Risk Area Alert Through Heterogeneous Mobile Networks: A New Approach to Fight COVID-19 and Beyond

Yao Sun, Qing Xue, Lei Zhang, Lina Mohjazi, Bin Cao, Muhammad Ali Imran

***Abstract*—COVID-19 has now been sweeping the whole world, and fundamentally affecting our daily life. An effective mechanism to further fight against COVID-19 and prevent the spread of this pandemic is to alert people when they are in the vicinity of areas with a high infection risk, yielding them to adjust their routes and consequently, leave these areas. Inspired by the fact that mobile communication networks are capable of precise positioning, data processing and information broadcasting, as well as are available for almost every person, in this paper, we propose a mobile network assisted Risk arEa ALerting scheme, named REAL, which exploits heterogeneous mobile networks to alert users who are in/near to the areas with high risks of COVID-19 infection. Specifically, in REAL scheme, all base stations (BSs) periodically estimate their serving users' locations, which are then analyzed by macro BSs (MBSs) to identify risk areas. Next, each MBS transmits the information about risk areas to small BSs (SBSs), which in their turn adjust the beamforming direction to cover these areas and send alerts to users located therein. Simulation results validate the effectiveness of the proposed REAL scheme. In addition, some key challenges associated with implementing REAL are discussed at the end.**

I. Introduction

In December of 2019, a case of pneumonia termed coronavirus disease 2019 (COVID-19) has been identified as an infectious respiratory disease caused by the Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) [1]. The most frightening thing is that the virus has an unimaginable infectious speed among people. Globally, as of 29 March 2021, there have been 126,890,643 confirmed cases, including 2,778,619 deaths, across 218 countries and territories [2].

A. Background

With respect to the unexpected outbreak and rapid spread of COVID-19, many countries have put into place tough restriction policies on daily life to curb the virus' spread. Specifically, managing the lockdown implementation for the city or even the whole country is an unprecedented but absolutely effective measure taken by governments to cope with the large-scale outbreak of COVID-19. Many public areas such as restaurants, pubs, and parks have been forced to either close or remain open but with very limited access permissions. Moreover, most countries have gradually adopted the self-quarantine policy to relieve the pressure imposed on medical systems and reduce the disease transmission speed as well.

Before the global roll-out of vaccines is completed, humans have to well prepare for the long-term 'new normal' to campaign against COVID-19. Based on this situation, we should realize that besides the restrictions put on travel, measures for guaranteeing people to go out while being exposed to low infection risk should be conducted. To this end, governments have already introduced some measures to drive down the infection rate, such as keeping social distance, wearing masks, and even contact tracing. Although these measures could be effective to some extent, the disease is still rapidly spreading in many areas around the world. This urgently calls for the need to explore innovative and more efficient mechanisms to decrease the probability of infection and to further prevent the spread of COVID-19.

B. Motivation

One direct and highly effective approach is to apply real-time risk area alerting, such that people outside can receive risk alerting messages when they are in the proximity of a high-risk area. According to the characteristics of COVID-19, a *high-risk area* can be defined as the area where user density stays above a threshold for several minutes (say 5 minutes). Please note that the number of users counted for calculating user density should be those who have visited this area over a certain time period (say 30 minutes) instead of the current users staying in this area, since the COVID-19 virus can survive for a certain period of time [1]. Hence, people who enter this area may suffer a high risk of being infected. To this effect, if people can be alerted in a timely manner, they can promptly adjust their routes to avoid passing through these high-risk areas. Therefore, real-time risk area alerting can play a central role in controlling the spread of the virus.

It is worth mentioning that risk area alerting is essentially different from other existing protection measures. Basically, besides much effort has been paid from a biomedical perspective, some researchers propose solutions for the pandemic by exploiting digital technologies. These digital technology based solutions can be roughly divided into the following three categories. 1) Digital Contact Tracing [3]. This aims to identify the people who may have come into contact with an infected person and subsequently, collect further information about these contacts. 2) Social Network Analysis [4]. This

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kind of solution analyzes users' social behavior to virtually construct a virus network, where some potential risk areas as well as risky people can be predicted. 3) Environment Sensing [5]. This method exploits wearable devices or other Internet of Things (IoT) nodes to collect the required information and send alerts to people (e.g., keeping social distance, wearing masks). Besides these tremendous studies, risk area alerting should be a complementary measure with the cooperation of these existing measures to slow down and even control the spread of COVID-19.

After realizing the potential effectiveness and necessity of risk area alerting, we next discuss how to design a systematic framework to underpin an efficient risk area alerting scheme. An intuitive way is based on the human-counted method, where people count neighbors by themselves and once the number of neighbors is large enough, they will move away from this area. The major drawback of this rough and simple method is that people are aware of the current status only and not the past. This results in the lack of necessary alerting information. For example, people may not be aware of the risk when there are few neighbors nearby currently but many just before. Hence, it is essential to develop a precise yet efficient mechanism to conduct risk area alerting, and thus, motivate our work.

Performing risk area alerting requires precise positioning, ability of data processing, function of information broadcasting, large coverage, and easy availability of access. With respect to these requirements, the exploitation of mobile communication networks is particularly appealing to design an efficient and powerful risk area alerting scheme. Specifically, the current emerging heterogeneous networks (HetNets) could be an appropriate architecture, where traditional macro base station (MBS), small BSs (SBSs) and/or millimeter wave (mmWave) SBSs are hierarchically deployed [6] providing an extreme coverage for mobile users. In addition, HetNets are expected to achieve very high positioning accuracy (the error can be less than 0.1 meters) with a delay of several milliseconds [7]. Also, HetNets have a data processing ability which is capable of handling computing tasks in risk area alerting scheme. Therefore, the merits of HetNets can be reaped to design a risk area alerting scheme with good prospects.

C. Contributions and Organization

To fight against COVID-19 and beyond, in this paper, we propose a mobile network assisted Risk arEa ALerting (REAL) scheme. REAL is underpinned by HetNets, in which all BSs periodically estimate the location of their own serving users. In REAL, MBSs analyze these positions to identify risk areas, then SBSs/*m-SBSs* adjust the beamforming direction to cover these risk areas, and alert users located within. Moreover, we conduct numerical simulations to evaluate the performance of REAL scheme, and the effectiveness is validated under different scenarios.

The main contributions of this work are:

- In order to determine the risk level of COVID-19 infection, user density is introduced as the evaluation index. The user location information is obtained by exploiting the positioning function of mobile HetNet systems.
- We propose two functions of REAL scheme, risk level alerting for an individual user and risk level evaluation for an area. The operators can select one or both of the two functions depending on practical requirements.
- Some open issues including user privacy, mmWave link robustness, hybrid spectrum coexistence, and scheme implementations have been discussed at the end of this paper. For each of these issues, we give some potential solutions to facilitate the implementation of REAL.

The rest of this paper is organized as follows. In Section II, we introduce the architecture of HetNets. Section III presents REAL solution for COVID-19 based on this architecture. Experiment results are presented in Section IV and some challenges of REAL are discussed in Section V. Conclusions are drawn in the last section.

II. Preliminary: Heterogeneous Networks Architecture

Fig. 1 illustrates the considered HetNet in which multiple SBSs are located within the coverage area of one MBS. The MBS performs centralized handover and scheduling decisions (such as resource scheduling and beamforming policy of SBSs) [6]. There are three types of SBSs: SBSs using conventional microwave band (denoted as *μ-SBS*), SBSs using mmWave band (denoted as *m-SBS*) and SBSs using the both bands (i.e., dual-mode SBS, denoted as *d-SBS*). The BSs are inter-connected via traditional high capacity X2-based backhaul links to exchange information.

One of the fundamental challenges of HetNets is that the received signal-to-interference-plus-noise ratio (SINR) from SBSs could be very poor due to the low transmit power, which leads to an unstable connection as well as a low transmission rate [8]. In addition, the received SINR of mmWave communication can be even worse due to the high path loss caused by the propagation features of mmWave frequency [9]. To address this challenge, massive antenna arrays can be packed into transceivers, thus to exploit beamforming [10] techniques to improve SINR. Hence, in this work, we assume that all SBSs have the capability to perform beamforming.

In HetNets, user equipments (UEs) can be associated with one SBS or an MBS. Under the HetNet architecture shown in Fig. 1, there are four UE association scenarios as follows.

1) Associated with an MBS: The UE with high mobility or no suitable SBSs nearby is associated with an MBS for increasing transmission reliability. We call this type of UE as *long-range UE*.
2) Associated with μ-SBS: The UE is associated with a nearby μ-SBS. A μ-SBS operates with several static wide beams, and the UE can perform beam switching while moving around.
3) Associated with *m-SBS*: The UE is associated with a nearby *m-SBS*. An *m-SBS* operates with several dynamic narrow beams, and the coverage of these beams can be adjusted.
4) Associated with *d-SBS*: The UEs associated with a *d-SBS* have two transmission modes, where the close-by UEs are served by mmWave links, and farther-away UEs with a poor SINR experience are served by μWave links.

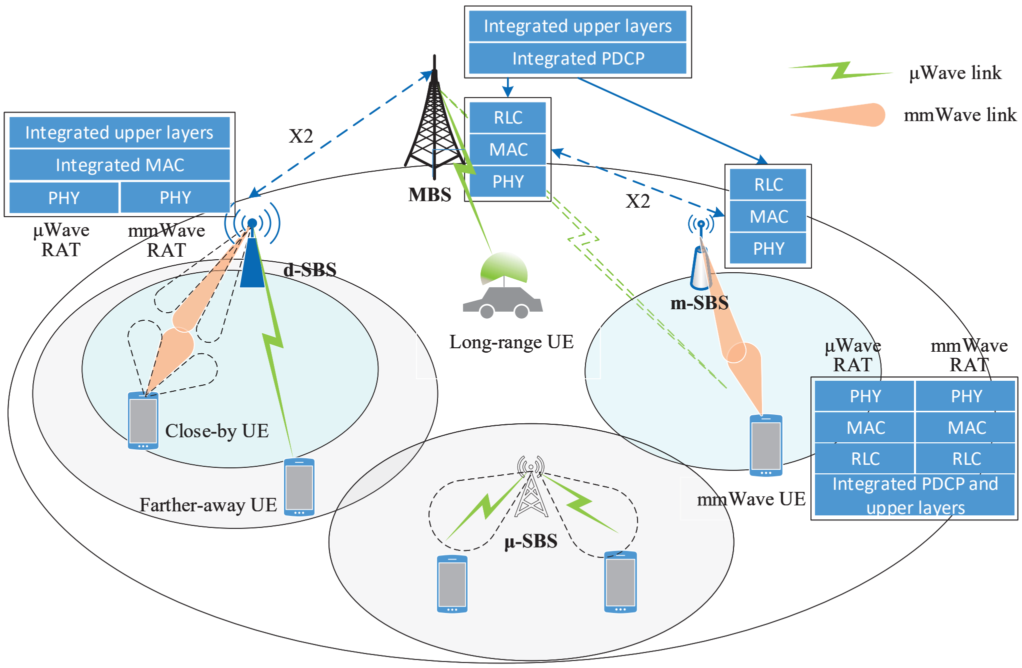

Fig. 1. HetNet architecture with integration of μWave-mmWave radio access technology. (In order to make the figure clear, we do not show the side lobes of beams here.)

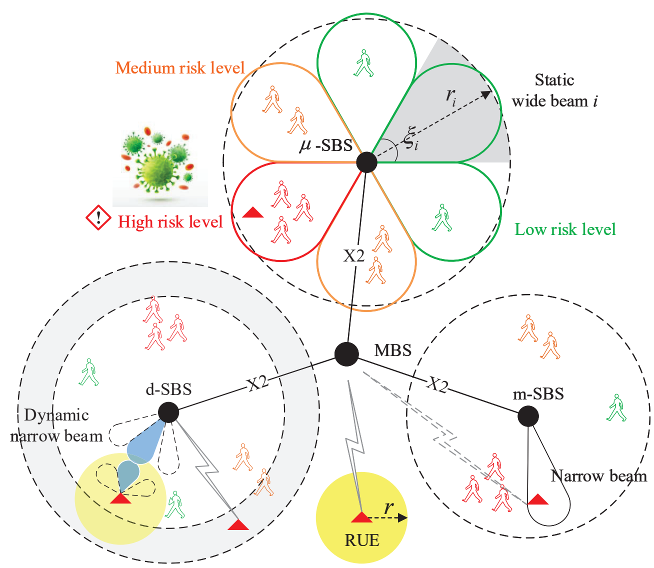

Fig. 2. Schematic diagram of risk assessment area for the RUE.

III. Solution of Risk Area Alerting for COVID-19

To alert users who are in or near to the areas with high risk of COVID-19 infection, we propose our novel REAL scheme, by exploiting a HetNet shown in Fig. 1.

In REAL scheme, user density is used as an index to evaluate the risk level of COVID-19 infection for a certain area. User density is calculated based on two factors, the number of UEs who have visited this area S during a specific time period (say 30 minutes), and the size of area S. The number of UEs can be counted by BSs while the area size is defined in different ways for different communication scenarios as shown in Fig. 2. Here, a reference UE (e.g., RUE) is taken as an example to illustrate.

(a) If the RUE is a long-range UE, S is the circular area where the RUE is located at the center, and the radius r is set according to the spread characteristics of COVID-19.

(b) If the RUE is served via a μ-SBS link with static wide beams, S corresponds to the coverage of each beam. For tractability of the analysis, we use the sectored antenna model to approximate the beamforming patterns.

(c) If the RUE is served by an *m-SBS* operating with dynamic narrow beams, S is calculated following the method in (a).

(d) If the RUE is served by a *d-SBS*, S is calculated in the way of scenario (b) when the RUE is connected to μWave link, and scenario (a) for mmWave link.

After getting the value of user density, the risk level can be obtained. Specifically, let us set two thresholds of user density, namely density-low and density-high. When the user density is lower than the threshold density-low, the area is at a low risk level; when the user density is between the two thresholds, the risk is in medium level; otherwise, the area is at a high risk level. Note that more thresholds of user density can be set to achieve a more accurate risk level assessment.

Based on the above illustration, REAL can fulfill two functions: risk level alerting for an individual user and risk level evaluation for an area. The two functions can be performed in parallel, and the operators can select one or the both depending on practical requirements. As shown in Fig.3, the basic procedures of the two functions are stated as follows.

Function 1: risk level alerting for an individual user

- (a) The RUE is associated with an appropriate BS (the MBS or an SBS), and establishes a communication link

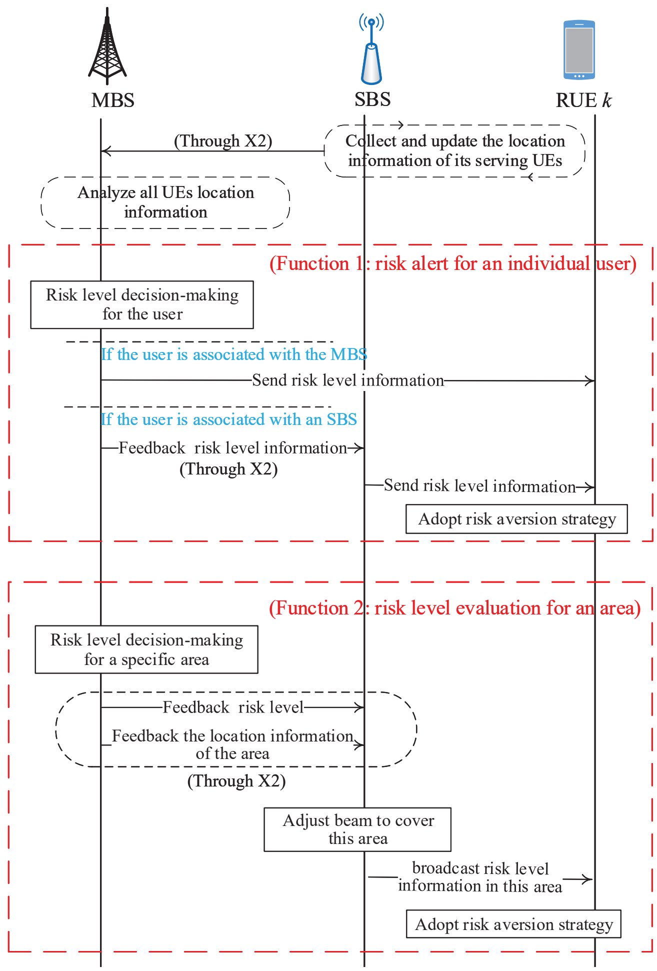

Fig. 3. Procedures of two functions of REAL scheme.

with the serving BS.

- (b) Each BS in the HetNet periodically detects and records the position information of serving UEs. Meanwhile, all the three types of SBSs send the measured results to the MBS.
- (c) The MBS integrates the detection information of each cell and then calculates the user density around the RUE based on the aforementioned rule.
- (d) According to the user density, the MBS makes a risk level decision for the RUE.
- (e) If the RUE is served by an SBS, the MBS needs to send feedback on the risk level to the corresponding SBS.
- (f) The RUE obtains the risk level from the serving BS and determines whether to implement a risk aversion strategy.

Function 2: risk level evaluation for an area

- (a) Each BS in the HetNet periodically detects and records the position information of serving UEs. Meanwhile, all SBSs send the measured results to the MBS.
- (b) The MBS integrates the detection information of each cell and then calculates user density for a specific area.
- (c) According to the user density, the MBS makes risk level decision for this area.
- (d) If the risk level is higher than a threshold, the MBS needs to inform the nearest SBS to adjust the beam to cover this area.
- (e) The SBS periodically broadcasts risk alerting information in this area.

Generally, function 1 of REAL is performed to send alert to the users once the user density nearby is higher than the predefined threshold. Then the user can take some actions, for example, change the travel plan, have a COVID test or even conduct self-isolated. Function 2 is to monitor the risk level for a hot-spot area. Once the area is at high risk, the BSs will broadcast alerts to the nearby users, thus the users can leave or do not enter this area.

Besides the proposed two functions, there are twofold positive impacts of REAL on designing risk prediction solutions. The first is that we can use the detected high-risk areas to predict other penitential high-risk areas for a later time slot. The other point is that we can analyze user density collected by REAL scheme to extract the patterns of user behavior thus to predict high-risk areas.

To implement REAL scheme, the current used LTE Positioning Protocol (LPP) can be exploited to achieve positioning function in REAL, and the whole positioning procedure is illustrated in 3GPP TS 36.355 [11]. In this way, the proposed two functions shown in Fig.3 can be supported. Furthermore, there is not much extra cost incurred since both the communication overhead (only user locations and alert information) and computation resource consumption (only for calculating user density) are quite low. Even if the mobile devices should keep the positioning function on and periodically report location to the BS, the energy consumption on devices should not be high due to the simple positioning function.

IV. Simulation Results and Discussions

In this section, we conduct simulations to evaluate the performance of our proposed REAL scheme. Our numerical computations are implemented with MATLAB codes and carried out on a PC equipped with an Intel-i5 4 core 3.2GHz processor and 8G RAM. We set the number of mobile users as 500, and all these users are randomly distributed in the considered area with radius 500 meters. The MBS is deployed at the center of this area. For user movement, we assume that they move at a random speed along with a certain direction in a straight line, and they will bounce in a random direction once reaching the edge of the considered area. We consider two scenarios *high speed* with an average value of 2 m/s and *low speed* with an average of 0.5 m/s. We consider the total time as 120 minutes.

In the simulations, we only set two risk levels of an area, i.e., risk and non-risk. With respect to the characteristics of COVID-19, we define a **risk area** as a sector with radius 50 meters and angle 60° in which more than 10 people stay for over 5 minutes. Please note that since the size of each area is fixed, using the metric of number of users and user density are equivalent in our simulations. We consider the coverage of an SBS beam to be a sector with the same size (i.e., radius is 50 meters, angle is 60°), and each SBS has three such

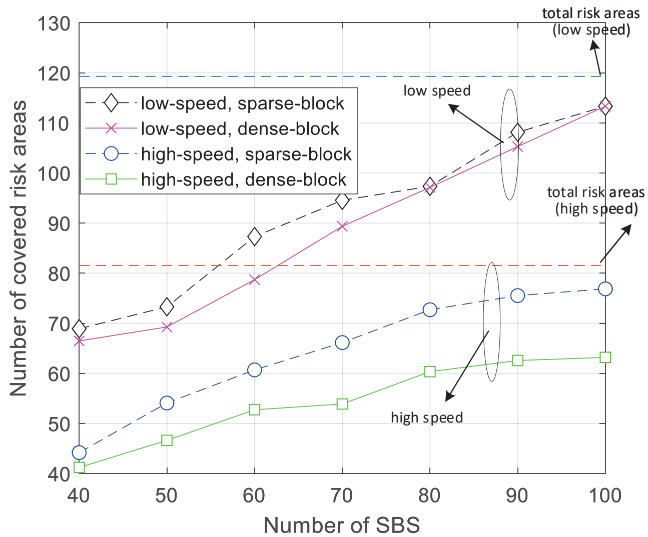

Fig. 4. Comparisons of number of covered risk areas.

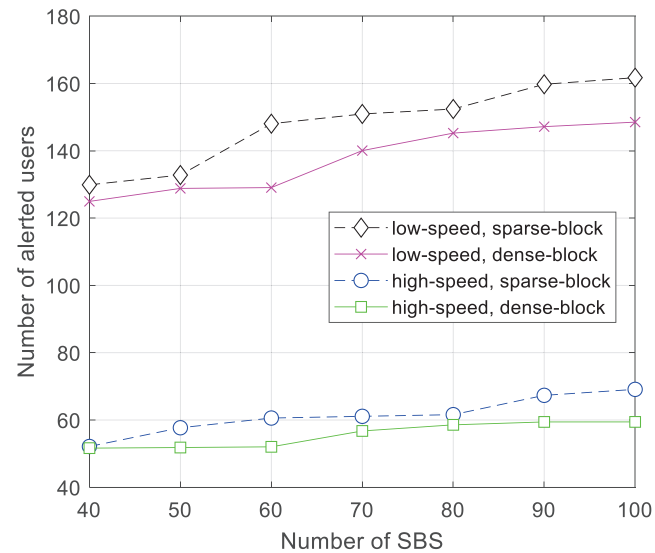

Fig. 5. Comparisons of number of alerted users.

beams to cover 3 different sectors. Considering that *m-SBS* is sensitive to blockages, we should simulate the distribution of blockages. We consider two scenarios *dense blockage* and *sparse blockage*, where the probability of non-line of sight (NLOS) is 22% and 10%, respectively. Once receiving alerting information, the user will randomly change the movement direction with a certain probability. In this article, we do not optimize the way of changing direction as this is beyond the scope of this work.

In the first simulation, we evaluate the number of risk areas discovered by REAL scheme under different number of SBSs, as shown in Fig.4. In this simulation, we consider 4 scenarios with different levels of user movement speed and blockage density. From Fig.4, we can see that the number of covered risk areas increases with the number of deployed SBSs for all four scenarios. This is because increasing the number of SBSs can cover more areas, thus the number of covered risk areas is increased although the total number of risk areas remains unchanged. Moreover, we find that the number of risk areas is much more when the user speed is low, and the accurate number is 120 for a low-speed scenario and 81 for high-speed. The rationale behind this difference is that users tend to stay in an area for a longer time when the movement speed is low. As a result, such areas become of high-risk based on the rule of more than 10 people staying over 5 minutes. In addition, as expected, the number of covered risk areas should be less under the scenario of dense blockage, since some risk areas cannot be covered by *m-SBSs* due to the blockages.

Fig.5 compares the number of alerted users under the same four scenarios as the first simulation. The *alerted users* are defined as the users who can correctly receive the alerting information when they are in the risk areas. We can see that the number of alerted users increases with the number of deployed SBSs for all four scenarios due to the increased coverage of SBSs. Similar to that in the first simulation, the number of alerted users is much more under the low-speed scenario. The reason is that there are more risk areas under low-speed scenario and more users should receive alert information. In addition, the number of alerted users is less under the scenario of dense blockage since more transmissions would be blocked.

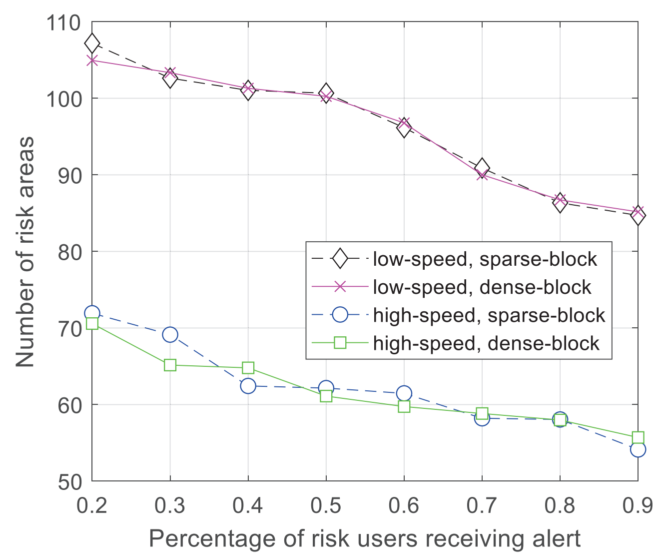

Fig. 6. Relationship between number of risk areas and percentage of alerted users.

Last, we investigate the effectiveness of using REAL to help users decrease the risk of COVID-19 infection. Fig.6 shows the number of risk areas versus the percentage of users who have correctly received alerting information. We assume that the user will randomly change the movement direction once receiving an alerting message. As expected, it is observed that the number of risk areas decreases with the percentage of risk users who can correctly receive the alert information. Accurately, the number of risk areas is about 85 and 55 for low-speed and high speed scenarios respectively when 90% users can correctly receive alerts. Compared with the number of total risk areas, 120 (low-speed) and 81 (high -

speed) obtained from the first simulation, REAL can reduce the number of risk areas by about 30% and 32% for low-speed and high-speed scenarios, respectively. It is highlighted that the number of risk areas can be further reduced if users adopt a smarter way of changing movement trajectory when they receive alert information rather than randomly changing the moving direction in this simulation.

V. Challenges and Discussions

Although REAL is expected to bring forward many benefits to the COVID-19 infection risk alerting, there still remain some associated challenges that should be addressed before unlocking the full potentials of this scheme.

A. User Privacy

There are two factors attributed to the privacy issues in REAL. The first is the leakage of user location information. In REAL, the location information of each user should be collected and analyzed timely by BSs to identify the high-risk areas. As the location information is closely related to users' privacy, it could be quite sensitive and dangerous for users if the location information is leaked to others. One potential solution to protect user location information is to use a pseudo ID, where mobile users periodically generate pseudo IDs and then the BSs collect these pseudo IDs with the corresponding location information. In this way, the information of the matched pair user, location will not be leaked, and only the total number of users in an area should be collected.

Another privacy/security concern of REAL is that the central MBS may be unreliable or even be attacked under some scenarios, leading to a wrong alerting information obtained. To solve this security issue, we propose two potential ways. One is to exploit physical layer authentication technology, where spatial decorrelation property (obtained based on physical information including received signal strength indicators, channel phase response, channel impulse responses, etc.) is adopted to distinguish radio transmitters, thus to detect spoofing attacks. Another potential solution is resorting to blockchain technology for designing REAL in a distributed way. Specifically, each SBS collects the location information independently, and the collected data can be seen as transactions recorded in the blockchain system. Accordingly, these data or transactions are transparent and almost impossible to be tempered (except under some extreme scenarios such as a BS has more than 51% of the total computing power of the system).

B. Robustness of mmWave Wireless Channel

Another challenging issue of REAL system is the robustness of mmWave wireless channel, since mmWave link is easily blocked by obstacles. Hence, the alerts may not be received properly by the users located in areas with many obstacles. To address this challenge, some potential solutions are discussed here. Basically, blockage can be classified into two categories, fixed blockages and random moving blockages. For random moving blockages, we assume that the effect can be ignored, as *m-SBSs* will transmit alerts periodically during a certain time period (say 30 minutes according to the characteristics of the COVID virus) before changing beam direction. Thus, the random moving blockages can hardly block these periodical transmissions. For fixed blockages, some measures can be adopted. First, the relay technology can be exploited to assist mmWave signals to propagate around obstacles by creating alternative propagation paths with the aid of relays. Thus, relay-aided transmission can improve the reliability and even the throughput as well as the coverage of REAL system. Moreover, in some dense blockage areas, we can deploy some SBSs using traditional band (i.e., 2GHz around), which is not sensitive to blockages, to transmit alerting informations. Moreover, spatial diversity and spatial multiplexing can be expected to play an important role to enhance robustness in mmWave networks.

C. Hybrid mmWave and Microwave Network Deployment

In REAL scheme, it is expected that the number of SBSs should be abundant enough to cover all the risk areas and thus broadcasting the alerting information to users near/in these areas. However, one key challenge is how to efficiently achieve the coexistence of sub-6GHz and millimeter-wave cellular networks [9]. Some hybrid MBS and SBS cooperation schemes can be proposed to enhance the performance of HetNet in terms of coverage, throughput, and data rate of boundary users [12].

Moreover, the current wireless communication system may have a limited number of SBSs deployed in some regions. Hence, it is necessary to explore how REAL can achieve a high accuracy of risk area coverage as well as the efficient real-time alerting under the case of limited SBSs. Device to device communication (D2D) can be seen as a potential way to address the challenge of insufficient SBSs. D2D communication refers to direct transmission between proximate devices, without relaying information through BS [13]. Thus, once a user receives the alerting information from the BS (could be MBS or SBS), it will broadcast this alert to nearby users by using D2D communication.

D. REAL Scheme Implementation on Mobile Device

To implement REAL scheme, it is required to develop a mobile application installed on user devices. The application should be compatible with different operating systems (typically Android, iOS and Windows), hence it is for all users, and obtains an accurate user density. One challenge is on the information/data exchanges with BSs for those devices without the ability of accessing mobile data service. In this case, those devices cannot transmit/receive data to/from BSs, thus the localization information cannot be obtained directly. One potential solution is that these devices can exploit Bluetooth to connect to nearby devices, and the location information can be transmitted to BSs by their neighbors. Another challenge is the high energy consumption when running this application to support REAL scheme, which is caused by performing sensing and transmission frequently. To relieve the burden on energy consumption, besides optimizing software performance, a more effective way is to deploy energy-efficient hardwares.

VI. Conclusions

In this work, we have proposed to exploit mobile communication networks to control the fast spread of COVID-19. We have designed a risk area alerting scheme named REAL under HetNets. In REAL, the MBS collects and analyzes user location information to periodically identify risk areas, while SBSs adjust their own beam directions trying to cover these risk areas and send alerts to the users located inside those areas. We have conducted simulations under different scenarios, and the results have demonstrated the effectiveness of REAL in the battle against COVID-19.

Moreover, we have also discussed some of the challenges and their potential solutions to facilitate the implementation of REAL in practice. More importantly, this work can be regarded as a pioneer in exploiting wireless communication systems for controlling pandemics through positioning and sending risk alert information to outdoor mobile users.

VII. Acknowledgment

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