Lightweight 3D Beamforming Design in 5G UAV Broadcasting Communications

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***Abstract*—Owning the merits of flexible networking, rapid deployment, strong line-of-sight communications and so on, Unmanned Aerial Vehicle (UAV) has been regarded as a promising technology for the Fifth-Generation (5G) wireless network to realise its ambition of ubiquitous connectivity to support the various applications, e.g. broadcasting/multicasting services. However, the unique features of the UAV systems, e.g. highly agile mobility in the three-dimensional space, and the significant size, weight and power constraints, pose new challenges for 5G broadcasting communications. In order to fully harvest the benefits of UAV-aided 5G communications for broadcasting services, a new position based lightweight beamforming technology is proposed in this paper to enhance the capability of signal reception in 5G UAV broadcasting communications. Instead of relying on the channel estimation to form beams, which would cause significant broadband consumption, the position and mobility information of UAV system is exploited to predict UAV movement and form narrow beams to track UAV for signal enhancement and interference cancellation. To flight against the inherent position error, a new position correction method is designed to jointly utilise the DoA information of 5G system and the position information of the UAV system. Comprehensive simulation experiments are conducted based on 3GPP 5G specifications and the results show that the proposed algorithm outperforms the benchmark Zero-Forcing (ZF) without position prediction and position-based beamforming without position correction.**

***Index Terms*—Broadcasting, Unmanned Aerial Vehicle, 3D Beamforming, 5G.**

I. Introduction

Recent years have witnessed an astonishing growth of mobile devices and various applications and services running on these devices, e.g. ultra-high-definition (UHD) video, Three Dimensional (3D)/multi-view products, and emerging augmented and virtual reality services. According to Cisco 2019 Visual Networking index [1], there will be more than 12.3 billion mobile devices by 2022, each of which will averagely generate 11 GB mobile traffic every month. To address such huge amount of mobile traffic and satisfy various strict performance requirements in terms of throughput, latency and connectivity density, the Fifth Generation (5G) wireless communication system has been proposed to revolutionise the design, operation and management of current 4G communication through exploiting the higher transmission frequency, much smaller cells, massive Multiple-Input-Multiple-Output (MIMO) antennas, centralised network management, virtualised network function deployment and so on [2]. 5G will support three kinds of new scenarios, ultra-reliable low latency communications (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communications (mMTC) to meet the performance of various services and applications, such as sports event, festival parties, etc. In addition, multicast and broadcast services are also considered as a useful means for 5G system to improve the bandwidth efficiency of radio resources since it allows a group of users to be served by a single transmission. Although the convergence of the broadcast and 5G broadband is highly beneficial, new challenging issues arise because of different design mechanisms between the two systems. For instance, compared with the unicast transmission, broadcast/multicast service guarantees the fairness among the receivers, while at the cost of the throughput of the users with good channel conditions [3], which is deviated from the 5G broadband design. This is because the broadcasting system adopts a data rate to send streaming contents to all receivers. This rate is determined, not by the users with good channel condition, but by the ones with the least reliable signal transmissions [4], potentially lowering the entire system throughput. Therefore how to improve the transmission performance for UEs with unreliable channel condition plays a critical role in the convergence of broadcast services and 5G wireless broadband system. In this context, owning the advantages of flexible networking, quick deployment, cheap operation, and strong Line-of-Sight (LoS) communications, Unmanned Aerial Vehicle (UAV) is regarded as an important component in 5G broadband system to improve the link quality of UEs suffering from the poor channel conditions.

In the 5G UAV broadcasting system, multiple UAVs are flying in the air, each of which covers a certain ground area. In this system, 5G Base Station (known as gNB) is responsible for exploiting the massive antenna array to form beams to transmit the broadcasting contents to UAVs. With the LoS transmission link, UAVs are responsible for broadcasting the content to the ground UEs. Due to the potentials of the UAV system for 5G broadcasting system, tremendous research efforts have been made in this UAV-aided 5G communications. For instance, Xiao et al. in [5] designed a hierarchical beamforming codebook structure to improve the transmission capacity of millimetre wave UAV cellular networks. Lu et al. in [6] proposed a training based beam tracking method in UAV communications, which investigates how frequently the beam training should be conducted and how to design the optimal beam according to the flying range. The work in [7] demonstrated that more interferences are generated in the UAV communication compared with the ground cellular networks. To deal with this issue, Liu et al. in [8] designed a cooperative interference cancellation method for the uplink transmission in UAV communication. The proposed algorithm aims to eliminate the interferences for the ground base station and maximise the sum-rate in the system level. Although, significant progress has been made in the area of UAV-aided cellular communication, most of the existing work relies on the prediction and feedback of Channel State Information (CSI) in algorithm design and system optimisation, which would result in significant transmission overhead, bandwidth waste and energy consumption. This is because, in massive 5G MIMO systems, UAVs are required to assist gNB to estimate CSI for downlink broadcasting transmission. While the high-speed mobility, three-dimensional operations and serious inter-cell interferences forces UAVs to conduct this kind of assistances more frequently than the ground UEs. In addition, UAV devices are constrained by the resources of energy, size, computation power, and memory. The depletion of any resource would result in serious consequences, e.g. broadcasting service disruption even UAV crash. Therefore, for enhancing the 5G UAV broadcasting transmission, it is necessary and beneficial to design lightweight and bandwidth-efficient beamforming algorithm by exploiting the unique features of the UAV system.

To bridge this gap, a novel position-based beamforming algorithm is proposed in this work to improve the backhaul transmission of 5G UAV broadcasting system. Instead of relying on the sufficient and frequent pilot signal transmission for CSI estimation, which leads to inefficient broadband utilisation, the proposed algorithm exploits the position information of UAV system to track the UAVs mobility and steer the antenna beam to target the interesting UAVs, minimising the interferences leaked into the neighbour cells. Different from the ground cellular system, the mobility and position information of UAV devices is already available to gNBs for the flight safety check and mission decision making. Therefore, by recycling such position information in the design of 5G beamforming, the proposed algorithm does not involve extra wireless communication burden, improving the broadband efficiency compared with the CSI-based beamforming design. However, the inherent position errors exist in the UAV system due to the inaccuracy of time clock, distance estimation and hardware on UAV, therefore, how to reduce the inherent position errors plays an important role in the proposed position-based robust beamforming design. To address this issue, a position-correction algorithm is designed through complementarily exploiting the DoA information of 5G signal reception and 3D coordinates of the UAV system. By minimising the position errors of 3D coordinates and the tapered surfaces formed by the horizontal and vertical DoAs, the designed algorithm reduces the impacts of the inherent position errors on the performance of broadcasting signal receptions in 5G UAV system. The main contributions of this work can be summarised as follows,

- A new lightweight robust beamforming algorithm is proposed to improve the transmission performance of 5G UAV broadcasting/multicasting system through exploiting the mobility and position information of the UAV system, which could maximise the signal reception of the relay UAVs and reduce the interferences leaked into the neighbour cells.
- An analysis of the inherent position errors of mainstream UAV devices is conducted to identify the impact of the position errors on the beamforming performance of signal receptions. The results provide the foundation to utilise the position information for beamforming design.
- A position-correction algorithm is designed through jointly integrating the DoA information of 5G wireless communication system and the position information of the UAV-based broadcasting system, which could effectively address the performance degradation caused by the inherent position errors.
- Comprehensive experiments are conducted and the results show that the proposed algorithm obtains better performance in terms of DoA estimation accuracy, the signal strength of broadcasting UAVs and interference migration of neighbour cells compared with the benchmark algorithms, including Zero Forcing (ZF) based beamforming without position prediction and position based beamforming without position correction.

The remainder of this work is organised as follows. Section II presents the related work of beamforming design in 5G UAV broadcasting/multicasting system. Section III introduces the methodology of the proposed position-based lightweight beamforming algorithm. Section IV analyses the impact of the inherent position error on the performance of beamforming design. A novel 3D position correction method is described in Section V followed by Section VI to estimate the performance of the proposed algorithm. Finally, we conclude this work in Section VII.

II. Related Work

Equipped with the higher bandwidth and more transmission antennas, 5G network provides better transmission quality for broadcasting/multicasting service, especially the real-time information delivery such as TV programs, software updates and online streaming. UAV has been regarded as an important approach to enhance the signal strength and the network coverage of cellular network for content broadcasting services. In the 5G UAV broadcasting system, the broadcasting content would be transmitted from the cloud servers to multiple UEs through 5G gNB and UAVs. A lot of research efforts have been made to improve the transmission efficiency of content broadcasting/multicasting through 5G UAVs networks. For instance, Wu *et al.* in [9] analysed the capability of a UAV-based broadcasting channel and investigated the joint optimisation problem considering UAV's trajectory, transmit power, flight speed and system throughput. Similar to [9], the authors in [10] developed a fly-hover-and-communication protocol to optimise the flight altitude and antenna beam-width for the system throughput maximisation. The ground UEs are partitioned into different clusters. When UAVs are flying over certain UE clusters, the proposed protocol is capable of adjusting the flight status and antenna radiation pattern to improve transmission throughput. To improve the broadcasting efficiency for large-sized content delivery, a UAV based content dissemination system was developed in [11] to exploit UAVs to improve the transmission efficiency of RaptorQ-based content dissemination for multiple moving receivers.

Although significant research progress has been made in the 5G UAV system design for broadcasting services transmission, the above work mainly focuses on exploiting the UAV to extend the transmission range and improving the link quality of 5G cellular network, paying little attention to the challenges introduced by UAV system, e.g. serve inter-cell interference. For instance, the work in [7] conducted cellular-based UAV field experiments and demonstrated that the SINR received by UAV during the downlink backhaul link is 5 dB lower than the counterpart of the ground cellular network. Therefore, it is important to take the interference cancellation and migration in the design of 5G UAV backhaul transmission for broadcasting services. In this context, a cooperative interference cancellation approach was designed in [8] in the uplink UAV communication. To improve the ergodic weighted sum rate of broadcasting communication, the authors in [12] proposed a closed-form beamformer through integrating the zero-forcing and channel projection, the aim of which is to obtain a good tradeoff between the throughput and interferences. The authors in [13] designed an UAV-based relaying system in cellular network. The maximal data rate is obtained with the constraints of the power consumption in both the gNB and UAV relay nodes. These papers provide good performance for interference cancellation and migration, while heavily relying on the accurate CSI estimation. The authors in [14] pointed out that it is a challenging issue for UAV to obtain accurate CSI estimation due to the high dynamic movement. Although it is possible to deploy more powerful UAVs in the air to conduct frequent CSI estimation and computation, it would be more beneficial to design the lightweight beamforming algorithm to relieve the requirements of bandwidth transmission and resource consumption in beamforming design. To address the above issue, a novel lightweight robust 3D beamforming technology is proposed in this work through exploiting UAV position information to enhance the performance of 5G broadcasting communication for aerial UAVs.

III. Robust 3D Beamforming Design

A 5G UAV downlink broadcasting system is considered in this study as shown in Fig. 1, where gNBs are equipped with uniform planar antenna array and UAV is equipped with a single antenna. The number of the antenna in each row and column is M and N. The distances between two adjacent antennas in a row and a column are d_h and d_v respectively. Assume the number of UAVs in a 5G cellular network is K, and the channel between the 5G gNB and the kth UAV can be represented as H_k, which is a $M \times N$ matrix. Let s_k denote the signal sent from the gNB for kth UAV, then the signal received by the kth UAV can be written as,

$$y_k = H_k \omega_k s_k + \sum_{i=1, i\neq k}^{M} H_k \omega_i s_i + n_k \tag{1}$$

where n_k is the additive white Gaussian noise at the antenna of the kth UAV, $n_k \sim N(0, \sigma_k^2)$. The first term in Eq.(1) is the useful signal and the second term refers to the interference signal. According to the flight control and regulation, UAVs should be operated within LoS for the security and reliability guarantee. Therefore, the transmission path between the UAVs and gNB is dominated by the line-of-sight (LoS). According to [15], vector H_k can be written as,

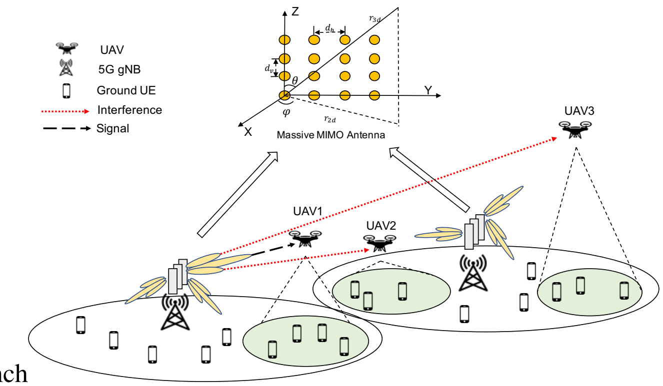

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Fig. 1. System Architecture of 5G UAV Broadcasting Communication

$$H_k = \bar{H}_k \hat{H}_k \alpha(\theta_k, \phi_k) \tag{2}$$

where $\bar{H}_k$, $\hat{H}_k$ and $\alpha(\theta_k, \phi_k)$ are large-scale pathloss component, small-scale channel fading matrix, and steering vector of the transmission antennas respectively. $\hat{H}_k$ has a distribution of $CN(0, \sigma_e^2)$. For massive MIMO antenna arrays, $\alpha(\theta_k, \phi_k)$ can be written as [16],

$$\alpha(\theta_k, \phi_k) = \alpha^{(v)}(\theta_k) \otimes \alpha^{(h)}(\theta_k, \phi_k) \tag{3}$$

where $\alpha^{(v)}(\theta_k)$ and $\alpha^{(h)}(\phi_k)$ are the steering vectors of vertical and horizontal directions respectively, and can be written as,

$$\alpha^{v}(\theta_k) = \left[1, e^{-j2\pi \frac{d}{\lambda} \cos\theta_k}, ..., e^{-j2\pi(M-1)\frac{d}{\lambda} \cos\theta_k}\right]^T \tag{4}$$

and

$$\alpha^{h}(\phi_k) = \left[1, e^{-j2\pi \frac{d}{\lambda} \sin\theta_k \cos\phi_k}, ..., e^{-j2\pi(N-1)\frac{d}{\lambda} \sin\theta_k \cos\phi_k}\right]^T \tag{5}$$

With the beamforming vector ω_k, the Signal to Interference and Noise Ratio (SINR) of the kth UAV can be represented as

$$S_k = \frac{|H_k \omega_k s_k|^2}{\sum_{i=1, i\neq k}^{K} |H_k \omega_i s_i|^2 + \sigma_k^2} \tag{6}$$

It can be seen that breamforming vector significantly affects the quality of signal reception with the given channel condition and interference level. The aim of this study is to choose the optimal value of w_k to maximise the overall system throughput,

$$\max \sum_{k=1}^{K} \left\{ B_k \log_2 (1 + SINR_k) \right\} \tag{7}$$

where B_k is the bandwidth of the kth UAV. Eq. (7) calculates the overall system throughput, which is related to two factors: the allocated bandwidth and the received SINR. This work aims to design a robust beamforming algorithm to improve the received SINR through exploiting the position and mobility information of the UAV system to assist gNBs to conduct beamforming. With the improved SINR, 5G gNB uses Eq. (7) to calculate and configure the bandwidth assignment at each resource allocation frame for UAVs to satisfy their transmission throughput requirements. In order to maximise the UAV's throughput, gNB antenna radiation pattern should be designed to make the antenna's main beam targeting to the desired UAV and set null points to avoid the interference to the others.

In this study, we focus on the linear processing technologies due to its good balance between complexity and performance. The work of [17] has listed linear beamforming methods as the most promising technology for 5G DL signal processing. Let P_k denote the transmission power for the kth UAV and the problem of maximising the throughput of Eq. (7) can be rewritten as,

$$\begin{aligned} \min \quad & \left|\omega_k^H H_k^H H_k \omega_k\right|^2 \\ \text{s.t.} \quad & H_k \omega_k = 1 \end{aligned} \tag{8}$$

The optimal beamforming vector can be calculated as,

$$\omega_k = H_k^H \left(H_k H_k^H\right)^{-1} \tag{9}$$

It can be seen that this is the standard representation of the ZF beamforming algorithms. ZF and its evolution algorithms, e.g. regularised ZF ($H_k^H \left(\xi I + H_k H_k^H\right)^{-1}$), have been deployed used in the cellular network.

However, when these algorithms are applied to 5G UAV broadcasting communication, there are new challenges that need to be carefully addressed. For instance, ZF based beamforming algorithms rely heavily on CSI information, including both the large-scale pathloss and small-scale fading. In this context, the high mobility and three-dimensional movement of UAV make it challenging to accurately estimate CSI between gNB and UAVs, deteriorating the CSI-based beamforming performances. Furthermore, for frequency-division duplex based 5G system, gNB sends dedicated signal to measure wireless channel quality. UAVs estimates the CSI based on the received signal and feeds it back to gNB. The high dynamic gNB-UAV channel condition requires high-frequent CSI measurement and estimation. This poses the issue of high communication overheads of 5G system and consumes extra energy for energy-constrained UAV devices.

Given the fact that Line-of-Sight (LoS) channel dominates the communication channel between UAVs and gNB, we modify Eq. (9) to the following optimisation problem,

$$\begin{aligned} \min \quad & \left|\omega_k^H \alpha(\theta_k, \phi_k)(\alpha(\theta_k, \phi_k))^H \omega_k\right|^2 \\ \text{s.t.} \quad & \omega_k^H \alpha(\theta_k, \phi_k) = 1 \end{aligned} \tag{10}$$

Eq. (11) focuses on steering the main beam to the UAVs in serving cell and minimise the energy leaked to the neighbour cells. It does not require the CSI information, therefore improving the bandwidth utilisation. Applying the Lagrange multiplier, the optimal beamforming vector could be calculated by,

$$\omega_k = \frac{\alpha(\theta_k, \phi_k)^H}{[\alpha(\theta_k, \phi_k)]^T \alpha(\theta_k, \phi_k)^H} \tag{11}$$

IV. GPS Error Analysis

To achieve the optimal performance of beamforming design, gNB needs to calculate the accurate DoA information, θ_k and ϕ_k from the signal received. However, due to the high mobility of the UAV system, the accuracy of the DoA estimation is greatly affected by the UAV flight status and channel condition. To address this issue, our solution is to integrate the DoA information of wireless communication and mobility and position information of the UAV system. For 5G UAV broadcasting communication, the value of the position information for beamforming algorithm has two-folds: 1) to assist the DoA estimation; and 2) to predict the trajectory of UAV and help beamformer track UAV movement. Let $\mathbf{A}\left(x_k, y_k, z_k\right)$ denote the coordinate of the kth user. The following equation demonstrates how to obtain DoA from UAV coordinate,

$$\theta_k = \arctan \frac{\sqrt{(x_k)^2 + (y_k)^2}}{z_k}, \qquad \phi_k = \arctan \frac{y_k}{x_k} \tag{12}$$

Let $\mathbf{V}(t)\left(v_x, v_y, v_z\right)$ be the speed of a UAV at the time t. After a time interval Δt, the updated position could be obtained by the following equation,

$$R(t + \Delta t) = R(t) + \int_t^{t+\Delta t} \vec{\mathbf{V}(t)} dt \tag{13}$$

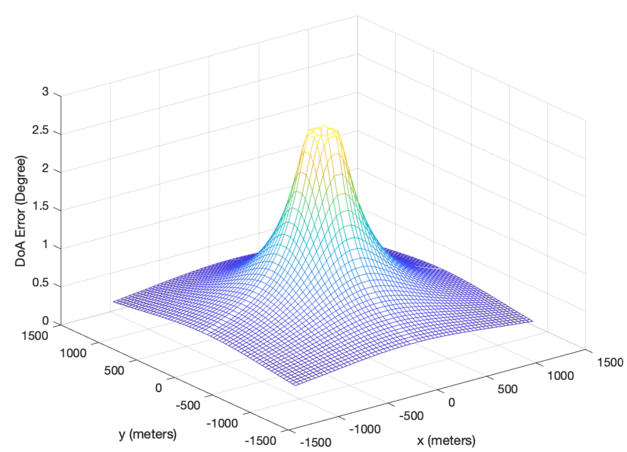

Fig. 2. The Impact of Position Error on DoA Estimation

Before harvesting the benefits of position data on beamforming design, we need to carefully consider the impact of the inherent position error on the performance of beamforming algorithm. Due to the issues of hardware maintenance and software implementation, there is an inevitable error in the position information from UAV GPS receiver, varying from the levels of centimetres to meters. The accuracy of GPS coordinate information is critically important for position based DoA estimation. The same level of GPS error would cause different DoA errors at the different spatial position. Eq. (12) gave the method to calculate the DoA from the coordinate information. From the Eqs. (14) and (15), we can observe that the same amount of position error, $(\Delta x, \Delta y, \Delta z)$, could result in the higher DoA error when UAV is flying near to gNB (smaller values of $(x,\ y,\ z)$) as shown in the following equations,

$$\theta_k + \Delta\theta = \arctan \frac{\sqrt{(x_k + \Delta x)^2 + (y_k + \Delta y)^2}}{z_k + \Delta z} \tag{14}$$

$$\phi_k + \Delta\phi = \arctan \frac{y_k + \Delta y}{x_k + \Delta x} \tag{15}$$

In order to study the relationship between GPS coordinate error and DoA estimation error, we conducted simulation experiments in this study by setting the GPS error as 5m, 10m, 15m and 20m. UAVs are operated at the altitudes of 10m, 50m, 100m, 200m, and 300m; the largest horizontal distance is set to be 1500m. Due to the space limitation, we present the simulation results in the horizontal direction when UAVs suffer from 10m coordinate error and are at the altitude of 100m. The collected data is shown in Fig. 2. The results suggest that the 10m coordinate error causes DoA error ranging from 0 to 2.5 degrees, which brings significant performance degradation on beamforming output, calling for an effective approach to improve the estimation accuracy for position-based DoA estimation. Serious performance degradation would be inevitable if the estimation results are directly applied to Eq. (11). To handle this issue, we develop a novel position correction algorithm in Section V, which is capable of reducing the position error and enabling beamformer to accurately track the UAV's movements.

V. GPS Coordinate Error reduction

As discussed in the previous section, when UAVs are flying near to the gNB, the inherent position error would cause serious performance degradation. To address this issue, we proposed a new 3D coordinate error reduction method through complementarily integrating the DoA information of 5G cellular network and the position information of UAV system. The motivation of this integration is to overcome their shortcomings and achieve accurate position prediction for beam tracking. As shown in Fig. 3, let $\mathbf{E}(x_k^e, y_k^e, z_k^e)$ and $\mathbf{T}(x_k^t, y_k^t, z_k^t)$ be the position information received by gNB and the true UAV position. The aim of this subsection is to correct $\mathbf{E}(x_k^e, y_k^e, z_k^e)$ to approach $\mathbf{T}(x_k^t, y_k^t, z_k^t)$. Let $\mathbf{C}(x_k^c, y_k^c, z_k^c)$ denote the corrected position point. The methodology of achieving this aim is to exploited the DoA information of the previous transmission frame to correct the UAV position. The position correction could be described as an optimisation problem in Eq. (16),

$$\begin{aligned} \min_{x_k^c, y_k^c, z_k^c} \quad & \sqrt{(x_k^c - x_k^e)^2 + (y_k^c - y_k^e)^2 + (z_k^c - z_k^b - z_k^e)^2} \\ \text{s.t.} \quad & \tan\phi_k = \frac{\sqrt{(y_k^c)^2 + (z_k^c - z_k^b)^2}}{x_k} \\ & \tan\theta_k = \frac{\sqrt{(x_k^c)^2 + (y_k^c)^2}}{z_k^c - z_k^b} \end{aligned} \tag{16}$$

The constraints in Eq. (16) are used to force the corrected coordinate to be on the cone formed by the horizontal DoA and the cone formed by the vertical DoA. This brings the benefit that the position-based method could obtain the similar performance in the DoA estimation as that of the MUSIC algorithm. However, the MUSIC based algorithm could not predict and track the DoA changes between resource allocation slot, which is critically important for the near-gNB UAV operations. To address this issue, the optimisation target of Eq. (16) is to map the original GPS coordinate into the space set formed by the two constraints to identify the unique correction coordinate. Coupled with the mobility information, gNB is capable of forming the beam to track UAV based on the current corrected coordinate.

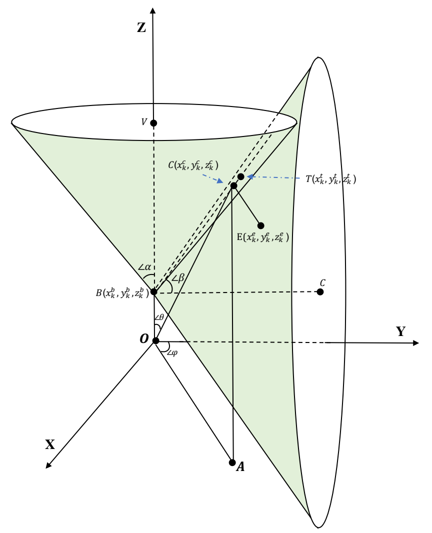

Fig. 3. GPS Coordinate Mapping and reduction

The values of θ_k ϕ_k are calculated by applying MUSIC algorithm to the signal received by gNB [18]. For DoA estimation, the gNB firstly calculates the correlation matrix of the signal it received in the previous frame, conducts the eigen decomposition for the correlation matrix to form signal space and noise space, and calculates the spectrum function as follows,

$$P_f(\theta) = \frac{1}{[\alpha^v(\theta)]^H U_n U_n^H \alpha^v(\theta)} \tag{17}$$

where U_n is the noise eigenvectors and $\alpha^v(\theta)$ is the vertical steering vector obtained from Eq. (4). By searching the peak of spectrum function with different values of θ, the gNB obtains the estimated value of DoA. It can be seen that MUSIC algorithm estimates DoAs through searching the frequency content of signal autocorrelation matrix in the eigenspace. The stronger the signal strength is, the larger frequency content can be searched and the higher accuracy DoA estimation could be obtained. By applying MUSIC algorithm to the horizontal direction, the DoA ϕ could also be obtained similar to θ.

As shown in Fig. 3, there are two cones, one is formed by the horizontal DoA arrival, $\angle\beta$, and the other formed by the vertical DoA, $\angle\alpha$. As the signals received by the vertical and horizontal antennas are from the same source, the signal source should be on the cross lines of two cones. There should be two lines in the 3D space. The constraints of Eq. (16) are to limit the point $\mathbf{C}(x_k^c, y_k^c, z_k^c)$ on the line L_{BCT}. The

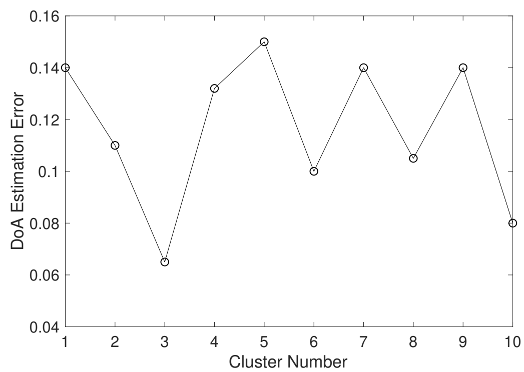

Fig. 4. DoA estimation error of MUSIC algorithm with different cluster numbers in 5G RMa scenario

optimisation target is to minimise the distance between the point $\mathbf{E}(x_k^e, y_k^e, z_k^e)$ and L_{BCT} to identify the point $\mathbf{C}(x_k^c, y_k^c, z_k^c)$.

After a series of derivation in the APPENDIX, the corrected UAV's coordinate, $\mathbf{C}(x_k, y_k, z_k)$ can be calculated from the Eqs. (18-19),

$$
\begin{aligned}
x_k^c &= \left(z_k^c - z_k^b\right) \frac{\sqrt{(\tan\theta_k \tan\phi_k)^2 - 1}}{\sqrt{1 + (\tan\phi_k)^2}} \\
y_k^c &= \left(z_k^c - z_k^b\right) \frac{\sqrt{1 + (\tan\theta_k)^2}}{\sqrt{1 + (\tan\phi_k)^2}}
\end{aligned}
\tag{19}
$$

The optimisation problem is to find a point, $\mathbf{C}(x_k^c, y_k^c, z_k^c)$, which resides on the line L_{BCT} and has the shortest distance to $\mathbf{E}(x_k^e, y_k^e, z_k^e)$. This is the process to map the point $\mathbf{E}(x_k^e, y_k^e, z_k^e)$ to the line L_{BCT}. Let $\angle BTE$ denote the angle of line L_{BT} and line L_{CE}. As $\mathbf{C}(x_k^c, y_k^c, z_k^c)$ is the mapping point of $\mathbf{E}(x_k^e, y_k^e, z_k^e)$ on the line L_{BCT}. The distance between $\mathbf{C}(x_k^c, y_k^c, z_k^c)$ and $\mathbf{T}(x_k^t, y_k^t, z_k^t)$, denoted as D_{CT}, and the distance between $\mathbf{E}(x_k^e, y_k^e, z_k^e)$ and $\mathbf{T}(x_k^t, y_k^t, z_k^t)$, denoted as D_{ET}, hold the relationship, $\sin(\angle OTE) = \frac{D_{CE}}{D_{TE}}$, which gives $D_{CE} < D_{TE}$. In addition, $\mathbf{C}(x_k^c, y_k^c, z_k^c)$ and $\mathbf{T}(x_k^t, y_k^t, z_k^t)$ are both on the cross line L_{BCT}. They hold the same values of β and α, effectively reducing the performance degradation caused by inaccurate position information.

It should be noticed that if the DoA estimation is accurate, the signal source would be on the cross line of two cones. However, this assumption does not always hold in the practical 5G communication system. This is because, due to the search resolution, signal strength, unideal channel condition, it is inevitable to have some errors in the DoA estimation. Let $\Delta\theta$ and $\Delta\phi$ denote the estimate errors. In the horizontal direction, the signal source should be in the overlapped area of two cones formed by ϕ-$\Delta\phi$ and ϕ+$\Delta\phi$, and in the vertical direction, in the overlapped area of two cones formed by θ-$\Delta\theta$ and θ+$\Delta\theta$, therefore, the signal source should be in the overlapped area formed by these four cones in the practical wireless system.

To obtain a deep understanding of MUSIC based DoA estimation method, we conducted a simulation experiment under 5G macros scenario. Totally up to 100 rays are generated in the simulation, each of which is allocated with different delay, power and DoA information. According to [19], the power distribution is related to a delay profile, which is generated by an exponential distribution. DoAs are obtained by applying the inverse Laplacian function with input power distribution and the angle spread. The simulations are conducted by varying the cluster numbers received by gNB to reflect the different channel configurations. The simulation results are shown in Fig. 4. It can be seen that the estimation error of MUSIC is between 0.05^o and 0.15^o with different channel conditions.

TABLE I
SIMULATION PARAMETER CONFIGURATION

Parameters	Values
Carrier frequency (f_c)	$29GHz$
Light speed (c)	$3.0 * 10^8 m/s$
Signal wavelength (λ)	c/f_c
Number of Antenna at gNB (N)	64
Number of Antenna at gNB (M)	32
UAV speed (V)	$40km/h$, $160km/h$
Flight heights ($h_{UAV(1,2,3)}$)	$50m$, $100m$, $150m$
BS heights (h_{gNB})	$15m$
BS coverage (h_{gNB})	$500m$
UAV transmission power (P_s)	$23dbm$
Coordinates of UAV1 (x, y, z)	$(50m, 50m, 50m)$, $(150m, 150m, 50m)$, $(300m, 300m, 50m)$
Coordinate of UAV2 (x, y, z)	$(500m, 600m, 100m)$
Coordinate of UAV3 (x, y, z)	$(550m, 650m, 150m)$
Search radium in SRCM model (S_r)	$(25m, 75m)$
Antenna inter-element distance (d)	$\lambda/2$
Signal-to-Noise-Ratio (SNR)	$10db$
MUSIC Search Resolution ($Search$)	0.1^o
GPS Error (GPS_e)	N(μ, σ^2), with μ = 15m and σ = 5m
Bandwidth (B)	$40MHz$
Channel Model (h)	RMa Scenario in 3GPP specifications in [19]

VI. PERFORMANCE VALIDATION AND ANALYSIS

In this section, comprehensive simulation experiments are conducted to evaluate the performance of the proposed beamforming algorithm. The parameter configuration is summarised in Table I, which is based on the 3GPP 5G specification defined in [19]. According to commercial UAV products [19], GPS signals are generated at the frequency of 10 Hz and the position errors are generated by Gaussian distribution, $N(\mu, \sigma^2)$, with $\mu = 15$ and $\sigma = 5$. There are three UAVs used to broadcast the content to the ground UEs in the system. To capture the characteristics of the real-world cellular-enabled UAV communication, is allocated in the serving gNB and UAV2 and UAV3 in the neighbouring gNBs, which receive the interference signals from the serving gNB. The Semi-Random Circular Movement (SRCM) mobility [20] is adopted in the simulation to update the UAV positions at each transmission frame. SRCM is an important UAV mobility model, mainly used in the scenarios where a potential target location is known, and UAVs are dispatched to collect information in the nearby area, e.g. Search and Rescue. The results are collected and averaged from 100 runs; each lasting 120 and 1200 resource allocation frames. The performance of different algorithms is analysed in terms of DoA error, signal power,

$$z_k^c = \frac{x_k^e \sqrt{\left((\tan\theta_k \tan\phi_k)^2 - 1\right)\left(1 + (\tan\phi_k)^2\right)} + y_k^e \sqrt{\left(1 + (\tan\theta_k)^2\right)\left(1 + (\tan\phi_k)^2\right)} + z_k^e \left(1 + (\tan\phi_k)^2\right)}{1 + (\tan\theta_k)^2 + (\tan\phi_k)^2 + (\tan\theta_k \tan\phi_k)^2} + z_k^b \tag{18}$$

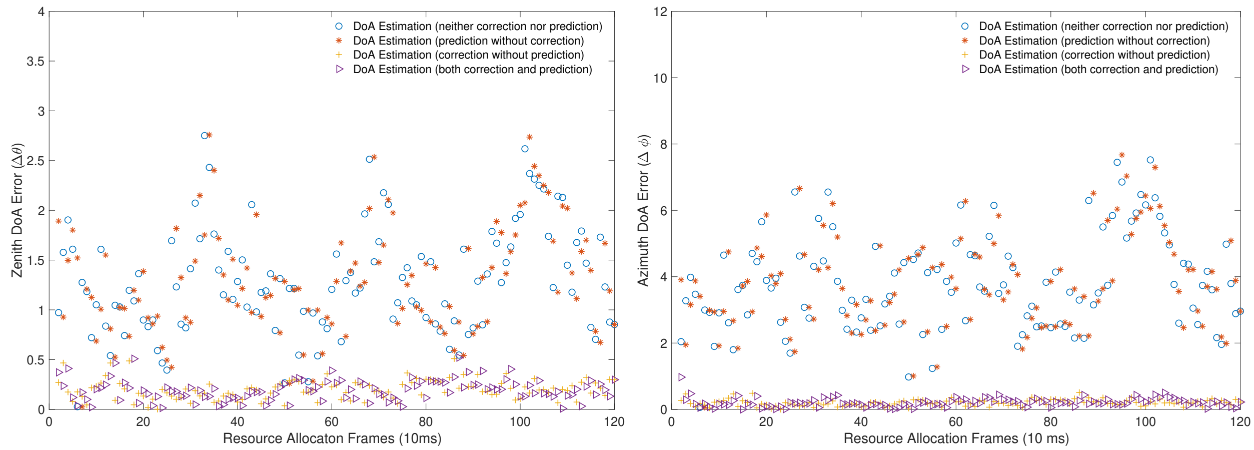

Fig. 5. DoA estimation error of position-based algorithm ($V = 160km/h$, $(x_1, y_1, z_1) = (50m, 50m, 50m)$, $(x_2, y_2, z_2) = (500m, 600m, 100m)$, $(x_3, y_3, z_3) = (550m, 650m, 150m)$, $S_r = 25m$)

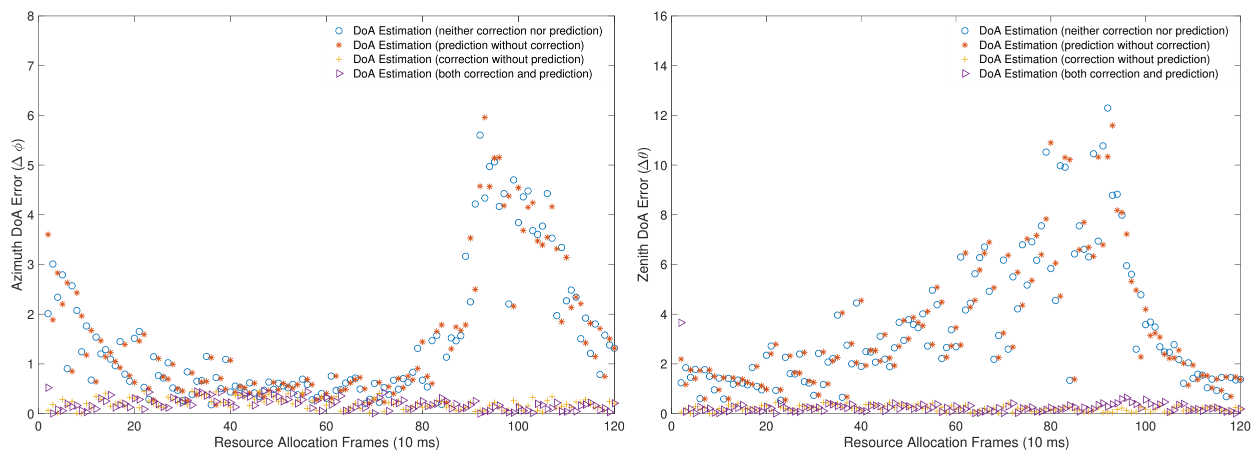

Fig. 6. DoA estimation error of position-based algorithm ($V = 160km/h$, $(x_1, y_1, z_1) = (50m, 50m, 50m)$, $(x_2, y_2, z_2) = (500m, 600m, 100m)$, $(x_3, y_3, z_3) = (550m, 650m, 150m)$, $S_r = 75m$)

and Signal Interference Ratio (SIR). The well-known ZF-based beamforming and position-based algorithm without position correction are chosen as the benchmark algorithms for performance comparison. It should be clarified that the position correction algorithm is conducted on UAV 1, not for all three UAVs.

In Figs. 5 to 7, we investigate the DoA errors, $\Delta\theta$ and $\Delta\phi$, for different beamforming algorithms under different search radius and flying speeds; $\Delta\theta$ and $\Delta\phi$ are defined as the absolute difference between real DoA and estimated DoA, $\Delta\theta = \left|\theta^t - \theta^e\right|$ and $\Delta\phi = \left|\phi^t - \phi^e\right|$. We could see that the proposed algorithm with the position correction approach shows a significant gain over the position-based DoA estimation without prediction and correction. compared with the other three approaches, the proposed method could achieve a reduction of 90-99% DoA error. From Figs. 5 and 6, it can be seen that the proposed algorithm periodically obtains better performance than the other algorithms. This is because DoA estimation error is largely determined by the UAV flight status. As introduced in the previous paragraph, the flight path is generated by the SRCM model and is flying around a certain point; after a certain amount of flight time, would finish one round search and start the next round; DoA estimation error is closely related to the direction of the signal sent out and the distance between UAV and gNB. When the UAV is at the nearest point, the proposed algorithm provides better performance, e.g. around the 100th resource allocation frame in Fig. 6. When UAV is at the farthest point (from 40th to 60th resource allocation frames), the proposed algorithm obtains a similar performance as the other three methods. In addition, by comparing Fig. 5 and Fig. 7, it can be seen that the lower flying speed would reduce the dynamicity of both wireless transmission and UAV operation. The proposed algorithm provides the better performance in terms of DoA

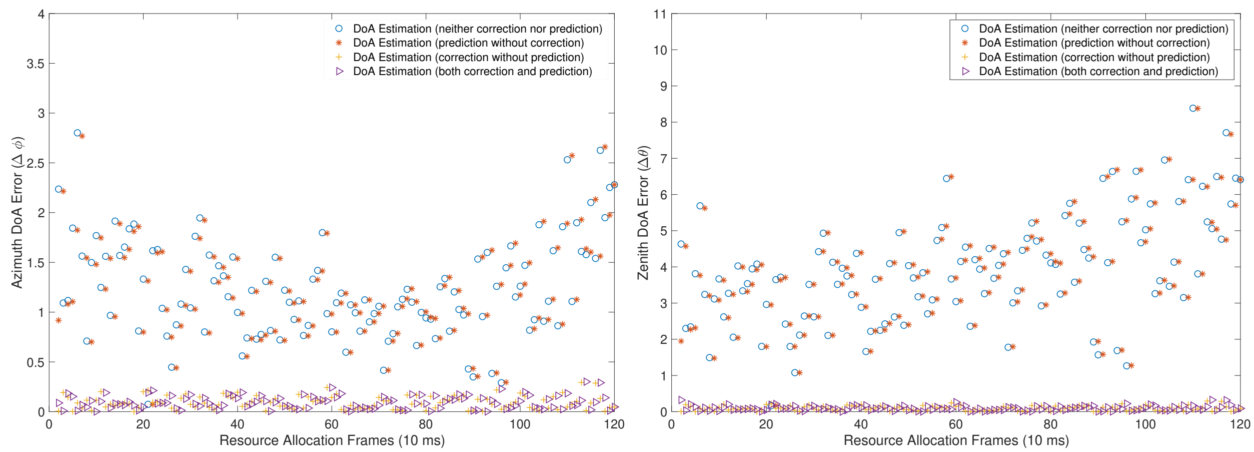

Fig. 7. DoA estimation error of position-based algorithm ($V = 40km/h$, $(x_1, y_1, z_1) = (50m, 50m, 50m)$, $(x_2, y_2, z_2) = (500m, 600m, 100m)$, $(x_3, y_3, z_3) = (550m, 650m, 150m)$, $S_r = 25m$)

estimation error reduction.

In Fig. 8, we investigate the performance of the proposed algorithm in terms of SIR compared with ZF beamforming and position-based beamforming without position correction. To clearly show the performance gains in the long term system operation, the simulation experiments are running over 1200 resource allocation frames. The first subfigure in Fig. 8 shows that the proposed algorithm outperforms the other two approaches. Due to the reduction of DoA error, the proposed robust beamforming has least position error for calculating the steering vector in Eq. (12) and beamforming weight vector in Eq. (11), achieving good SIR output. Also, as shown in Fig. 8, position-based algorithm without position prediction and ZF-based beamforming algorithm without prediction can occasionally achieve good SIR performance, but could not provide stable SIR output. The reason for this phenomenon is that when UAV is operated in vertical direction of gNB, slight DoA error is introduced between two resource allocation frames and the good performance of the receiving SIR could be achieved, however, when UAV changes its flight status according to the mission requirements, the large scale of DoA error would be generated, which results in the low SIR received. In this case, the position correction process proposed in this work can be used to reduce the DoA error and achieve good and stable receiving SIR. In addition, we further analyze the Cumulative Distribution Function (CDF) of SIR for different beamforming algorithms in the second subfigure of Fig. 8. The results reveal that the proposed location-based beamforming algorithm obtains a significant SIR gain against the other two algorithms. It can be seen that the proposed algorithm obtains 90% of probability that the received SIR is larger than 2 dB, while the other two algorithms have more than 70% of probability that the received SIR is lower than 1 dB. This is because the proposed algorithm achieves a smaller DoA error as shown in Fig. 5.

The signal strength received by the interesting UAV is critically important for 5G UAV broadcasting system. Therefore, we investigate the performance of the proposed algorithm in terms of signal strength received by the interesting UAV. As shown in the Fig.9, the proposed algorithm has much higher signal strength compared with ZF-based beamforming without position prediction and position-based beamforming algorithm without correction. As shown in Eq. (9), the first constraint condition guarantees that the signal from interesting UAVs could be responded without any power loss after multiplying the beamforming weight solution ω. This guarantees that the power is sent out in the direction of the interesting UAVs, and minimizing the power leaked in the other directions. Also, after jointly combining the DoA information and mobility information, the proposed algorithm could reduce the impact of the inherent position error on DoA updating. Because DoA error would result in the leakage of interfering power, correcting the position error brings the benefits of reducing the power leakage and enhancing signal strength received by the interesting UAV.

Furthermore, we draw the CDF of the signal strength received by UAV1 as shown in the second subfigure of Fig. 9. It can be seen that the proposed algorithm obtains around 90% probability that the received power is higher than 0.1 dbw, while the counterparts suffer from more than 60% probability that the received power is smaller than 0.04 dbw. Therefore, compared with the benchmark algorithms, the proposed algorithm significantly improves the signal strength for UAV1 and reduces the power leaked to the neighbour cells under the constrained transmission power of gNB. In addition, to investigate the initial search point on the performance of SIR and power received, we set different initial search ranges for UAV1, $(x_1, y_1, z_1) = (50m, 50m, 50m)$, $(150m, 150m, 50m)$, $(300m, 300m, 50m)$ respectively. The results are shown in third subfigures of Figs. 8 and 9, which demonstrate that the proposed beamforming algorithm provides better performance when UAV1 is at the coordinate of $(x_1, y_1, z_1) = (50m, 50m, 50m)$, compared with the the coordinates of $(x_1, y_1, z_1) = (150m, 150m, 50m)$, $(300m, 300m, 50m)$. This means the shorter distance between the UAV and gNB, the better performance the proposed algorithm could provide.

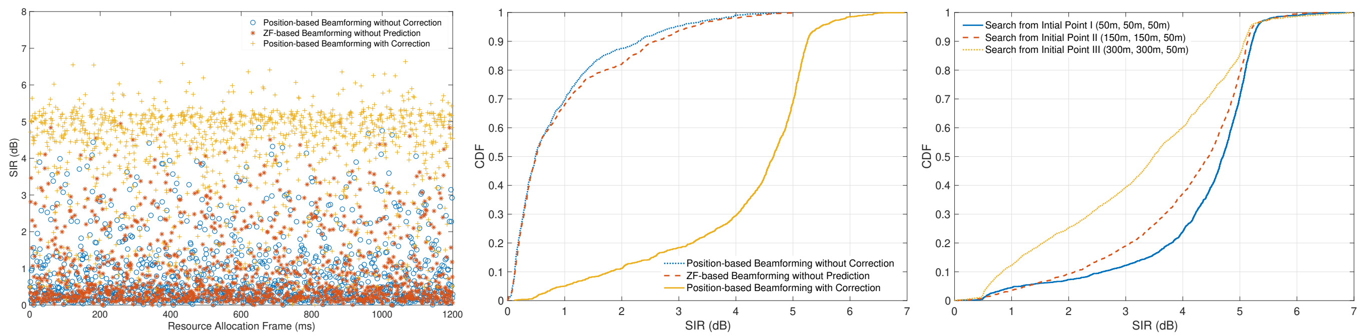

Fig. 8. Performance comparison of three beamforming in terms of Signal Interference Ratio (SIR) and CDF distribution ($V = 160km/h$, $(x_1, y_1, z_1) = (50m, 50m, 50m)$, $(x_2, y_2, z_2) = (500m, 600m, 100m)$, $(x_3, y_3, z_3) = (550m, 650m, 150m)$, $S_r = 25m$)

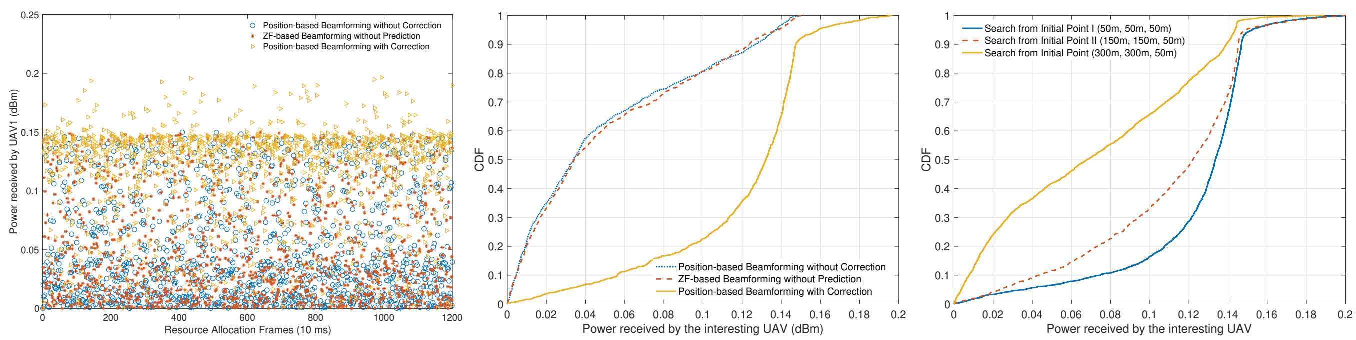

Fig. 9. Performance comparison of three beamforming in terms of the power received by UAV1 ($V = 160km/h$, $(x_1, y_1, z_1) = (50m, 50m, 50m)$, $(x_2, y_2, z_2) = (500m, 600m, 100m)$, $(x_3, y_3, z_3) = (550m, 650m, 150m)$, $S_r = 25m$)

VII. Conclusion

A lightweight beamforming algorithm was proposed in this paper to improve the performance of 5G UAV broadcasting transmission. Instead of exploiting the full/partial CSI information, the proposed algorithm uses the position information to form beams to predict and track UAV's mobility, which relieves the transmission burden for uplink transmission. However, due to the inherent position error, direct utilisation of position information in beamforming design would results in performance degradation, especially when UAVs are flying near to gNB. To address this issue, a new position correction approach was designed in the proposed beamforming algorithm, which jointly considered the DoA information of the wireless communication system and mobility information of the UAV system. Comprehensive simulations were conducted based on 5G specifications and the results show that the proposed algorithm outperformed the well-known ZF beamforming and position-based method without position correction in terms of DoA estimation accuracy, signal strength and interference cancellation level.

Appendix

Determination between Eq. (18) and Eq. (19).

After applying Lagrange multiplier to the optimisation problem in Eq. (16), we can obtain the following equation,

$$\begin{aligned} Ł =& \left(x_k^c - x_k^e\right)^2 + \left(y_k^c - y_k^e\right)^2 + \left(z_k^c - z_k^b - z_k^e\right)^2 + \\ & \zeta\left(\left(x_k^c\right)^2 + \left(y_k^c\right)^2 - (\tan\theta_k)^2\left(z_k^c - z_k^b\right)^2\right) + \\ & \eta\left(\left(y_k^c\right)^2 + \left(z_k^c - z_k^b\right)^2 - (\tan\phi_k)^2\left(x_k^c\right)^2\right) \end{aligned} \tag{20}$$

For the above multivariable function Ł, we calculate the partial derivatives of Ł to x_k^c, y_k^c, z_k^c as follows,

$$\begin{aligned} &\frac{\partial Ł}{\partial x_k^c} = x_k^c - x_k^e + \zeta x_k^c - \eta(\tan\phi_k)^2 x_k^c = 0 \\ &\frac{\partial Ł}{\partial y_k^c} = y_k^c - y_k^e + \zeta y_k^c + \eta y_k^c = 0 \\ &\frac{\partial Ł}{\partial z_k^c} = z_k^c - z_k^b - z_k^e - \zeta(\tan\theta_k)^2(z_k^c - z_k^b) + \eta(z_k^c - z_k^b) = 0 \\ &\frac{\partial Ł}{\partial \zeta} = \left(x_k^c\right)^2 + \left(y_k^c\right)^2 - (\tan\theta_k)^2\left(z_k^c - z_k^b\right)^2 = 0 \\ &\frac{\partial Ł}{\partial \eta} = \left(y_k^c\right)^2 + \left(z_k^c - z_k^b\right)^2 - (\tan\phi_k)^2\left(x_k^c\right)^2 = 0 \end{aligned} \tag{21}$$

After a series of derivations, we can obtain the expression of x_k^c, y_k^c, z_k^c in terms of ζ and η as follows,

$$\begin{aligned} z_k^c &= \frac{Ax_k^e + By_k^e + z_k^e}{A^2 + B^2 + 1} + z_k^b \\ y_k^c &= \left(z_k^c - z_k^b\right)B \\ x_k^c &= \left(z_k^c - z_k^b\right)A \end{aligned} \tag{22}$$

where $A = \frac{\sqrt{(\tan\theta_k \tan\phi_k)^2 - 1}}{\sqrt{1+(\tan\phi_k)^2}}$ and $B = \frac{\sqrt{1+(\tan\theta_k)^2}}{\sqrt{1+(\tan\phi_k)^2}}$.

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