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Intelligent Dynamic Indoor Aerosol Sensing using Terahertz Band Wireless Communication Systems

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***Abstract*—We investigate how an IRS (Intelligent Reflective Surface) deployment within a terahertz (THz) band communication system, can detect and classify indoor vapour clouds expelled in violent expiratory events, such as coughing. This detection is of interest for public health systems. Since indoor spaces are sites for deployment of wireless communication infrastructure in any case, combined sensing and communication is an attractive solution. Using 6G networks to accomplish this while not affecting communication performance, is a relevant and useful application of THz signal's properties. We use machine learning to distinguish between violent expiratory events and other aerosol emissions.**

***Index Terms*—Terahertz, 6G, Wireless Sensing, Aerosol Cloud Detection, IRS**

I. Introduction

One of the biggest challenges in today's communications at high frequencies is to allow the signal to move through indoor obstacles without being affected by possible signal degradation effects [1]. This creates an opportunity for technologies such as intelligent reflective surfaces (IRS) as already explored in the literature [2], and other technologies that may help to counter these sources of signal degradation by also detecting what such sources actually are [3].

Researchers have been trying to characterise signal degradation from airborne particulate matters through various means. First there are non-biological sources, e.g. water molecular vapour or airborne pollutants [4], i.e. aerosol clouds that form a condensed high concentration of molecules that disperse the THz signals. But we can also mention biological sources, such as clouds of molecular droplets (that include viruses or other agents) that are expelled from people or animals while talking, breathing, sneezing or coughing [5]. Both of these cases have largely been seen as limitation of the THz spectrum because on their possible detrimental impact on performance, however we argue that they can be of great benefit for wireless sensing tasks by indoor agents.

Research in the field of integrated sensing and communication for the THz band ranges from using shared spectrum for communication to higher levels of information sharing in order to develop a technology that can sense human activity, helping predict THz signal transmission strategies for performance improvement [3]. However the main challenges are not only in terms of the technology itself, e.g., how can we share resources, but also related to how can we modify signal propagation so that airborne cloud interference is detected, classified, and modelled in order to achieve intelligent sensing–one that goes beyond merely registering an increase in attenuation.

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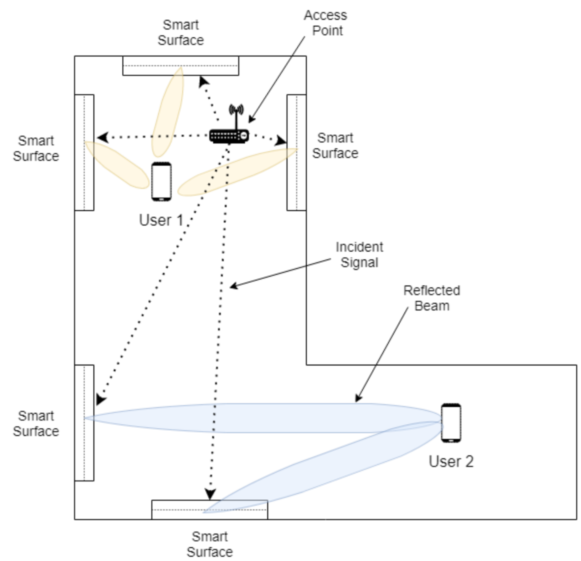

Fig. 1. System model with a THz access point, users, and smart surfaces.

Building on work from [5], [6], we propose a new airborne cloud detection scanning algorithm using IRS to detect a cloud's location more accurately, based on difference of signals' attenuation between the space with and without aerosol. In comparison to [5], in this paper we introduce realistic, dynamic models of aerosol emissions mirroring the real-world behaviour, developing an intelligent solution to distinguish these emissions and their temporal evolution from other aerosol events. We also consider a temperature and humidity distribution of this respiratory event from [7].

This paper is organised as follows: Section II presents the system model, Section III introduces the proposed solution, Section IV discusses the effect of the detection service on the communication performance, Section V presents and analysis our numerical results, and Section VI concludes the paper.

II. System Model

We consider an indoor scenario (Fig. 1) including:

- `Access point`: Base station able to radiate THz signals in any direction, and is able to aim incident THz signals to smart surfaces in order to reflect signals to the users.
- `Users`: The users are receivers in the indoor scenario, measuring the received signal and related metrics at a determined location.
- `Smart surfaces`: Fig. 1 shows how IRS can focus reflecting beams toward a particular receiver, creating a line of sight with the user.

To model the received power from the THz signals propagating in the indoor environment, we used link budget analysis:

$$R_{px} = P_{tx} + G_{tx} + G_{rx} - a(f,r) - \gamma, \quad (1)$$

This model efficiently captures the essence of the THz communication channel, and has been used in previous studies involving millimetre-wave and terahertz communication systems [8]. R_{px} is the received power, P_{tx} is the transmitted power, G_{tx} is the antenna gain in the transmitter, G_{rx} is the antenna gain in the receiver and γ is the loss resulting from shadowing. We only use model components relevant to indoor scenarios; from [9], Eq. (2) was used with parameter values from [8]: P_{tx} = 1 dBm with 7.4 dB conversion loss, and G_{tx} and G_{rx} = 30 dBi. The receiver has a conversion gain of 8 dB with a 7.5 dB noise figure given by [10], and γ = -74 dBm. Finally, by using such parameter values, the receiver model leads to,

$$R_{pi} = 127.7 - a(f,r). \quad (2)$$

III. Aerosol Cloud Detection and Classification

A. Path loss of terahertz signals

The path loss of a propagating electromagnetic wave in the THz band is given by the spreading loss in addition to the absorption loss [4]. The spreading loss accounts for the attenuation of the signal as it expands through the medium it is travelling through, and is given by Eq. (3) where d is the total path length, f is the frequency of the electromagnetic wave, and c stands for the speed of light in a vacuum.

$$A_{spread}(f,d)[\text{dB}] = 20 \log \frac{4\pi f d}{c} \quad (3)$$

The absorption loss accounts for the attenuation of the signal caused by the molecules it is propagating through that are absorbing its energy. This depends on the medium and is given by Eq. (4) where *k(f)* is the medium absorption coefficient. Values from the HITRAN database [11] are used to calculate this absorption coefficient for different media.

$$A_{abs}(f,d)[\text{dB}] = k(f) d 10 \log_{10} e \quad (4)$$

This approach was used to calculate line of sight path loss, while the method discussed in [9] was used to calculate losses and attenuation caused by scattering and interference for non-line of sight paths.

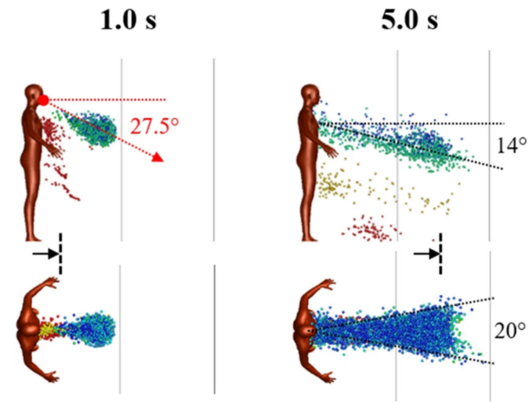

Fig. 2. Temporal evolution of cough cloud as implemented in our simulation model [12].

B. Realistic cough cloud temporal evolution

Building on [5], making the model for an exhaled cough cloud as accurate as possible and matching to a measured example, was important for the system to be applicable to a real-life scenario. In addition to the spatial model being as accurate as possible, an element of time evolution was required to be incorporated as expiratory events are not an instantaneous and short-term time evolution is crucial to their detection.

To distinguish between the reference indoor air and the exhaled air via THz attenuation characteristics, we used temperature and relative humidity thresholds of 35°C and 98% relative humidity respectively. The area of the regions where a cloud presence could be deduced, is dependent on the resolution of the IRS mirrors placed on the perimeter of the room. In our case a resolution of 10×10 cm was implemented.

It is not enough to simply check if a region could potentially contain air from an exhaled cough cloud, as many other common events in indoor settings could produce aerosol clouds, meeting similar local thresholds (e.g. kettle boiling).

To distinguish the sensed signal, a measured temporal model of an exhaled cough cloud from [12] was used to create these characteristic developments in time and space. It was found that a 20° outward plane from the cough cloud origin contained the majority of the cough cloud droplets, so this was used in conjunction with the 10×10 cm grid system to determine grids where a cough cloud could develop form a specified origin. This characteristic behaviour as seen in Fig. 2 was then implemented in the simulation model. [12] also shows measured results of the time evolution of a cough cloud within the first five seconds, in regards to how far the plume has travelled away from the origin, on a second by second basis. This information was also used in initialising the first five seconds of a cough cloud's spatio-temporal evolution in our simulated system.

C. Classification model

In order to reliably detect a cough cloud, and differentiate it from other aerosol clouds which would be expected to arise in an indoor environment, a linear regression model was built using features generated from the simulation model.

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Features for the trained model are second-by-second scans of coordinates where a cloud generation has been detected via signal attenuation. From those, a cloud can be classified as a cough cloud or not, and notification of its presence and its origin is given.

To train this model, ideal cough clouds in random locations were generated, and their detected grid coordinates from each scan were fed to a linear regression network. These ideal cough clouds were paired with *'detected, origin x, origin y'* targets. Along with ideal clouds to train the model, aerosol clouds resembling radiator plumes, draught from opening doors, and additional random cloud formations to introduce noise, were fed to the model with *'not detected'* targets.

D. Detection service algorithm pseudocode

For this service to be deployable in 6G networks, its operation must be defined in detail, e.g. how often the scans are performed, how are the findings stored. Pseudocode for this proposed pipeline can be seen in Algorithm 1. The minimum scan frequency can be derived from [13] for a healthy adult's measured cough frequency.

Algorithm 1 Pseudocode for detection service operation

```
min_scan_frequency = intermittent scanning of environment
no_users = number of users using network environment
cough_maybe = true if scans are returning a profile consistent with
evolution of a cough
choose_diff_path = use IRSs to select path to avoid blockage

while no_users > 2 do
    scan_frequency = min_scan_frequency * no_users (max 1 per
second)
    Every Scan_frequency seconds:
    perform Scan
    if cough_maybe == True then
        while cough_maybe == True: do
            scan_frequency = 1/s
            export detected coordinates to ML model
            if confirmed cough: then
                ALERT and report origin coordinates
            else:
                choose_diff_path()
                scan_frequency = min_scan_frequency * no_users
(max 1 per second)
```

This algorithm optimises the detection service in terms of network resources. It does this by varying the interval between performing scans: the scanning frequency is dependent on the current likelihood of successfully detecting a respiratory aerosol cloud. This likelihood is affected by the number of people present in the environment and if early signs of a respiratory aerosol cloud's evolution are detected. Intermittent scanning frequency is scaled by the number of users in the room, as probability of a cough cloud will increase as more users are present. Scans are then performed at this frequency until signs of a cough at any stage of its temporal evolution are detected, at which point the scanning frequency increases to its maximum, one scan per second. The coordinates of detected grids are then stored and fed to the classification model, which makes a decision as to whether the cloud is indeed a cough and stores its time stamp and predicted origin coordinates. If the cloud detected is deemed not to be a cough, the system proceeds to change the signal path utilising the IRSs. This is done to avoid the obstructive aerosol cloud and removes the absorption loss attenuation suffered by the signal.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
User location	x = 40, y = 15
Base station location	x = 20, y = 50
Perimeter IRS coverage	10% - 100%
Number of clouds	1 - 6
Respiratory cloud temperature	36.5° C
Respiratory cloud relative humidity	99%
Ambient room temperature	22.8° C
Ambient room relative humidity	50%
Operating frequency	1.16 THz

E. Simulation parameters

We have built a simulation tool in Python, extending the features of tool used in [5]. There are a number of parameters to be selected in the simulation in advance of performing a scan. The parameter value choice made for the detection and classification experiments can be seen in Table I.

The user and base station's locations in the room were arbitrary. The perimeter IRS coverage (how much of the room perimeter is covered with IRS) and number of cough clouds present in the room were varied when investigating the effect of the detection service on the communication performance. The respiratory cloud temperature and humidity values were chosen as they are consistent with measured values of human coughs [12], and the operating frequency of 1.16 THz is in the range of operation of the simulation tool, 1-10 THz.

IV. EFFECT OF DETECTION SERVICE ON THE COMMUNICATION PERFORMANCE

An important effect to consider when testing this cloud detection service is how the physical sensing affects the system's communication performance itself. As received power was the metric measured and used for predicting the presence of aerosol clouds in the simulation tool, a received power comparison was implemented between a simulation room (room with the clouds present) and a control room (with reference atmosphere, no clouds), to measure the effect of passing through the clouds on the communication signals.

During each simulation, the aggregate received power from each signal path used to scan each specific grid, was calculated in both the simulation room and control room. This value was further decomposed to calculate the average received power per-ray (i.e. THz beam), per-scan value of each simulation. If a certain location is scanned and the attenuation of the signals used to scan it matches that of the control room, grids that those signals pass through can be designated as not containing an aerosol cloud. Otherwise, we use the value of attenuation to determine the quantity of aerosol and its location in the scanned grids.

Fig. 3 shows how this comparison operated with the aggregate received power for each scan of a particular grid equalling

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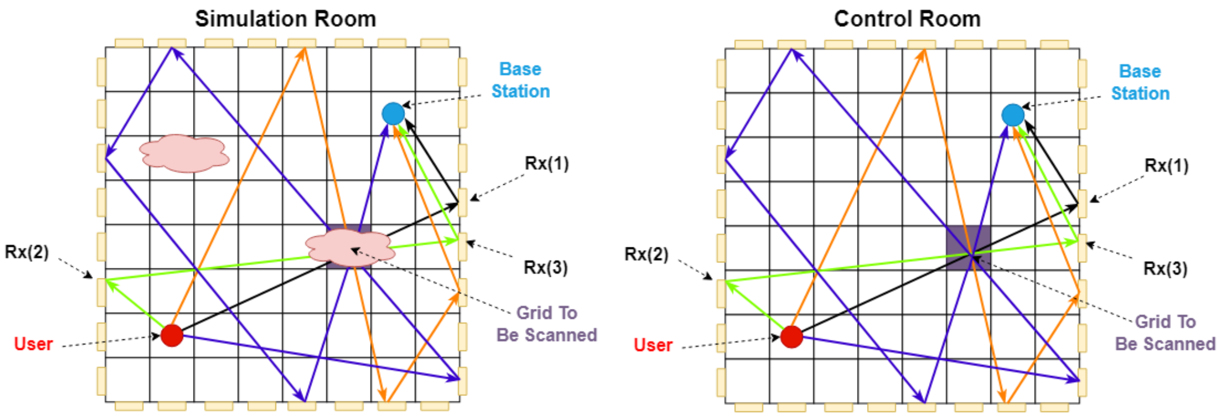

Fig. 3. Received power comparison between simulation room with two initialised clouds and control room showing the first three received power points.

TABLE II
INITIAL RUN RESULTS

Cloud No.	1	2	3	4	5	6
Recall	0.968	0.984	0.969	0.984	1	0.984
Precision	0.738	0.692	0.765	0.741	0.696	0.697
Accuracy	0.996	0.997	0.998	0.998	0.9970	0.997

TABLE III
POWER COMPARISON

Cloud No.	1	2	3	4	5	6
Control (dB)	97.74	98.1	99.28	97.92	99.0	97.76
Aerosol (dB)	95.08	94.36	94.26	91.94	90.8	89.6

$R_x(1)+R_x(2)+...+R_x(n)$, i.e., the sum of the received power measurements from all n of the the IRS reflections.

Another parameter which affected the communication performance in terms of received power was the perimeter IRS coverage. Similar experiments were performed this time varying the percentage of the perimeter IRS cover. The received power model discussed previously and shown in Eq. (2) was used to calculate the average aggregate received power of all signal paths used in each scan.

V. RESULTS

A. Initialisation and detection of cough cloud model

A simulation of a cough cloud consistent with the temporal evolution measured in [12] was initialised in a simulation environment, that contained a perimeter of IRS mirrors with one user and one base station. An array of initialised aerosol clouds can be seen in Fig. 4, with each colour representing the next second of temporal evolution.

The base station (cyan dot), and user (red dot) are also visualised. A scan of the 'room' is then performed using five varying signal paths utilising the IRSs, i.e. differing number of reflections between user and base station. This produces a report of detected aerosol which can be seen in Fig. 5.

The success of these scans was determined by accuracy, precision and recall metrics, tabulated in Table II, for the initial run. The mean recall, precision and accuracy were 0.9814, 0.7215 and 0.9975, respectively. The x-y coordinates of each grid are reported from each scan and stored for classification.

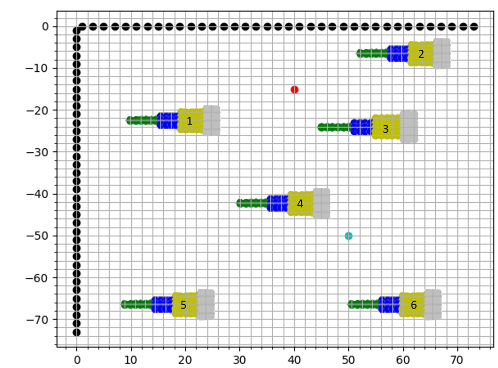

Fig. 4. Initialised ideal cough clouds.

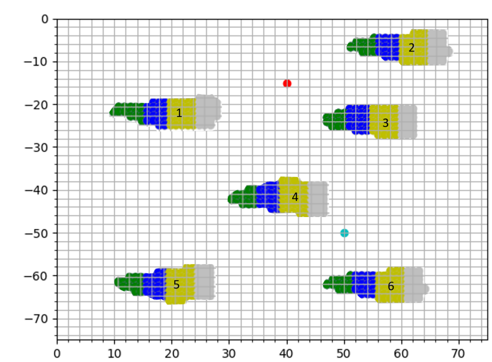

Fig. 5. Detected cough clouds from scans.

B. Detection and classification performance

A test set of $\approx$ 10% of the number of training points was used, with equal number of cough clouds and other aerosol clouds of various profiles (e.g. kettle fumes), as well as random aerosol formations. Ideal cough clouds were detected with 0% error with their origin coordinates returned with $\approx$ 2% error. This performance could be increased with a higher IRS mirror resolution (at an increased hardware cost). This functionality enables the system to correctly detect and classify a potentially harmful aerosol cloud, while accurately reporting its point of origin for alert and cloud dispersion purposes.

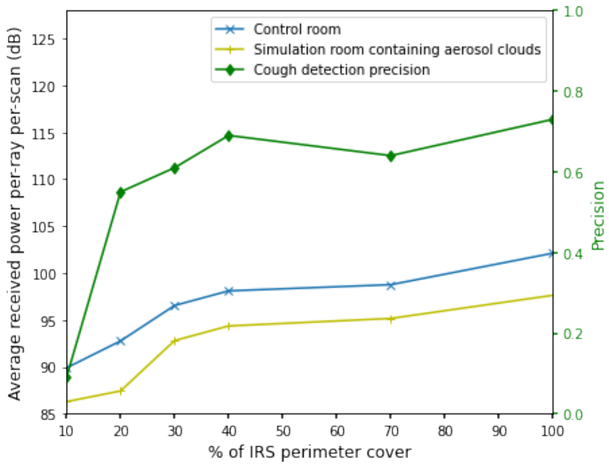

Fig. 6. Average received power of control room and simulation room with a varying number of IRSs. Simulations carried out with 2 cough clouds present.

C. Received power comparison

Tests were carried out with different numbers of clouds in the simulation room to investigate how this parameter affects the received power of the communication system. The average received power per-ray, per-scan for each simulation was recorded and compared to the average received power measured using the same path propagation in the standard control room. Table III lists the received power values.

The received power of the communication system is impacted by the signal's propagation through the indoor environment with a 0 power loss signal having a received power of 127.7 dB from Eq. (2). Attenuation increases when the beams are passing through aerosol clouds–cough clouds in this case. As the purpose of the cough detection service is to force signals to pass through these regions of attenuation to discern if a respiratory aerosol cloud is present, and not avoid them by changing their propagation paths to the base station or user utilising the IRSs, this received power loss will affect the signal strength of the user's communication when this service is active, with the attenuation growing with increasing numbers of aerosol clouds.

Fig. 6 shows how increasing the percentage cover of IRSs increases the received power of the communications system, as a more diverse set of signal paths can be utilised. We also confirm that increasing the percentage IRS perimeter coverage increases the scanning resolution and improves the precision of detection. Notably, there is not a large improvement beyond utilising 40% perimeter IRS coverage: not requiring the entire perimeter to be covered with IRS cuts down the hardware costs and matches the requirements for communications coverage.

VI. Conclusion

In this paper, we deal with the issue of high-accuracy detection of clouds that form from droplets expelled by the human body, while using THz frequency band and being assisted by intelligent reflective surfaces. Our results show that in terms of accuracy, our algorithm shows great promise achieving close the 100% classification accuracy and recall. Additionally, the impact of this service on the power loss of the communication signals does not appear to be substantial, hence it is not disrupting the communications.

The measured temporal distribution of an exhaled cough cloud used in this paper was specific to an adult male, however this data may differ between individuals of different sex, age, disability conditions, as well as particular expiratory events (e.g. sequential coughs) [14]. Increasing the diversity of cough clouds used to train the classification model is an essential component of a fully functioning and inclusive detection service. Our future work will also include the optimization of this algorithm to deal with communication requirements (data rate, energy cost, etc.) improving the performance of both communication and sensing/classification.

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