mathbb{R}^{3 \times n}$ and $\bar{\mathbf{x}}^{g,pos} \in \mathbb{R}^{3 \times m}$ represent the position of UAVs and ground nodes, respectively.

While such a metric has several advantages such as ability to fix many weak connections at once and maximising the number of improved connections in the group, it has some disadvantages. One of key disadvantage of this metric is the fact that it can sometimes ignore very weak connections, to improve a group of already good ones if sum of them would bring bigger benefit than improving weak one. To mitigate that other communication performance metrics could have

been used such as worst case connectivity or modified global message connectivity [12]. First one would make UAV improve weakest connection while second one would look to improve a set of connections of strength below pre-specified threshold.

C. City Model

To compliment aforementioned communication model same environment model as defined in [13] was used. One of the biggest advantages of this model is that city can be randomly generated from a set of pre-specified parameters. The urban environment model used in that paper was proposed by The International Telecommunication Union (ITU-R) in [16]. The model can be fully characterised by three parameters: α_0, β_0 and γ_0 which describe an urban environment in a statistical manner. In particular, α_0 is a ratio of land cover by buildings to total land area, β_0 is a mean number of building per unit area and γ_0 is a scale factor that describes the buildings heights in Rayleigh probability density function as:

$$P(h) = \frac{h}{\gamma_0^2} \exp\left(-\frac{h^2}{2\gamma_0^2}\right) \quad (6)$$

where h is building heights in meters. The model considers four environments: (i) Suburban, (ii) Urban, (iii) Dense urban (iv) Highrise Urban. In this paper, suburban environment type is used with $\alpha_0 = 0.1$, $\beta_0 = 750$ and $\gamma_0 = 8$.

Fig. 4. Sample city generated with parameters: $\alpha_0 = 0.1$, $\beta_0 = 750$ and $\gamma_0 = 8$.

To fully define the city model not only parameters α_0, β_0 and γ_0 needs to be known but also a layout of a city. While cities may follow similar distribution in terms of buildings overall area and sizes, the layout varies significantly from city to city. This paper follows a ‘standard city’ layout as defined by [13] as shown in Fig. 4.

D. Gaussian Process

Many previous approaches used a priori model of communication. Such an approach has several disadvantages. The communication environment is likely to be changed by the time the model is used. Additionally, it is possible that additional noise interference is present in the area further reducing the feasibility of pre-computed communication map. In this section, we propose the use of a learning approach to learn positions and effect of unpredicted noise (in this work in the form of shadow fading).

Generally, GP can be formulated as [17]:

$$f \sim GP(\mathbf{m}(x), \mathbf{k}(x', x)) \quad (7)$$

where $\mathbf{m}(x)$ is a $N \times 1$ vector of mean function, N is a number of collected learning points, and $\mathbf{k}(x', x)$ is a $N \times 1$ vector of covariance function between learning points and the test point. x is a $N \times 4$ training data matrix consisting of the position of UAVs and ground nodes. x' is a $N \times 1$ test point vector. Both $\mathbf{m}(x)$ and $\mathbf{k}(x', x)$ are characterised by a set of hyperparameters which describe how data is correlated to each other. The number and effect of each hyperparameter are individual to each covariance and mean function type.

The main purpose of training GP is to find a set of hyperparameters such that chosen mean and covariance function fit the learning data best. This is achieved by using log marginal likelihood which can be expressed as:

$$L = \log(\mathbf{y}|\mathbf{x}, \boldsymbol{\theta}) = -\frac{1}{2} \log|\mathbf{C}_n| - \frac{1}{2} (\mathbf{y} - \mathbf{m}(x))^T (\mathbf{C}_n)^{-1} (\mathbf{y} - \mathbf{m}(x)) - \frac{n}{2} \log(2\pi) \quad (8)$$

where $\mathbf{C}_n = \Sigma + \sigma_n^2 \mathbf{I}$ in which Σ denotes a set of covariance functions of $N \times N$ size with entries $k_{ij} = k(x_i, x_j)$ for $i, j = 1, \dots, N$ and σ_n^2 is a hyperparameter responsible for accounting for noisy data, $\mathbf{y}$ is a set of measured communication strength of $N \times 1$ size and $\boldsymbol{\theta}$ is a set of hyperparameters.

Finally, to find hyperparameters using Eq. (8), the conjugate gradients method is used [10]:

$$\boldsymbol{\theta}^* = \arg \max_{\boldsymbol{\theta}} (L) \quad (9)$$

Once hyperparameters are computed predicted mean and variance at position x' can be found as:

$$\mu_p(x') = \mathbf{m}(x') + \boldsymbol{\mu}(x') + (\mathbf{C}_n^{-1}(\mathbf{y} - \mathbf{m}(x'))) \quad (10)$$

$$\sigma_p(x') = \mathbf{k}(x', x') - \mathbf{k}(x, x')^T (\mathbf{C}_n)^{-1} \mathbf{k}(x, x'). \quad (11)$$

It is worth noting that $\sigma_p(x')$ not only represents predicted variance but also uncertainty of prediction.

E. Covariance and Mean Functions

For GP to work well, best mean and covariance function for a given scenario needs to be chosen. Generally, there are two types of covariance functions: stationary and non-stationary. In this work, a non-stationary covariance function is used as it is applicable to situations when no visible mathematical pattern is present. Due to the random spread of buildings and node positions, this is the case in this work as illustrated in Fig. 5. This figure shows the surface plot of the mean of shadow fading component from Eq. (1) for a sum of four ground nodes and changing positions of the UAV at 150 meters high. In Fig. 5, areas of high mean shadow fading are generally spaced irregularly, thus non-stationary function is more appropriate.

Several non-stationary covariance functions such as neural network, linear, polynomial and squared exponential with spatially varying lengthscale parameters exist. In this work squared exponential with spatially lengthscale parameters covariance function is used as an example of non-stationary

Fig. 5. Shadow fading with (792,935) position of ground node and UAV flying at 150 meters height.

covariance function Squared exponential with spatially varying lengthscale parameters covariance function is formulated as:

$$k(x', x) = \sigma_f^2 \left(\frac{a}{b} \right)^{\frac{n}{2}} \exp\left(-\frac{\|x - x'\|^2}{b} \right) \quad (12)$$

where $a = 2l(x)l(x')$, $b = 2l^2(x) + l^2(x')$ and n is a number of variables being correlated as defined previously. Finally $l(x)$ and $l(x')$ are spatially varying lengthscale parameters which are of the same form as a mean function.

The mean function was chosen to best compliment covariance functions. Through experimentation, it was found that constant mean works best with squared exponential with spatially varying lengthscale covariance function in considered scenarios. Such a mean function is denoted as:

$$m(x', x) = c \quad (13)$$

where c is a hyperparameter to optimise.

IV. NMPC-BASED TRAJECTORY PLANNER FOR UAV COMMUNICATION RELAY

In this section, nonlinear model predictive control (NMPC)-based trajectory planner for UAV communication relay is briefly presented. The NMPC-based trajectory planning approach is chosen for several reasons. First, in the NMPC with GP implementation, the communication model is updated periodically during the mission as new communication measurements arrive. Thus, the NMPC is ideally suited to account for such a change. Second, although stationary nodes are used in this initial proof of concept, an extension with mobile ground nodes is planned in the future. Finally, as the NMPC-based approach only optimises up to a certain length (rather than a full scenario), the problem space is reduced, leading to the less computational time. For more details, readers are referred to [12].

A. UAV Kinematic Model

This work utilises a simple two-dimensional UAV kinematic model by assuming the UAV speed is constant and the UAV flies at the constant altitude. The UAV model is

given as:

$$\begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\psi} \\ \dot{\omega} \end{pmatrix} = f(\mathbf{x}, u_\omega) = \begin{pmatrix} v \cos \psi \\ v \sin \psi \\ \omega \\ -\frac{1}{\tau_\omega} \omega + \frac{1}{\tau_\omega} u_\omega \end{pmatrix} \quad (14)$$

where $\mathbf{x} = (x \ y \ \psi \ \omega)^T$ are the inertial position, heading, speed and yaw rate of the UAV, respectively. τ_ω is time constant accounting for actuator response delay, which can be determined experimentally for given UAV model. u_ω is a command input in form of turning rate. In this work, the command is constrained by:

$$|u_\omega| \leq \omega_{max} \quad (15)$$

$$|u_{\omega,k} - u_{\omega,k-1}| = 0.1 \quad (16)$$

where k is a current time step. The first constraint limits the maximum heading rate of the UAV. The second constraint limits the rate at which heading changes and allows for discretisation of the controller. Both constraints are the result of dynamic limits of a fixed-wing UAV. The UAV model from Eq. (14) is discretised using Euler integration as:

$$\mathbf{x}_{k+1} = f_d(\mathbf{x}_{\omega,k}, u_k) = \mathbf{x}_k + T_s f(\mathbf{x}_k, u_{\omega,k}) \quad (17)$$

where $\mathbf{x}_k = (x_k \ y_k \ \psi_k \ \omega_k)^T$ and T_s is a sampling time.

B. NMPC-Based Trajectory Planning

The kinematic model is combined with the NMPC-based trajectory planner to determine the optimal trajectory for UAV communication relay. Such an approach relies on the finite time horizon with the nonlinear model of the UAV. Time horizon defines how far into the future UAV behaviour is predicted. Optimisation is used to determine the best set of control inputs over the horizon length. Only first step is fed into the actual controller and the optimisation procedure repeats for the next time step.

C. Performance Index

Dynamic constraints of UAVs are combined with the performance metric defined in Section III-B to create a cost function needed for NMPC trajectory planner formulation as:

$$J_d = \Phi(\bar{x}_N, \bar{x}_N^g) + \sum_{k=0}^{N-1} L(\bar{x}_k, \bar{x}_k^g, u_{\omega,k}) \quad (18)$$

s.t.

$$\mathbf{x}_{k+1} = f_d(\mathbf{x}_k, u_{\omega,k}) \quad (19)$$

$$\omega_{min} \leq u_{\omega,k} \leq \omega_{max} \quad (20)$$

$$|u_{\omega,k} - u_{\omega,k-1}| = \Delta u_\omega \quad (21)$$

where:

$$\Phi(\bar{x}_N, \bar{x}_N^g) = p_c J_z(\bar{x}_N^{pos}, \bar{x}_N^{g,pos}) \quad (22)$$

$$L(\bar{x}_N, \bar{x}_N^g, u_{\omega,k}) = \frac{1}{2} \left[q_c J_{GMC}(\bar{x}_k^{pos}, \bar{x}_k^{g,pos}) + r_v \left(\frac{u_{\omega,k}}{\omega_{max}} \right)^2 \right] \quad (23)$$

where J_{GMC} represents the GMC performance index and $\bar{x}_k^{pos}$ and $\bar{x}_k^{g,pos}$ are x and y position of UAVs and ground nodes, respectively. p_c , q_c and r_v are constant weighting factors. The control sequence $U = (u_{\omega,0}, u_{\omega,1}, \dots, u_{\omega,N-1})$ (where N is a horizon step) which optimises the cost function are found by using the **custom** genetic algorithm (**described in more detail in [12]**).

Such a formulation allows inclusion of both final position as well as positions at each time step. weighting parameters p_c and q_c are designed such that contribution of final cost is equal to sum of contributions of costs at each time step along the way. It is worth reiterating that as optimisation is repeated at every sampling time, only first element from the control sequence is used as a control input to the UAV.

V. NUMERICAL SIMULATION RESULTS

To validate the performance of using learning approaches for UAV communication relay, five implementation types are considered as described in Table I. **Each implementation had the same constant for all monte carlo simulation starting point (outlined in table III)**. First two methods were already described in Section II. B: Scan+NMPC with GP and NMPC with GP. Third one assumes full knowledge of the communication map including positions and sizes of buildings and noises and their effect on communication quality with NMPC. Fourth one is loiter without the map information at the starting point where the UAV just turns with a maximum heading rate. Finally, no knowledge of buildings and noise sources is used in the NMPC trajectory planner. In this implementation, the UAV assumes that it flies in an open space with no line-of-sight obstructions. This is to show the impact of buildings on the communication performance. Note that GP is used only for the prediction of A2G communication links while shadow fading is assumed to be known between ground nodes by assuming that ground nodes stay in given positions for long enough to collect enough data to calculate mean of shadow fading. Numerical

TABLE I
SCENARIOS CONSIDERED IN THIS WORK

Implementation	Predicted communication (for MST computation and optimisation)			
	A2G links		G2G links	
	Path loss	Shadow fading	Path loss	Shadow fading
Scan+NMPC with GP	known	predicted by GP	known	known
NMPC with GP		predicted by GP		
NMPC with map info.		known		
Loiter without map info.		assume all links are LOS only (for MST computation)		
NMPC without map info.		assume all links are LOS only		

simulations are used to compare proposed approaches. Table II shows radio communication parameters [13]. Parameters used for NMPC-based trajectory planner and the urban environment are shown in Table III. 30 Monte Carlo simulations were performed with different building heights, noise source

TABLE II
RADIO COMMUNICATION PARAMETER

Parameter	Value	Unit
Transmission power (P_t)	20	dBm
Frequency f_c	2.0	GHz
Attenuation factor (α)	3	n/a
Communication Properties k_1, k_2, g_1, g_2	11.25, 0.06, 32.17, 0.03	n/a
mean NLOS μ_{NLOS}	0.1	n/a
mean LOS μ_{LOS}	21	n/a

TABLE III
SIMULATION PARAMETER

Parameter	Value	Unit
Actuator delay (τ_ω)	1/3	s
UAV starting point (x, y)	(500, 500)	m
UAV speed (v)	20	m/s
Heading rate constraint ($\omega_{min}, \omega_{max}$)	(-0.4, 0.4)	rad/s
Receding horizon step (N)	5	N/A
Horizon steps	(0.5, 4.5, 5, 5, 5)	sec
Maximum heading rate change (ΔU_ω)	0.1	rad/s
Weighting factors (p_c, q_c, r_ω)	(-1000, $p_c/N, 1$)	N/A
Urban Environment Parameters ($\alpha_0, \beta_0, \gamma_0$)	(0.1, 750, 8)	N/A
data points number for scan+NMPC with GP (per ground node) μ_{LOS}	160	n/a
collection rate for NMPC with GP	2	s
computational time for NMPC with GP (per step, final step)	16	s
computational time for Scan+NMPC with GP (per step)	40	s

positions and sizes and positions of ground nodes. Note that, for fair comparison, the UAV starting position was the same for all scenarios. This means that, in the case of the scan+NMPC, the UAV returns to the starting position after scan and then performs a relay mission.

From Fig. 6 and Table IV, it is clear that loiter without the map information produces the worst result as the UAV just loiters with around a constant position. NMPC without the map information shows slightly better performance, but still the worst amongst implementations which performs NMPC trajectory planning. Without knowledge of building position and sizes, the UAV does not actively avoid LOS obstruction, thus most of the time all connection within MST are obstructed. NMPC with GP performs worse than scan+NMPC with GP. This implies that depending on user requirements (e.g. whether immediate/timely or better communication is important) different approaches should be chosen. NMPC with the map information performs the best of all implementations, with full knowledge of the communication environment and noise sources. In this ideal situation, the trajectory planner is able to plan the path optimally. A sample trajectory using scan+NMPC with GP is presented in Fig. 7 as an illustrative scenario.

TABLE IV
SUMMARY OF MEAN RESULTS

Implementation	Communication strength (dB)
Scan+NMPC with GP	-943.83
NMPC with GP	-956.14
NMPC with map	-924.48
NMPC without map	-966.89
Loiter without map	-982.27

p

One of the big limitation of of NMPC based control is computational time. As ti can be seen from table [?] real

Fig. 6. Comparison between implementations over 30 Monte Carlo simulations.

Fig. 7. A sample scenario using scan+NMPC with GP implementation.

time implementantion using matlab is not possible. However there exist several approaches to address this issue such as: i) implement the algorithm in C/C++, which would reduce computational time significantly; ii) Increase the size of first step time. This will increase the allowable iteration time but will likely reduce improvment in communciation caused by algorithm; and iii) the number of iterations or population size of the genetic algorithm can be reduced to achieve significant reduction of the computation time. However, this is likely to reduce the quality of solution.

VI. CONCLUSIONS AND FUTURE WORK

The use of GP in support of UAV communication relay was proposed. It was shown that creating a communication strength map using GP before the mission shows an advantage over creating communication map while performing the mission. However, collecting data during the mission means that there is a chance that the UAV can consider any instantaneous change in communication strength and adjust its position immediately. Therefore, an appropriate method should be chosen depending on mission environments. Future work includes extending the scenario to include mobile ground nodes and more realistic noise sources and realistic experiment to prove performance of algorithm. Mobile ground node scenario will use exactly same NMPC controller, however

two changes will have to be made: (i) assumption of lack of complete lack of knowledge about urban environment will be relaxed (ii) assumption about known g2g links will be replaced. More realistic noise sources will be added to better reflect real scenario

This paper adds to existing literature by considering addition of Machine learning to predict communication performance for UAV relay problem. Additionally the scenario considered is significantly more complex than scenarios in the past. This has created additional challenges for machine learning prompting usage of non-stationary covariance function. Finally two different implementation types were considered to show that if possible it is better to scan the area first, however if relay is needed immediately it can be used with some improvements over ignoring urban scenario completely.

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