Indoor 3D localization in emergency scenarios through drone based rapid 5G deployment

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***Abstract*— Drone based 5G services can be particularly attractive in emergency scenarios, with their rapid deployment and good SNR capabilities. We propose the use of multiple drones to conduct 3D indoor positioning in emergency situations in this paper. We estimate the performance metrics for such a system, when complying with 3GPP rel. 16 NR-positioning specifications. We also propose new designs for the PRS (positioning reference signal) used in the standards, when there are different SCS (sub-carrier spacing) involved. We develop a mapping function based on neural networks to map the multiple SNR from the drone base stations to the positioning error. The key finding from this work is that the common OTDOA (observed time difference of arrival) based positioning methods alone will not be able to meet the strict accuracy and reliability thresholds for this emergency use case. Adaptation and/or combination with other 3GPP and non-3GPP positioning methods will be required in this regard.**

Keywords*— *Critical communications, Drone RRH, Indoor positioning, Neural networks, OTDOA positioning

I. Introduction

5G has the potential to provide enhanced capabilities for critical communications in a multitude of applications. These can range from UHD video feeds through eMBB, highly responsive robotic control through URLLC and crowd sourced information gathering through mMTC capabilities. 5G emergence is in the context of a concerted effort by the critical communications sector to move away from the specialized communication protocols like TETRA to commercial cellular standards like LTE and subsequently 5G. Some of the early examples of this shift are the FirstNet in the US [1] and the developing ESN (Emergency Services Network) in the UK [2], which are both supported by LTE. An early adaptation of 5G, with its capabilities noted above, can help emergency services to improve their effectiveness and efficiencies significantly.

One of the key issues in this migration to 5G is the apparent long lead time needed for this transition. The first 5G networks are only covering the localized capacity hotspots, with the coverage continuity provided by the underlay LTE networks in the 3GPP NSA (Non-Stand-Alone) deployment model [3]. With the economic disruption stemming from the COVID-19 pandemic, the large scale expansion of 5G networks is very likely to get further delayed. For an emergency service, it is critical that a certain 5G application can be deployed anywhere within its service area, not just at the capacity hotspots. Hence early adaptation of 5G would depend largely on the ability to stretch and expand the 5G coverage area to align with the service area of an emergency service. A drone based 5G critical communication service was proposed in [4], where the limited 5G network can be stretched with drone relay stations, to potentially cover the entire service area.

In this paper, we extend the system model proposed in [4] for a drone based 5G eMBB service, to provide 3D indoor localization in indoor emergency scenarios. We propose to use multiple drones at different heights, which can also provide the eMBB services discussed in [4], in addition to the localization services. 3D localization is necessary for emergencies in multi-storey buildings, where the vertical height estimation can guide the emergency crews to the correct floor of the building. The typical emergencies where localization will be necessary include building fires, medical emergencies and terrorism/kidnap incidents etc. As the signal quality from outdoor ground base stations cannot be guaranteed at all locations inside the building and the indoor small cells can become dysfunctional in an emergency, this drone based solution can provide service guarantees even in extreme emergency scenarios.

The main contributions of this paper are three-fold. First is an assessment as to whether the 3GPP Release 16 specified NR-positioning signals and OTDOA methods are sufficient to meet the technical requirements (which were verified with the involvement of the emergency services) of this emergency use case. Second is the development of a novel mapping function from the SNR values (from multiple drones to the UE) to the positioning error, based on neural networks. This would be useful to assess the positioning accuracy in multi-storey complex buildings very quickly, without the need to run detailed link level simulations for all locations. Third is the proposal for a novel PRS (positioning reference signal) design for a scenario where some of the UEs would use a different SCS (sub-carrier spacing) to that used by the drone transmitters.

The layout of the remainder of the paper is as follows. In section II, we will develop the system configuration, with allowances to use different SCS. Section III details the required KPI (Key Performance Indicator) values this emergency localization service must achieve. The simulation set-up and the initial results in terms of these KPIs targets are provided in section IV. We also detail the neural network based mapping function from the 4 SNR values to the positioning error in this section. The conclusions from the current initial work and planned further work are stated in section V.

II. System configuration

This ad-hoc 5G network for the emergency scenario is configured with the help of communication drones, which act as remote radio heads (RRH) and are connected to a ground base station through wireless fronthaul links. As noted before, this is an extension to the model proposed in [4], for the provision of eMBB services with a single RRH drone. This model is extended to carry at least 4 RRH drones at the emergency site for the devices to derive 3D localization. We also propose some novel design configurations for the positioning reference signal (PRS) in this section.

A. Deployment model

The deployment model consists of a master RRH drone and 3 auxiliary drones to support the localization. The master drone also provides the eMBB connectivity as in [4] and is configured to transmit at 3dB higher power than the auxiliary drones. The transmissions from auxiliary drones and the master drone are time synchronized to help with the OTDOA (Observed Time Difference of Arrival) and other localization methods. The deployment model is illustrated below.

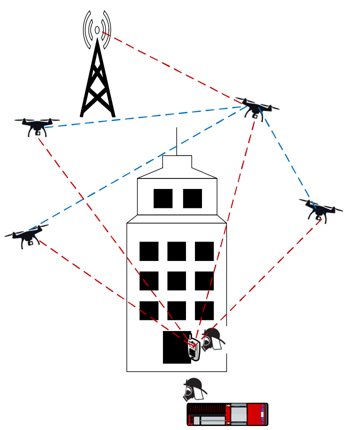

Fig. 1: The deployment model for drone based localization

The master RRH is assumed to transmit with the full available bandwidth needed to support the eMBB links and function with full capabilities of a 5G RRH. The auxiliary RRH drones, on the other hand, are configured with a narrow bandwidth to transmit only the broadcast information in the SSB (Synchronization Signal Block), the PRS and other reference signals needed for localization.

This configuration assumes that the drones are stable in their positioning and will be able to support the emergency event through the entire duration. In practice however, the drone positions are likely to suffer from some jitter (especially in windy conditions) and the drone battery (especially in the master drone) may run low and a drone replacement will be needed. Such deficiencies will be studied and solutions developed in the second project year.

B. The PRS design

The PRS is one of the main reference signals which was improved in 5G-NR Release 16 to aid downlink localization. The PRS is a Zadoff-Chu sequence [5] with very good autocorrelation and low cross correlation properties. Auto-correlating the incoming PRS signal from a base station with a local copy can determine the time delay for the signal to travel from the base station to the UE. In OTDOA methods, the time difference of arrival for the signals from one base station to signals from others is calculated and this difference can be expressed as paraboloids in distance. The point at which the paraboloids intersect gives an estimate for the UE position.

The resolution of the OTDOA localization method is governed by the sampling rate used, as the PRS signal is sampled and recorded at this rate. The use of wider bandwidths and higher sub-carrier spacing increase the sampling rate and will improve the localization resolution as a result. Increasing the bandwidth used for this drone based system will carry other penalties (as studied in [4]) so we would consider the use of higher sub-carrier spacing only as a means to improve the localization accuracy.

Although the drone RRHs and the UEs/ devices attached to the emergency crew can use a higher SCS, the victims' UEs are likely to operate at the most common SCS, i.e. 15 kHz. These UEs will sample the PRS signals from the drone RRHs at a lower rate, so the energy they will capture from the PRS signal will be low. As a solution to this issue, we propose to replicate the PRS signal in the subsequent slot(s) of the higher SCS transmissions, so that the lower SCS UEs can capture more energy from the PRS signal and thus improve the received signal quality. The repetition can be done μ times, where 2^{μ} is the ratio from the higher SCS to the lower SCS. An example PRS Comb-12 pattern, as specified in 3GPP [5], for the 15 kHz and 30 kHz SCS configurations is shown below in Fig. 2.

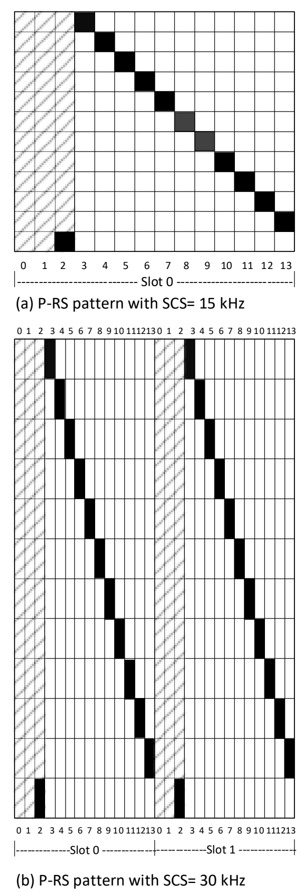

Fig. 2: Proposed PRS patterns with different SCS

As the sampling intervals in the 15 kHz SCS UE are twice the sampling width of the 30 kHz transmissions, such UEs would capture only a fraction of the energy of a PRS symbol in 30 kHz. By replicating the PRS pattern in the subsequent slot in the 30 kHz SCS transmissions, the 15 kHz UEs get an opportunity to capture more of the PRS sequence and re-configure it to the correct order before auto-correlating with the stored sequence. The 30 kHz UE can also use this repeated PRS sequence to enhance the signal quality or discard it if this is deemed unnecessary.

III. KPI REQUIREMENTS FOR THE EMERGENCY USE CASE

Within the LOCUS EU project [6], this emergency use case is extensively studied. The first task was to derive the technical KPIs with inputs from the emergency services themselves. We have initially used the KPI values proposed in [7] for such a communication service for fire services. Subsequently we have refined them through a number of discussions with the regional fire and emergency services in the UK, who are contributing to the development of the ESN [2]. The final KPI values, which we are targeting to achieve through our drone based solution are listed in Table I below.

TABLE I. KPI TARGET VALUES

KPI	Target Value
Horizontal Accuracy	±2 m
Vertical Accuracy	±1 m
Service Reliability	99.9%
Service Availability	98%
Location update interval	20 s (maximum)
Initial set-up time	135 s
Number of devices tracked	128 (maximum)

The horizontal accuracy level is based on the ability to detect a victim (or an emergency service crew member) correctly within a room or a cubicle in the building. The vertical accuracy levels are tighter and this relates to detecting the localization targets within the correct floor of the building. Moving between floors through stairways in an emergency like a fire is often difficult and hazardous, so the vertical accuracy is made tighter. The service reliability is the percentage of occurrences when the above accuracy levels can be met and this is set at a very high level. The event commander, who will have access to these localization inputs, will have to make critical decisions based on these inputs. The update rate, however, is quite low as the event commander needs time to assess the movements of multiple targets (which can be visualized on a screen with a map layer of the building) and make the decisions. In the technical solution design, this longer gap allows time to fuse data from multiple localization technologies and improve the accuracy levels to meet the very strict reliability targets. The service availability accounts for the possibility of some downtimes for this service, considering the dynamic nature of the network configuration. While some downtime in terms of drop in service accuracy can be accommodated, it is critical that the event commander is warned beforehand. Then he could factor this into his decision making and rely more on other communication modes like MC-PTT (Mission Critical Push To Talk) during these downtimes.

IV. SIMULATION SET-UP AND INITIAL RESULTS

In this initial analyses, we develop the 3GPP release 16 compliant simulation platform and investigate the performance levels provided by employing OTDOA based positioning using the downlink PRS. We also attempt to map the received SNR levels from the 4 drone RRH to the positioning error of OTDOA through an approach based on machine learning.

A. *Simultation set-up*

The physical layer for the PRS transmissions from the 4 drone RRH to the UEs inside the building is simulated for a single floor of the building. The channel model from 3GPP is selected as the UMi LOS channel, which matches closely with the channel conditions from the drone to the in-building UE. The building penetration losses for the signals are modelled as per the measured results reported in [8] for the mid-band 5G frequencies. As noted above, the transmit power of the master drone RRH is set at 3 dB higher than the other auxiliary drones. The transmit powers are set at a minimum required level, in order to extend the battery lives and the flight times for the drones. Also, the transmissions are assumed to be from a single antenna, without any beamforming.

The simulation parameters are listed below in Table II.

TABLE II. SIMULATION PARAMETERS

System Parameters	Value	
Centre frequency	4 GHz	
SCS	15 kHz	30 kHz
Bandwidth	100 MHz	
Tx power – master RRH	27 dBm	
Tx power – auxiliary RRH	24 dBm	
Localization Signal (PRS)	3GPP TS 38.211	
Path loss + Channel model	3GPP TS 38.901	
UE (with floor) height	10 m	
Building area	50 x 50 m	
Drone area	100 x 100 m	

B. *Initial simultation results*

In this first set of simulations, we consider only a basic building structure with walls and internal partitions and position the UE on multiple locations within a single floor. The 3D location estimates of a UE in terms of (x, y, z) co-ordinates are resolved into horizontal and vertical positions and the positioning errors are calculated. The CDFs (Cumulative Distribution Functions) for the positioning errors, when using the 15 kHz and 30 kHz SCS are depicted in Fig. 3 and Fig. 4 below. For the 30 kHz SCS scenario, it is assumed that the specialized critical communications devices for the emergency crew are operating at this SCS. The common UEs on 15kHz SCS can also read this PRS signal effectively as per the solutions proposed in section II(B), but the positioning accuracy will fall back to the 15 kHz SCS level.

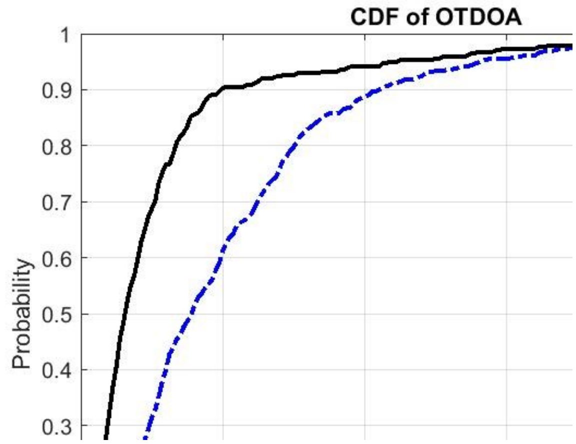

Fig. 3: Horizontal Positioning accuracy levels with different SCS values

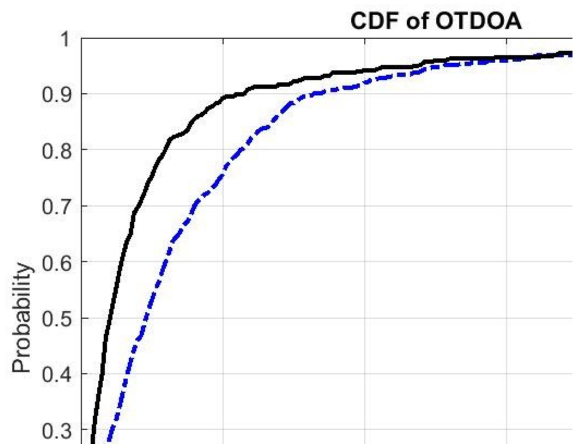

Fig. 4: Vertical Positioning accuracy levels with different SCS values

The horizontal accuracy threshold of 2 m is achieved 90% of the time and the vertical accuracy threshold of 1 m is achieved only 75% of the time with the SCS=30 kHz. The corresponding accuracy levels with SCS=15 kHz is significantly lower. These results show that in order to meet target reliability levels in Table I, the positioning accuracy levels must be improved at least by an order of magnitude in SCS=30 kHz deployments and by even higher margins in SCS=15 kHz deployments.

A simple solution would be to move the operating frequency to the high 5G bands (eg: 28 GHz), where much higher SCS is applicable and also provides wider bandwidths. However, these high band frequencies incur higher path loss and higher building penetration losses, so the received signal levels can be lower. Also, these frequencies would not allow common 5G consumer UEs to be detected with the aid of the drones, so the solution applicability to common emergency scenarios become questionable. We will look at some other possible avenues, particularly to improve the vertical accuracies, in further work in section V.

C. Mapping of SNR values to the positioning errors

While obtaining the SNR values from the 4 drone base stations is quite straight forward, obtaining the positioning error through PRS estimation requires detailed link level simulations. If the solution needs to be evaluated for a complex building structure with many floors, such simulations can take quite a lot of time to complete and/or some of the important localities can be lost in coarse sampling. If a mapping can be developed from the 4 SNR values to the positioning errors, it would be straight forward to evaluate the localization accuracies even at a larger scale.

Building a mathematical model to map the 4 dimensional SNR values to the 3D positioning error was deemed non-linear and highly complex. Hence a machine learning approach is attempted with modelling the problem through a neural network (NN). An NN can be built with those 4 SNR values as inputs and the predicted positioning error as the output. An example of the NN is depicted in Fig. 5.

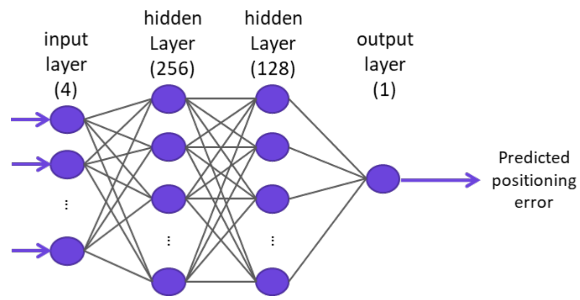

Fig. 5: The Neural Network model

In the NN, there are four layers. The input layer and the output layer has 4 neurons and 1 neuron, respectively. The two hidden layers are with 256 and 128 neurons. Mean squared error in the positioning estimate is chosen as the loss function. In the training process, stochastic gradient descent (SGD) [9] is used to update the weights of the NN. The NN is required to be trained via a large number of episodes, where each episode consists of 2000 measured samples from the link level simulation. Fig. 6 shows that the loss function decreases with the number of training episodes.

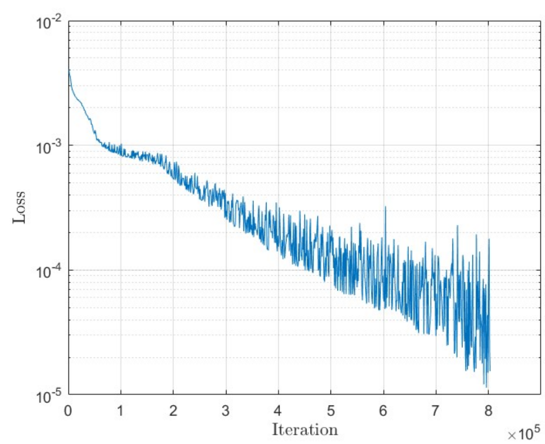

Fig. 6: The reduction of the loss function with training episodes

Even with a limited number of data points, these initial results show that the loss function does reduce towards the required 1×10^{-5} error level with successive training iterations. In the training data set, we have ensured that a one-to-one mapping between the 4 dimensional SNR data and the positioning error is maintained. These initial training results give us confidence that this NN model can be used to predict the positioning error in large scale simulations, given the inputs of 4-tuple SNR values.

V. CONCLUSIONS AND FURTHER WORK

The research on a drone based 3D indoor localization solution developed to assist the emergency services has been presented in this paper. The extensive work done to develop the appropriate technical KPIs with inputs from the UK emergency services and design solutions on the PRS to enable UEs with different SCS to operate within the proposed system are presented and discussed. The initial simulation results in terms of positioning errors in OTDOA based methods are covered. It is concluded that the OTDOA based methods on their own, even with higher SCS, are not sufficient to meet the stringent accuracy levels of this emergency use case. A neural network based modelling approach is suggested to map the 4-tuple SNR values (from the 4 drone RRHs) to the positioning error in this OTDOA method. While the early evaluations were conducted with limited training data, the results in terms of model convergence is encouraging for this NN model to be applied in large scale evaluations.

In the second year of this project, a number of additional investigations will be carried out with the insights gained from the presented work. The option to include 3D beamforming at the drone RRH will be studied, which will enable AoA (Angle of Arrival) based positioning to be combined with OTDOA. This is expected to increase the accuracy particularly in the vertical domain, as the vertical beam widths of such multi-beam transmissions is quite narrow. Also non-3GPP based techniques, like Wi-Fi finger printing from existing Wi-Fi nodes inside the buildings, will be studied. Some of these nodes can get dysfunctional in emergencies like building fires, but the use of even limited information from remaining nodes will be studied. The longer update intervals (in Table I) allow such different localization data to be fused and optimized through post-processing techniques.

In terms of system limitations, the positional jitter of the drones will be a main focus for investigation. We will source data for such jitters under varying wind conditions and would develop compensating algorithms in order to mitigate the impact on the positioning accuracy. Machine learning methods will be extensively used to develop such compensating algorithms.

The work on developing a neural network based mapping from the SNR values to the positioning error will be extended. More focus will be given to execute this mapping on a final solution, which may combine different localization methods and can achieve the technical KPIs. However the insights gained from the current work will be hugely useful in developing these final solutions.

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