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Smart homes that detect sneeze, cough, and face touching

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ABSTRACT

Coughing, sneezing, and face touching activities are three primary ways of spreading disease. With the onset of COVID-19 it is paramount to monitor these activities at home and practice good hygiene. To help stop the spread of disease, we have developed a wireless sensing system capable of detecting voluntary coughs, sneezes, and face touching with alert based notifications sent to a mobile application. Our system uses radio frequency technology to capture motion, speed, direction, and range information from human activities. It does this by using a combination of a continuous wave Doppler and frequency modulated continuous wave radar. By observing a set of features related to the sensed motion, we designed a set of *fuzzy* logic IF-THEN rules that can differentiate each activity from each other with an overall accuracy of 96%. In addition, our system enables smart homes to detect and localize these activities at different distances up to 2.74 m, through walls, and with multiple people. We envision our system helping not only with prevention of COVID-19, but supporting contact tracing efforts by monitoring people's activities at home.

1. Introduction

The rampant and rapid spread of COVID-19 is unrelenting and its impact on healthcare has been devastating. As the writing of this paper, there has been a total of 11, 590, 195 confirmed cases and 537,429 deaths globally with the United States leading with 2,935,008 confirmed cases and 130,284 deaths according to the Johns Hopkins University (JHU) (JHU 2020). To combat this pandemic, several guidelines have been issued by the Centers for Disease Control and Prevention (CDC) (CDC 2020) and the World Health Organization (WHO) (WHO 2020). The guidelines suggest that people wash their hands often, avoid close contact, cover their mouth and nose with a face cover, avoid touching their face, cover coughs and sneezes, clean and disinfect often, and monitor health daily. In addition, contacts with people testing positive for COVID-19 are asked to stay home and maintain social distance of six feet from others for at least fourteen days. Thus, there is a need for at home monitoring systems to track and locate people's activities in-order to help people properly clean and maintain proper hygiene and social distancing.

This has motivated us to research a new smart home monitoring system shown in Fig. 1, that alerts people of activities related to coughing, sneezing, face touching, and entering and leaving a room. In contrast to previous works which have mainly used audio sensing Birring et al. (2008); Sun et al. (2011a, pp. 425–434) or wearable and portable sensors Drugman et al. (2019); Jasmine and Jayanthy (2020), our system uses radio frequency (RF) technology to capture the motion characteristics of activities performed by humans. Previous systems are limited and suffer from environmental sounds and obstructions, are often required to be worn, making them obtrusive and uncomfortable, have dependence on batteries reducing monitoring time, and have privacy concerns because of

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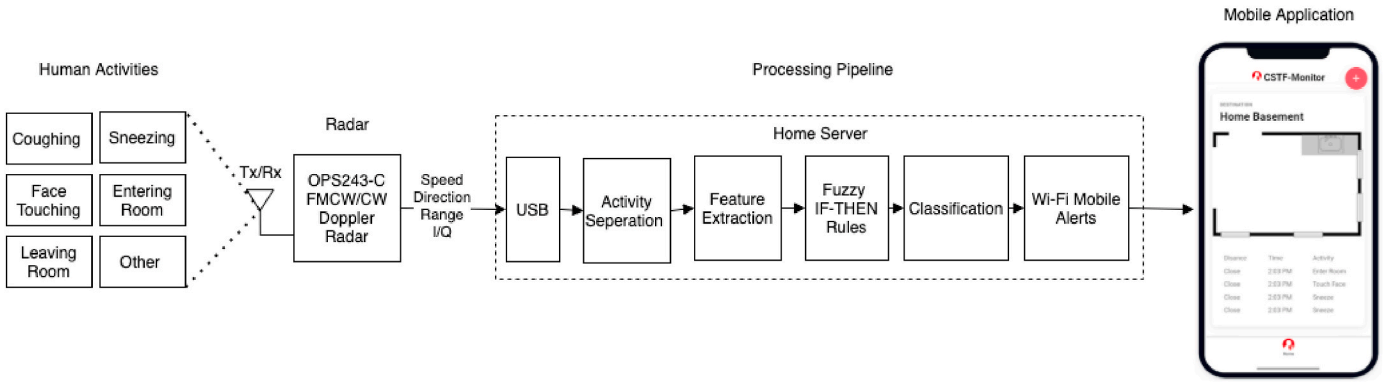


Fig. 1. This figure shows the system architecture from left to right: activities that a human can perform in front of the radar, the radar's transceiver that captures the human activity's motion and outputs the motion's speed, direction, range, and raw in-phase (I) and quadrature-phase (Q) signals, the processing pipeline which consists of a home server that connects to the radar by USB, performs the activity separation, feature extraction, applies the *fuzzy* IF-THEN rules, classifies the activity, and sends Wi-Fi alerts to a mobile phone, and finally the mobile application which displays the alters from the pipeline including the distance at which the activity was performed, the time the activity was captured, and the type of the activity classified.

microphone recordings. We address these issues by using a combined continuous wave (CW) and frequency modulated continuous wave (FMCW) radar that can detect motion, speed, direction, and range information from human activities. Our system is unobtrusive, as it can be mounted to a wall or stand in a room, and can continuously monitor activities with an overall accuracy of 96%. In addition our system can detect activities at different distances, through a wall, and with multiple people described in section 3 and section 4. We envision our system helping not only with prevention of COVID-19, but supporting contact tracing efforts by monitoring peoples activities at home.

The main contributions of our work include the following:

- We designed a new smart home activity monitoring system that detects coughing sneezing, face touching, and entering/leaving a room with an overall accuracy of 96%. The design includes a mobile application to alert people of the time, location, and type of activity detected. In addition our system is the first to use a combined CW and FMCW radar for sneeze, cough, and face touching activity detection in the home.
- We provide solutions for accurately separating activities with a CW and FMCW magnitude filter, and differentiating activities with two features and a set of *fuzzy* logic IF-THEN rules. The features include the interquartile range and relative direction feature of the activity's velocity.
- We provide an evaluation of our system in different scenarios. We show that with a single individual our system can achieve 96% accuracy. Our systems can detect activities at close, near, and far ranges with 100%, 100%, and 90% accuracy respectively. Our system can detect activities with obstructions such as through a wall with an accuracy of 81%. In addition our system can detect activities with multiple people with 95% accuracy.

1.1. Related work

There has been a proliferation of research Birring et al. (2008); Sun et al. (2011a, 2015, pp. 97–108); Hata et al. (2009, pp. 1–5); Matos et al. (2006); Monge et al. (2018); Larson et al. (2011, pp. 375–384); Di Perna et al. (2017, pp. 190–193); Amrulloha et al. (2015); Hoyos Barcelo et al. (2018); Pham (2016); Nguyen and Luo (2018); Sun et al. (2011b) focused on the use of audio signals as the primary way of detecting respiratory symptoms such as coughing and sneezing. Devices that include microphones worn as a necklace Birring et al. (2008); Larson et al. (2011, pp. 375–384) have been effective in detecting and counting the frequency of coughs as they are close to the source of the sound. Others have used smartphones Sun et al. (2015, pp. 97–108); Monge et al. (2018) or ubiquitous devices Sun et al. (2011a, pp. 425–434); De Silva (2009, pp. 223–229) and their built in microphones to detect the sound-related respiratory symptoms. Methods of detection using audio include the use of *fuzzy* IF-THEN logic, Hidden Markov Models, or engineered features used to train supervised and semi-supervised models for classification of coughs or sneezes. Most recently Laguarta et al. (2020) developed an AI speech (audio) processing framework that leverages acoustic biomarker feature extractors to pre-screen for COVID-19 from cough recordings using a convolution neural network (CNN). Despite their usefulness, audio sensing systems suffer from environmental noise and obstructions, limited monitoring time due to dependence on batteries, variations in recording conditions such as distance from the microphone, and privacy concerns as many systems continuously monitor audio with a microphone.

Beyond audio sensing other modalities for monitoring respiratory symptoms such as coughing and sneezing include the use of electrocardiogram (ECG), Thermistor, chest belts, Oximeter, and accelerometer, sensors Drugman et al. (2019); Jasmine and Jayanthy (2020). These devices have been effective in detecting voluntary coughs at various volume levels and with background noise, throat clearing, speech and laugh. Recently a new approach Soliński et al. (2020) that uses a portable spiromter device has been developed that can effectively classify the airflow of a cough versus a non-cough. Although promising, most of these devices are required to be worn at all times by the user, or carried by the user, can be uncomfortable, have limited battery life, and are affected by interference such as rubbing of skin or materials.

In contrast to these past systems, we use RF sensing to detect the motion characteristics of respiratory symptoms related to voluntary coughing and sneezing. The RF sensing technique has more robust properties as RF is not affected by lighting or environmental sounds, can travel through material, and can report motion information such as speed, direction, and range for an observed activity. For example, Yao et al. (2018, pp. 1718–1726) have shown that RF sensing can be used to detect human motion through walls. Also, privacy can also be preserved, to some extent, when using RF as shown by Li and Zhu (2016a, pp. 571–582). They explain how Doppler signatures are specific to locations of RF antennas in the room and not necessarily associated with an individual. Thus, we used RF to design our system to include: no invasion of personal privacy, by not monitoring conversations with a microphone, monitoring with multiple people in a home, at different distances, through wall detection, and detection without wearing a device or relying on battery power.

Furthermore, our system is not limited to sensing only two activities and can be extended to sense other activities such as face touching, and entering/leaving a room. To do this we designed a calibration process described in section 3.5, that allows our system to collect FMCW/CW signatures for any type of activity, which can then be used to define rules to classify the activity performed. These additional, non-respiratory activities, fall under more general activity recognition and have been thoroughly researched Wan et al. (2014); Chi et al. (2016); Li and Zhu (2016b, pp. 238–247); Chi et al. (2018, pp. 237–249); Khan et al. (2016, pp. 1–9); Mahmoud et al. (2020). In this study, we only evaluated a few external motion activities. We did not evaluate our system on internal motion activities such as blood glucose monitoring. Further research could be done to combine our external motion activity detection with smart health devices that do internal health monitoring such as Gao et al. (2017, 2016, pp. 199–208). Still activities such as touching the face and enter/leaving a room have not been combined with respiratory symptoms such as sneezing and coughing for activity recognition.

In regards to the use of RF sensing for coughs and sneezes, we found very little research. One technique Oncu (2016, pp. 5161–5164) designed a Doppler radar system, that can detect a cough and apnea, but only a small experiment was conducted with one observed cough event in a 40 s measurement. Majority of research that uses ambient sensing such as RF or Wi-Fi focus mainly on breathing and heart rate monitoring Nguyen & Tran (2020); Li, Valero, Shahriar, Khan, & Ahamed (2020); Adib et al. (2015, pp. 837–846); Kukkapalli et al. (2016, pp. 1–3); Liu et al. (2015, pp. 267–276). To our knowledge, our system is the first in smart home monitoring of voluntary coughs and sneezes, with the combination of other activities like face touching and entering/leaving a room, using Cw/FMCWFMCW/CW radar for sensing.

1.2. Theory of operation

Our system uses a combined CW Doppler and FMCW radar to detect motion, speed, direction, and range information from human activities. The basic principal of the radar utilizes the CW Doppler frequency shift to detect the speed and direction or velocity of an activity's motion and the FMCW time of flight (TOF) to detect the range or distance at which activities are performed. This process starts with the radar transmitting a signal. When a person is in the field of view (FoV) of the radar, the transmitted signal will bounce back off the person to the receiver of the radar. The received signal is then mixed with the transmitted signal to down convert to an intermediate frequency signal, representing either the Doppler frequency of the human motion performed by a person's activity or a time shift based on the distance to the person performing the activity. We refer the reader to Miller et al. (2019); Wan et al. (2014) and Adib et al. (2013); Solano-Pérez et al. (2020) for a detailed description on how CW Doppler and FMCW radars work. Each activity performed can then be characterized by its motion characteristics, velocity, direction, and distance from the radar. Our systems characterises five types of activities including coughing, sneezing, face touching, and entering and leaving a room.

It is important for us to explain the motion events and anatomy phases of each activity we detect. For each activity a different set of phases occur which produces different reflections back to the radar. These reflections travel further when an object is moving away from the radar and closer when an object is moving towards the radar. We use this principal to show that each activity will have a unique set of reflections which we can use to distinguish them apart from one another. We now explain the motion events and anatomy for each activity: coughing, sneezing, face touching, and enter/leaving a room.

Coughing Anatomy and Motions Events: The anatomy of coughing show in Fig. 2 is composed of three phases Umayahara et al. (2020): inspiration, compression, and expiration. In the first phase of **inspiration**, a person inhales air, pressure increases, and there is an expansion of air in the body. During this phase the glottis remains open allowing air in. The glottis is the part of the larynx consisting of the vocal cords and the opening between them. The movement of the chest will be forward or towards the radar as it expands, causing reflections to the radar to be closer or shorter. In addition, we assume that the head moves backward or away from the radar, which causes reflections to the radar to be father or longer. To our knowledge, there is no established or widely agreed upon explanation of the motion of the head in inspiration phase. We assume that inhalation naturally causes the head to move backwards. For the next two phases we also assume certain head motions. In the second phase of **compression**, the glottis temporarily closes, muscles compress the air in the lungs, and the head is assumed to start to move forward. The compression phase lasts approximately 0.2 s Umayahara et al. (2020). The increase in pressure causes the reflections from the chest to the radar to be shorter and the head is positioning to move forward and will now be closer to the radar causing the reflection to the radar to be shorter. In the final phase of **expiration**, the glottis opens resulting in a rapid discharge of the air from the lungs through the mouth. The chest will start to move away from the radar causing the reflection to the radar to be longer and the head is assumed to move forward causing reflection from the head to the radar to be shorter. In general the radar will receive several reflections, long and short, produced by each phase of coughing. Our system captures these reflections for coughing activities and calculates their, FMCW range and magnitude, and CW velocity, and magnitude depicted in Fig. 5.

Sneezing Anatomy and Motions Events: The anatomy of sneezing Songu and Cingi (2009) is shown in Fig. 3 composed of two phases: inspiration and expiration. Typically the inspiration and expiration happen together in a single phase, but we broke them out to

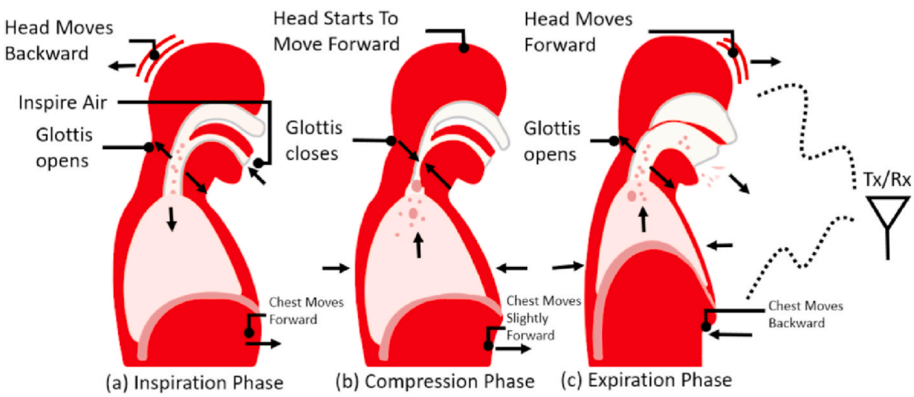


Fig. 2. Anatomy of the cough showing three phases, (inspiration, compression, expiration) and the motions of the chest and head performed during each phase causing short and long radar signal reflections back to the radar.

show the motion events during each phase. There is usually a phase before inspiration called the sensitive phase, where there is stimulation of the nasal mucosa by chemical or physical irritants Songu and Cingi (2009). In the **inspiration** phase of sneezing, a person inhales air, pressure increases, and there is an expansion of air in the body. The movement of the chest will be forward, causing reflection to the radar from the chest to be shorter. We assume that the head moves backwards causing reflection from the head to the radar to be longer. Also, we argue that the glottis does not close all the way, but rather the pallet lowers and the tongue raises as explained here you (2013). This causes the airway through the mouth to be smaller and the airway through the nose to be larger. This leads to the seconds phase, **expiration** where there is a lower increase in pressure since air is compressed less and expands less, during sneeze than cough. The air flow will then be expelled through the nose as the airway is larger when the pallet and tongue are raised. In this phase, the chest will move away from the radar causing reflections from the chest to the radar to be longer. For the motion of the head we assume that it moves forward, and closer to the radar than during coughing. This causes the reflections from the head to the radar to be shorter. From these two phases, the radar will receive several short and long reflections produced by sneezing. Our system captures these reflections for sneezing activities and calculates their, FMCW range and magnitude, and CW velocity and magnitude depicted in Fig. 5. We assume that sneezing will have more reflections that are shorter over the entire period of both phases. We assumed that when a person sneezes their head will move more forward and at a faster rate towards the radar than a cough. This is one way we can distinguish the coughing from the sneezing. Although this assumption wont hold for all cases, in our experiments in section 4 which used voluntary sneezes, we observed the subject moving their head closer to the radar during sneezing than when coughing. Thus, the overall motion of sneezing tends to be more forward or towards the radar than with coughing with a more positive direction as shown in Fig. 9 (b).

Motions Events for Face Touching: The motion events for face touching, depicted in Fig. 4 (a), can be described in three steps. In the first step we assumed that the person's arm starts at the side of their body naturally hanging down. This leads to the second step, by which the person starts to touch their face by swinging their arm up. The reflections from the arm and hand to the radar will start off shorter as the hand is raised, but over the period of time that the arm is moving towards the face, majority of the movement will be away from the radar, causing longer reflections back to the radar. In the third step, the person will touch their face and then start to swing their arm down moving towards the radar causing reflection from the radar to the arm and hand to be shorter. The arm will then go back to its natural position, hanging at the side of their person, and will move away from the radar casing reflection from the radar to the arm and hand to be longer. Majority of reflections from the radar during the third step tend to be towards the radar. Our system captures these reflections for each step of face touching and calculates their, FMCW range and magnitude, and CW velocity, and magnitude depicted in Fig. 5.

Motions Events for Entering/Leaving a Room: The motion events for entering and leaving a room, depicted in Fig. 4 (b), are described next. For entering the room we assumed that the radar was in a position so that when a person entered a room they would be walking away from the radar. The reflections from the radar to the person walking would start of short as the person entered and then get longer as they continued walking away from the radar entering the room. When leaving the room, the reflections from the radar to the person would start off longer, and then get shorter as the person walked towards the radar leaving the room. Our system captures these reflections for entering/leaving a room and calculates their, FMCW range and magnitude, and CW velocity, and magnitude depicted in Fig. 5. Compared to the motions events described previously for coughing, sneezing, and face touching, the direction away and towards for entering/leaving a room respectively, will be substantially different as show in 9 (b). We use this knowledge to differentiate the entering/leaving activities from all other activities we captured.

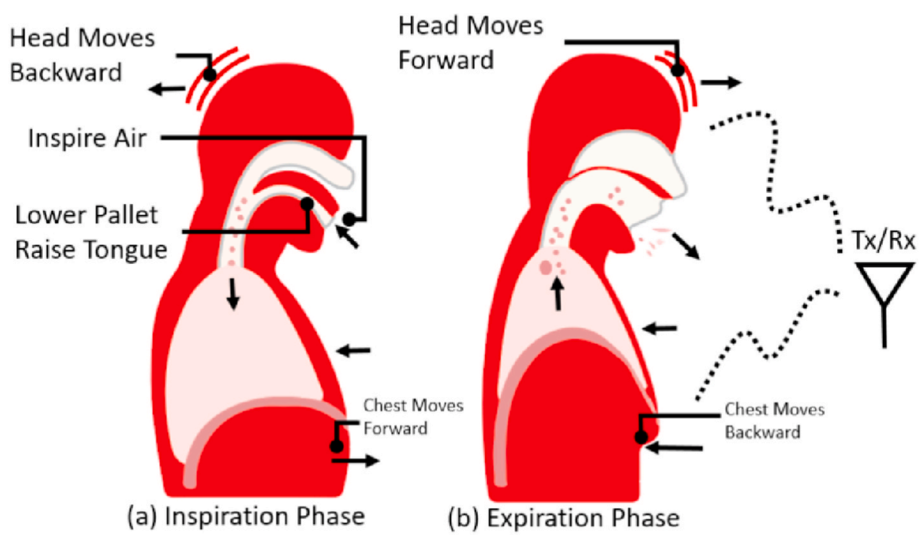
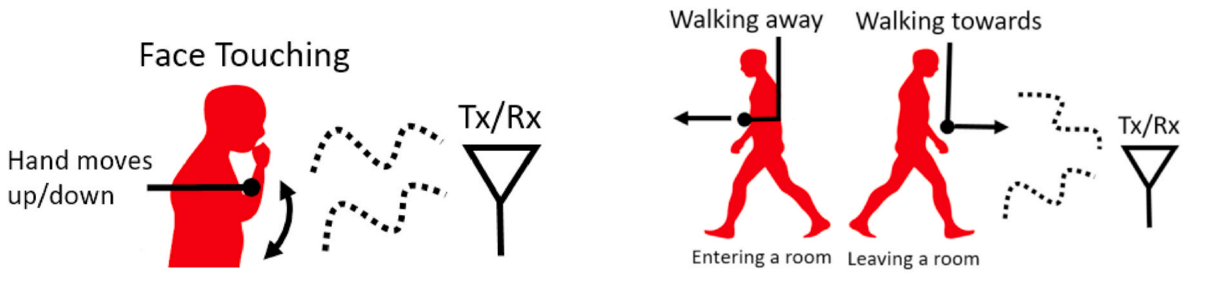


Fig. 3. Anatomy of the sneeze showing two phases, (inspiration and expiration) and the motions of the chest and head performed during each phase causing short and long radar signal reflections back to the radar.



(a) Touching the face with the hand

(b) Entering and leaving a room

Fig. 4. This figure shows the motion of the arm and hand moving up to touch the face and then back down to the side causing short and long radar signal reflections back to the radar (a) and shows that when a person is entering a room they are walking away from the radar and when a person is leaving a room they are walking towards the radar causing short and long radar signal reflections back to the radar (b).

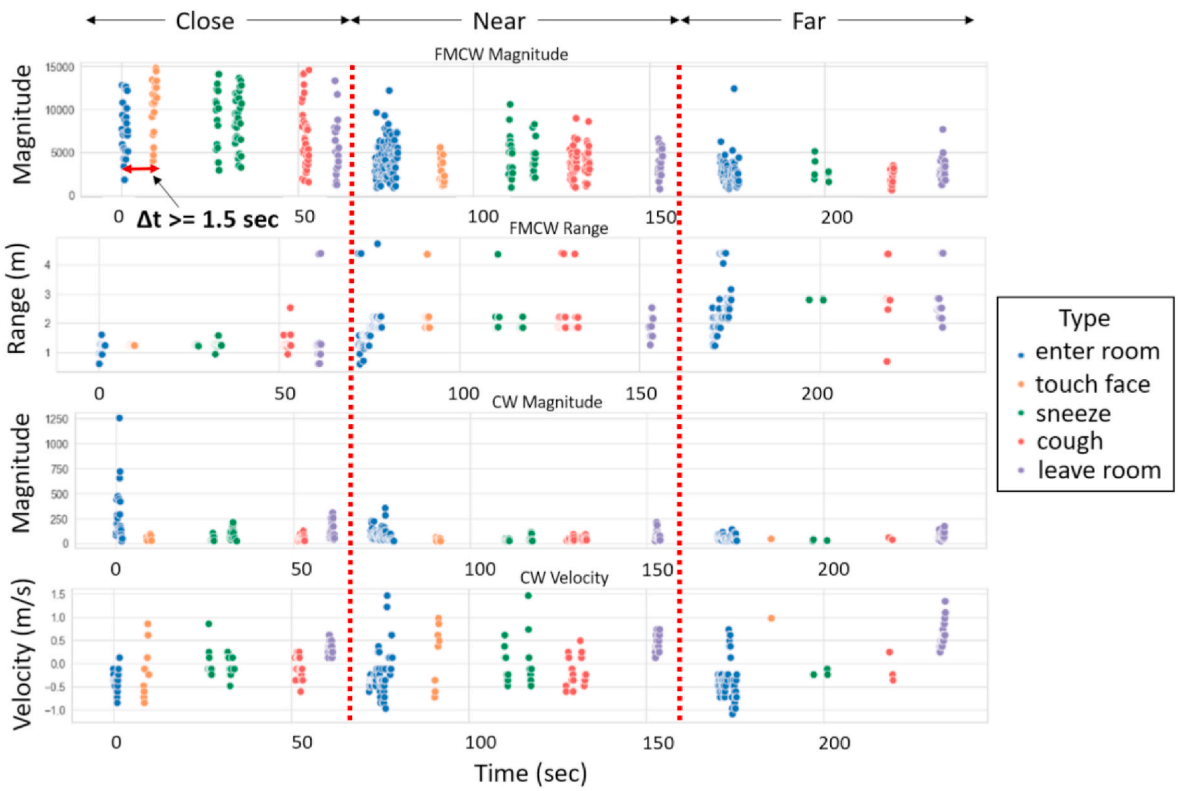


Fig. 5. A total of 19 activities captured over a 4 min continuous period. From top to bottom the figure shows the FMCW magnitude, FMCW range, CW magnitude, and CW velocity. Activities at close range include enter, touch face, sneeze, sneeze, cough and leave. Activities at near range include enter, touch face, sneeze, sneeze, cough, cough, and leave. Activities at far range include enter, touch face, sneeze, sneeze, cough, and leave. Each activity is separated by have a delta t greater than or equal to 1.5 s.

1.3. System architecture

Our systems characterises five types of activities including coughing, sneezing, face touching, and entering and leaving a room with a set of architectural components described next. The architectural components of our system include the OPS243–C FMCW/Doppler radar (OPS243-C 2020) for sensing an activity's motion, a home server that processes, classifies, and produces mobile alerts, and a mobile application that allows the user to view the alert based notifications shown in Fig. 1. The FMCW/Doppler radar is capable of detecting speed, direction, and range information for objects in its FoV. In addition the radar can report the demodulated I/Q signals for calculating the FMCW/CW magnitude. In our setup, we connected the radar via USB to a Raspberry Pi 4 which we used as a home server. The home server acquires the radar information for processing. The processing steps include activity separation, calibration, feature extraction, defining a set of *fuzzy* IF-THEN rules, classification, and the propagation of mobile alerts via Wi-Fi to a mobile application. None of the processed data is saved on the home server, but is saved on the mobile device storage for historical use. The mobile application, which we named CSTF-Monitor, for cough, sneeze, touch face monitor, can run on both iOS and Android, and allows the user to add a room where the sensor is located and view a table which shows the distance, time, and type of activity detected. The environmental setup used to test our system and processing steps to classify each activity are described next.

1.4. Experimental environment

The environment for our data collection experiments were done in a house in the basement shown in Fig. 6. The radar was placed 1 m above the ground on a stand. The only furniture in the environment was an office chair, for the subject to sit on. We marked three distances from the radar sensor with tape at 0.91 m, 1.83 m, and 2.74 m for close, near, and far locations. Following our approved institutional review board (IRB) protocol and CDC guidelines for CDC (2020), we made sure to sanitize the area before and after each data collection experiment. Participants were also asked to maintain 6 feet of distance separation from others, as well as wash their hands, use hand sanitizer regularly, and wear a face mask to not spread germs.

1.5. Capturing and separating activities

Our system uses the Doppler velocity magnitude and FMCW range magnitude as a filter to capture each activity separately. To do this we experimentally derived a minimum threshold value M_T of 20 for the Doppler velocity magnitude and FMCW range magnitude. The M_T threshold value is configurable and can be adjusted during calibration. The magnitude for both CW Doppler and FMCW were calculated using the demodulated in-phase I and quadrature-phase Q components of the intermediate frequency signal and calculating the magnitude M at time t as $M(t) = \sqrt{I(t)^2 + Q(t)^2}$. If an activity's magnitude for both the Doppler/FMCW were less than the threshold $(M < M_T)$, no measurements are reported, otherwise measurements are reported when $(M > M_T)$. Thus, when a subject is still and not moving very much and in front of the radar, the magnitude M will be below the threshold M_T and the radar will not report any data, otherwise if the user moves in front of the radar such that the motion causes the magnitude M to be greater than the threshold M_T then the radar will report motion data. When measurements are reported they include the FMCW magnitude, FMCW range, CW magnitude, and CW velocity shown in Fig. 5. In order to separate each event from one another, we look for a gap $\triangle t$ greater than or equal to 1.5 s between each reported value. The $\triangle t$ gap is configurable and can be adjusted during calibration for activities where $\triangle t$ happens at a faster or slower interval.

1.6. In home deployment and coordination

Our system is capable of being deployed throughout the home to monitor activities in different locations. We did not deploy our system throughout the home, but only deployed it in the basement of the home to conform to our IRB protocol which required a single controlled location for data collection in order to make it easier to follow CDC guidelines for CDC (2020). For deployment throughout a home, at least one of our radar systems would have to be setup in each location that needs monitoring shown in Fig. 7. Each radar can then be connected by USB to a home server, that contains our processing pipeline shown in Fig. 1, and a representational state transfer (REST) application programming interface (API) that allows for retrieving alert notifications for each location by hypertext transfer protocol (HTTP) GET methods used by the client mobile application. The home server and mobile application are connected to a wireless home network for communication. For our experiments we used a Raspberry Pi 4 module, which is a credit card sized

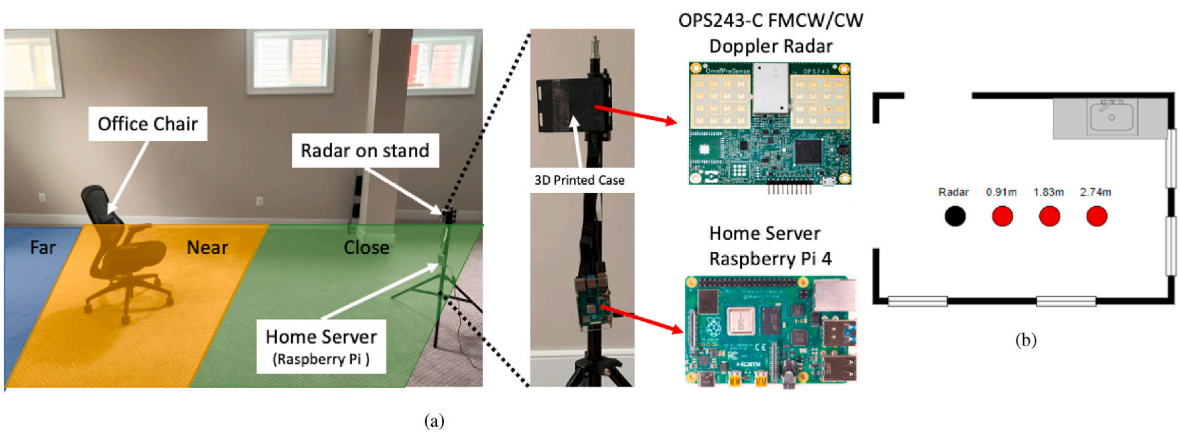


Fig. 6. The environmental setup for data collection experiments including the office chair, the radar and home server attached to a stand, and the locations of far, close, and near locations (a) and the blueprint layout showing the subject locations depicted as red circles at 0.91 m, 1.83 m, and 2.74 m from the radar (b). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

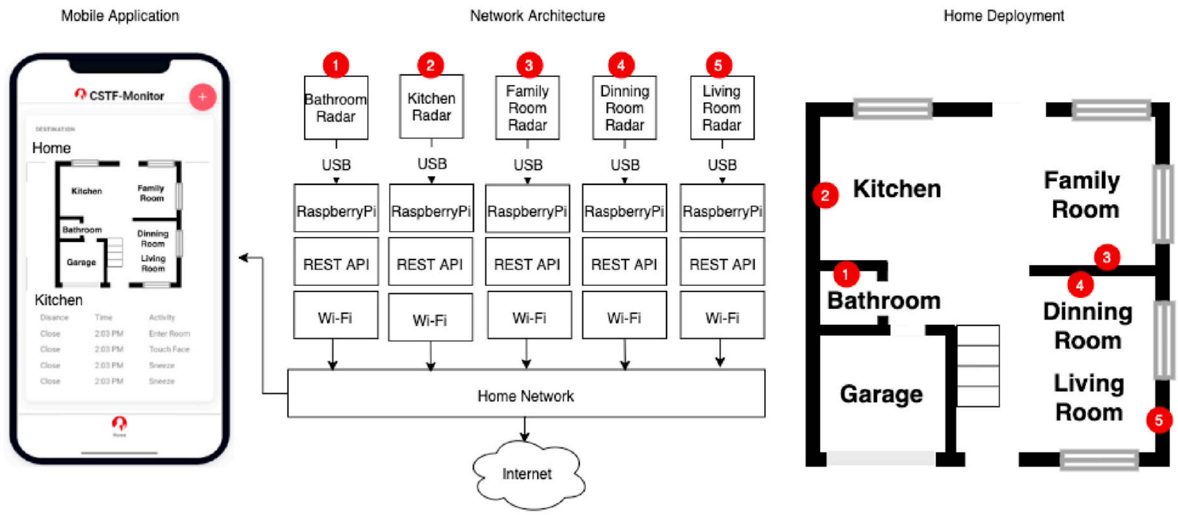


Fig. 7. Home deployment and coordination.

computer for our home server. To receive alerts, the mobile application client periodically polls the REST API by calling HTTP GET methods for each radar system for alerts. The mobile application can run on both ios and Android platforms and displays an image of the layout of the home, and for each location includes a table that shows the distance (close, near, far) where an activity happened, the time the activity happened, and the type of the activity that happened (sneeze, cough, face touching, entering/leaving a room).

1.7. System calibration process

Before our system can classify activities it must be calibrated. The calibration process shown in Fig. 8 is used to capture data related to a specific subject or group of subjects, such as a single family or multiple families. Our calibration process is not limited for data collection related to our specific set of activities (coughing, sneezing, face touching), but can be extended for collecting data related to other activities such as enter/leaving a room which we include in our study. The data captured during the calibration process is used to calculate a set of features which are used to create a set of *fuzzy* logic IF-THEN rules for accurately classifying activities in the home. The calibration process begins by enabling the calibration mode for the radar. The radar will then apply the magnitude filter we described earlier in section 3.3. Next, the subject will have to walk in front of the radar and sit still. In our setup we wanted to detect activities while sitting, but different positions such as standing could also be done. Then the calibration process will check if there is no motion $M < M_T$ (subject sitting still) for a period of time t for two cases:

- Case 1: $t > T_1$ and $t < T_2$
- Case 2: $t > T_2$

Where T_1 is the first time threshold and T_2 is the second time threshold. When Case 1 for the time of no motion t is true the radar will turn on a LED indicating that the subject can start to perform an activity. While the user is performing an activity the radar will sense and capture motion data if the magnitude $M > M_T$. When the user stops performing the activity the calibration process will then loop back to check for Case 1 or Case 2. When Case 2 is true the subject has either stopped moving for a period $t > T_2$ or has left the FoV of the radar. The radar will then save the captured data for when all Case 2 events were true and turn off the LED to indicate that the calibration processing is done. Lastly the features for creating the *fuzzy* logic IF-THEN rules will be calculated and the calibration process will stop.

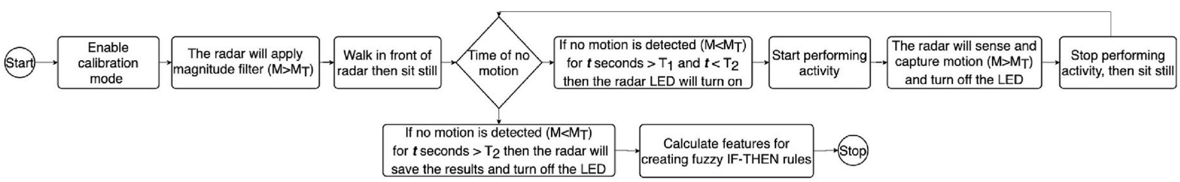


Fig. 8. System calibration process.

1.8. Initial calibration for a single subject

For initial experiments, for a single subject, we calibrated our system by collecting Doppler and FMCW intermediate frequency signal I/Q, magnitude, range, and velocity information for each activity. Before starting the experiments we made sure that the subject and principal investigator followed CDC guidelines for CDC (2020), by washing their hands, wearing a face mask, and practicing social distancing of 6 feet from others. The environment was also sanitized before and after a subject was in and out of the room. We used the calibration process described previously in Fig. 8 for three experiments with a single subject. The subject was asked to performed activities at each distance, 0.91 m, 1.83 m, and 2.74 m, for a total of nine experiments. For each experiment we started by having a subject stand behind the radar, then enter the room. The subject would walk in front of the radar to the labeled location, one of the three distances, and sit still on a chair. When the radar turned the LED on, the subject would perform an activity, and upon completing the activity would sit still again. This was repeated three times pausing for at least 5 s between each activity. Finally, the subject would get up from the chair and walk out of the room by walking towards the radar. We collected three observations for each activity, coughing, sneezing, toughing the face, entering/leaving the room, at each of the three distances for a total of 27 observations. For the sneezing activity we asked the subject to perform a voluntary sneeze by taking a deep breath, inhaling air, and mimic a sneeze as described in section 3, by which they would exhale out through their mouth. For the cough activity, we asked the subject to perform a voluntary cough by taking a deep breath, inhaling air, and mimic a cough as described in section 3, by which they would exhale and cough through their mouth at least two or three times. For the other activities the subject was asked to mimic the process as described in section 3. The data collection was done as a manual calibration step, required by our system. We used this set of data to define *fuzzy* logic IF-THEN rules for activity differentiation described next.

1.9. Feature extraction and classification

To differentiate each activity from each other, we calculated two features, the interquartile range (IQR) of the Doppler velocity and the number of positive Doppler velocity values minus the number of negative velocity values. The IQR describes how spread out the data points for the velocity are from the mean of the velocity for each activity. The positive minus the negative velocity values describes the relative direction of each activity, towards or away from the radar sensor. Using this feature set, we designed two control systems composed of *fuzzy* logic IF-THEN rules to differentiate and classify each activity. We refer the reader to Bai and Wang (2007, pp. 17–36) for fundamentals on *fuzzy* logic.

Touching the Face: From our initial data collection experiments we found that the IQR for the activity of touching the face, was the largest amongst all other activities at all distances shown in Fig. 9 (a). We use this knowledge to differentiate touching the face from all other activities using a set of *fuzzy* logic rules with linguistic variables {'LOW','HIGH'}. The following *fuzzy* IF-THEN rules were designed:

- Rule 1: If the IQR of the Doppler velocity is HIGH, THEN the activity measured is touching the face
- Rule 2: If the IQR of the Doppler velocity is LOW, THEN the activity measured is NOT touching the face

Entering and Leaving the Room: We also observed that the relative direction for entering the room was low and leaving the room was high when compared to all other activities at all distances shown in Fig. 9 (b). We use this knowledge to differentiate entering/leaving the room from all other activities using a set of *fuzzy* logic rules with linguistic variables {'AWAY','STEADY','TOWARDS'} The following *fuzzy* IF-THEN rules were designed:

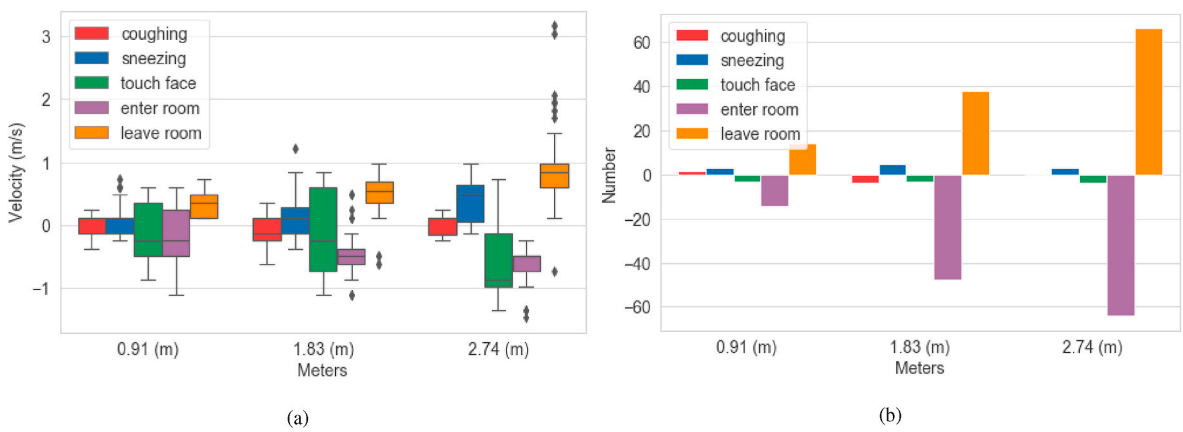
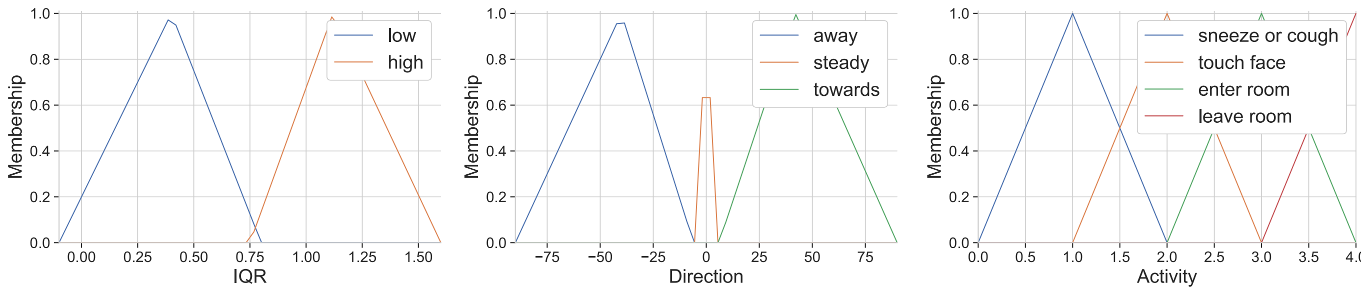


Fig. 9. This figure shows the interquartile range of the Doppler velocity at 0.91 m, 1.83 m, and 2.74 m for each activity (a) and the positive minus negative Doppler velocity feature at 0.91 m, 1.83 m, and 2.74 m for each activity (b).



(a) (b) (c)

Fig. 10. Control system 1 Doppler velocity IQR membership function (a), Doppler velocity direction membership function (b), and the activity membership function (c).

- Rule 1: If the direction of the Doppler velocity is AWAY, THEN the activity measured is entering the room
- Rule 2: If the direction of the Doppler velocity is TOWARDS, THEN the activity measured is leaving the room
- Rule 3: If the direction of the Doppler velocity is STEADY, THEN the activity measured is touching the face, coughing or sneezing

First Fuzzy Control System: We used the designed rules for the activities touching the face and entering/leaving the room to design an aggregate set of rules for our first *fuzzy* control system. The rules are used to differentiate touching the face from all other activities, and leaving/entering the room from all other activities respectively. The activities for coughing and sneezing are grouped into a single membership function and differentiated in a second control system. The universe variables and membership functions for Doppler velocity IQR and the relative direction features as well as the output membership function are shown in Fig. 10. The parameters were determined experimentally based on the previously collected data for a single subject. For the first control system the following *fuzzy* IF-THEN rules were designed:

- Rule 1: If the direction of the Doppler velocity is STEADY & the IQR of the Doppler velocity is LOW, THEN the activity measured is sneezing or coughing
- Rule 2: If the direction of the Doppler velocity is STEADY & the IQR of the Doppler velocity is HIGH, THEN the activity measured is touching the face
- Rule 3: If the direction of the Doppler velocity is AWAY, THEN the activity measured is entering the room
- Rule 4: If the direction of the Doppler velocity is TOWARDS, THEN the activity measured is leaving the room

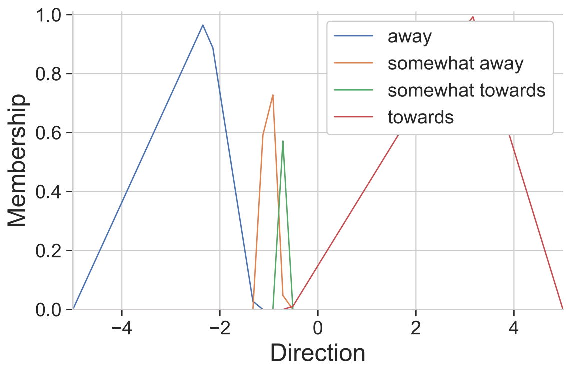
Second Fuzzy Control System: We used a second *fuzzy* control system to differentiate between a sneeze and a cough. The second system will be executed only when Rule 1 in the first control system evaluates to true. Then, we redefined the direction membership functions using linguistic variables {'AWAY', 'SOMEWHAT AWAY', 'SOMEWHAT TOWARDS', 'TOWARDS'}. By observing the Doppler velocity relative direction feature shown in Fig. 9 (b), we found that the sneeze and cough can be differentiated by this feature alone. We observed that the sneeze can be somewhat away or towards, while the cough can be somewhat towards and away. The universe variables and membership functions for the relative direction features as well as the output membership function are shown in Fig. 11. The parameters were determined experimentally based on the data collected previously. For the second control system the following *fuzzy* IF-THEN rules were designed:

- Rule 1: IF the direction of the Doppler velocity is SOMEWHAT AWAY *OR* TOWARDS THEN the activity measured is sneezing
- Rule 2: IF the direction of the Doppler velocity is SOMEWHAT TOWARDS *OR* AWAY, THEN the activity measured is coughing

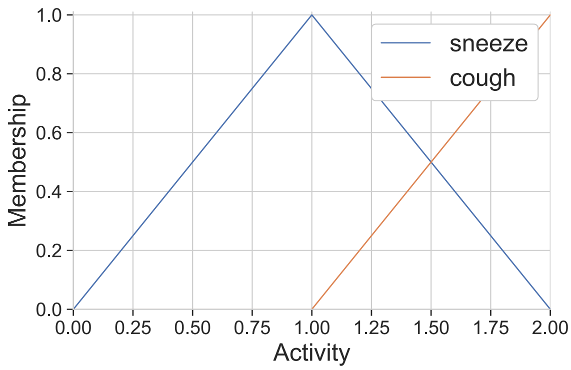
1.10. Definition of distances from the radar

Our system also detects where an activity happened, either close, near, or far from the radar sensor. The set of distances were defined using *fuzzy* logic rules with linguistic variables {'LOW', 'MEDIUM', 'HIGH'}. To define the *fuzzy* inputs for the distances we captured human activity range values using FMCW radar at 0.91 m, 1.83 m, and 2.74 m respectively from the radar sensor and observed their root mean square (RMS) distance show in Fig. 12 (a). The output membership function for the distances are shown in Fig 12 (b). The following *fuzzy* IF-THEN rules were designed:

- Rule 1: IF the RMS of FWMC range is LOW, THEN the activity measured was close
- Rule 2: IF the RMS of FWMC range is MEDIUM, THEN the activity measured was near



(a)



(b)

Fig. 11. Control system 2 Doppler velocity direction membership function (a), and the activity membership function (b).

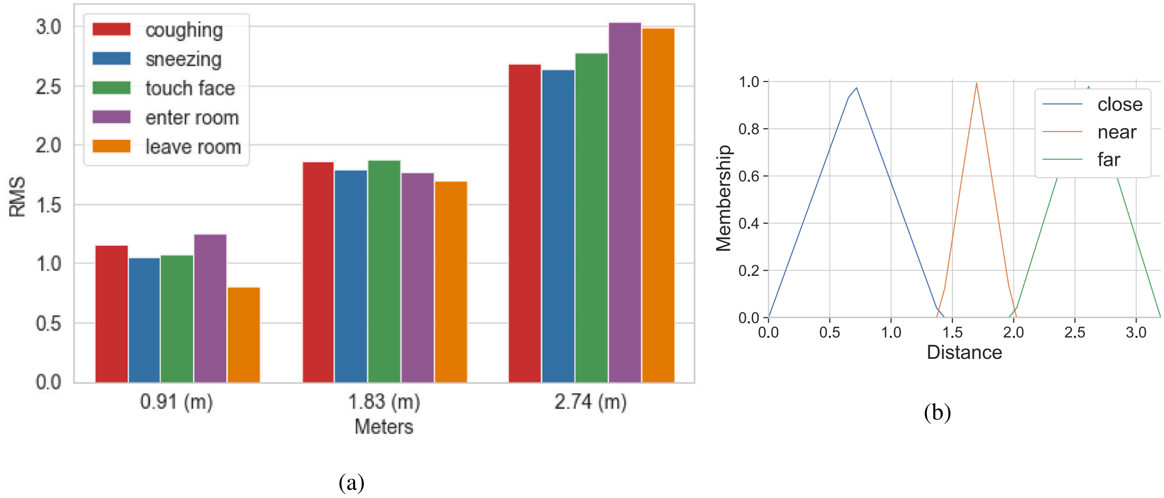


Fig. 12. This figure shows the FMCW RMS range values at 0.91 m, 1,83 m, and 2.74 m. The activities are ordered from left to right: coughing, sneezing, touching face, enter room, and leave room (a) and the FMCW range RMS membership function (b).

- Rule 3: IF the RMS of FWMC range is HIGH, THEN the activity measured was far

2. Experimental evaluation

We chose to evaluate how well our system can detect a person coughing, sneezing, touching their face, and entering or leaving a room in several different scenarios. The scenarios involved monitoring a single person's activity, monitoring a single person's activities at different distances, monitoring a single person's activities through a wall, and monitoring multiple people's activities. For the first scenario, we recorded a subject's activity for a total of 4 min shown in Fig. 5. The subject started behind the sensor then entered the room and sat on a chair. They performed a set of different activities, then left the room. This was repeated three times, at three different distances, for a total of 19 activities observed. We also recorded the subject's activities by observation as a ground truth, which captured a total of 20 activities. One cough activity was not detected at the far distance. As stated before, we followed CDC guidelines for CDC (2020), and had the subject and principal investigator wash their hands, wear a face mask, and practice social distancing of 6 feet from others.

Overall System Accuracy: When running our system for the experiment in Fig. 5, our system achieved 96% accuracy shown in Fig. 13. There was a single cough activity that was not captured at the far distance. In Fig. 5 there were a total of four cough activities, but our ground truth written observations captured a total of five cough activities. Our *fuzzy* logic rules and control system were able to detect and classify all 19 observations correctly.

System Accuracy at Different Distances: For each activity in the experiment shown in Fig. 5, we also applied our *fuzzy* IF-THEN rules defined for the three distances close, near and far. Our system was able to group each activity accordingly and classify them with 100% accuracy at close distance, 100% accuracy at near distance, and 90% accuracy at far distance shown in Fig. 14. There were two cough events recorded by written observation at the far distance, but only one was detected.

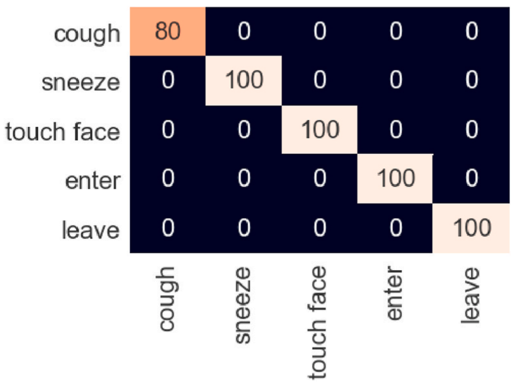
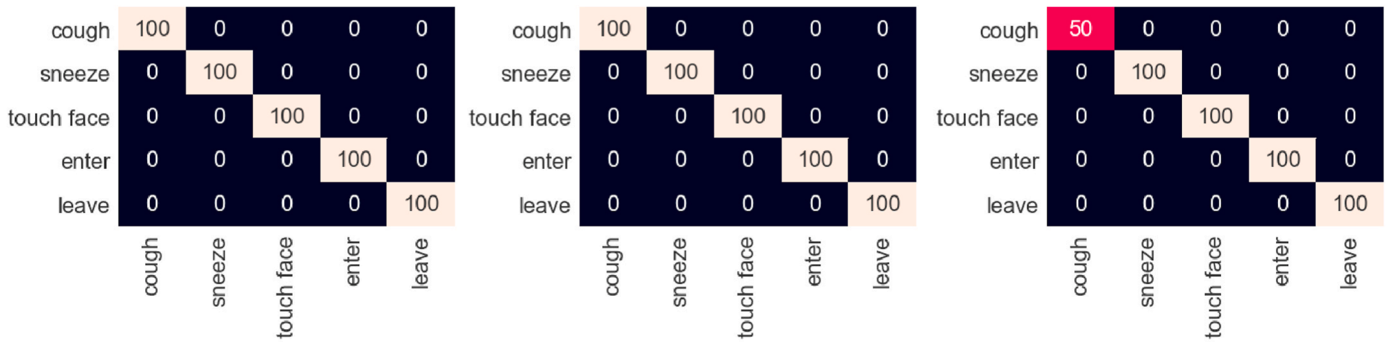
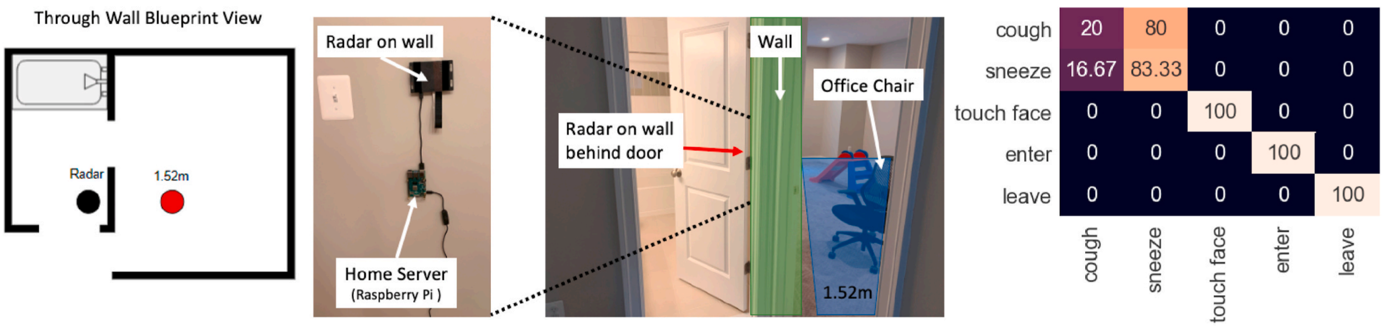


Fig. 13. This figure shows the overall system accuracy for a single subject with a confusion matrix showing the accuracy for each activity detected with total accuracy of 96%. Out of five cough events observed by ground truth video, one cough was not captured.



(a) (b) (c)

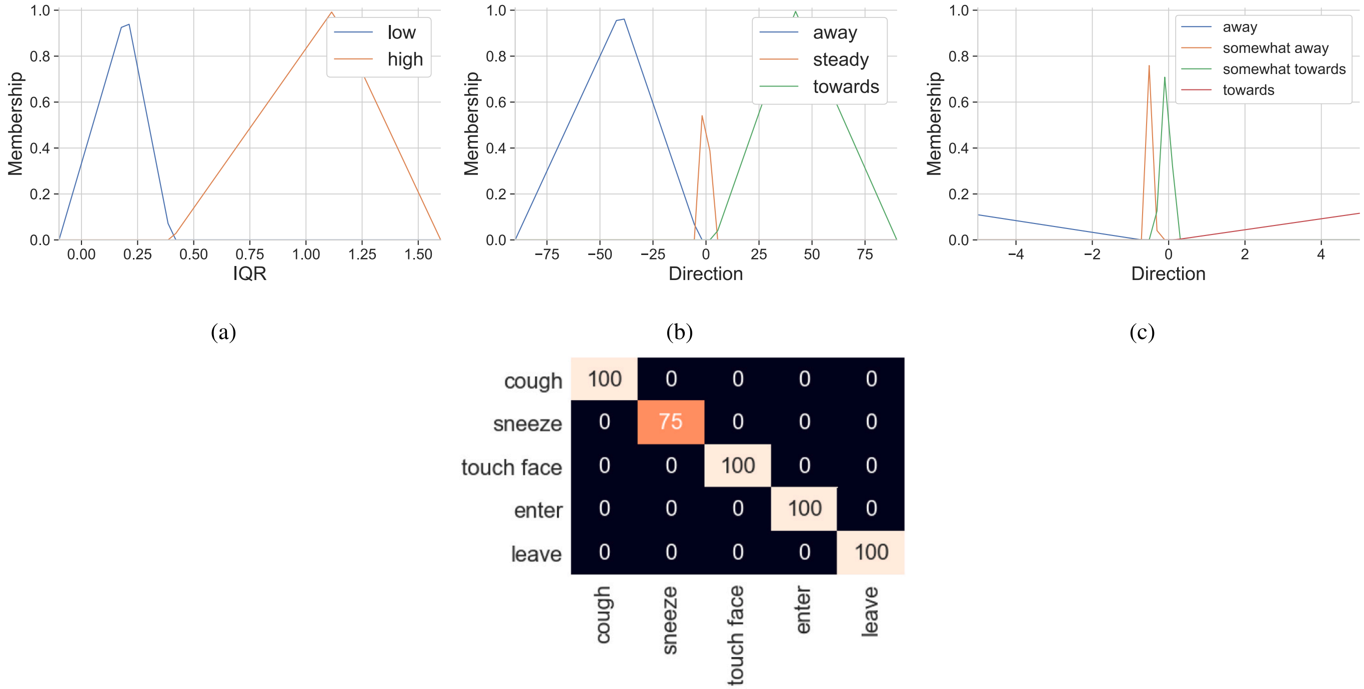
Fig. 14. This figure shows the system accuracy at different distances for a single subject with a confusion matrix showing the accuracy of activities at close with 100% accuracy (a), near with 100% accuracy (b), and far with 90% accuracy. (c) Ranges.



(a)

(b)

Fig. 15. The environment setup for through wall detection. From left to right shows a through wall blueprint showing a black circle for the radar position and the subject location at 1.52 m from the radar depicted by a red circle and the radar shown mounted to a wall in the bathroom behind the door, the wall, and the chair where the subject sat (a), and the confusion matrix showing 81% over all accuracy for activities detected through a wall. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)



(a) (b) (c)

(d)

Fig. 16. Multi-person Doppler velocity IQR membership function (a), Doppler velocity direction membership function for control system 1 (b), and the second Doppler velocity direction membership function membership function for control system 2 (c), and the confusion matrix showing the accuracy for each activity detected with multiple people with a total accuracy of 95% (d).

System Accuracy Through a Wall: We also conducted an experiment to test how well our system performs at detecting each activity through a wall. For this experiment, we placed the radar sensor in a bathroom behind a wall. Then we had the subject enter a bedroom adjacent to the bathroom and sit on a chair 1.52 m from the radar shown in Fig. 15 (a). The subject performed a set of activities and then left the room. This was repeated twice for a total of 23 observations. We used the same *fuzzy* IF-Then rules and membership functions as applied in the experiment in Fig. 5 and achieved an overall accuracy of 81% shown in Fig. 15 (b). We found that our first *fuzzy* control system grouped all activities with the membership function shown in Fig. 10 (c) with 100% accuracy. When differentiating the cough and sneeze with our second *fuzzy* control system using membership function shown in Fig. 11 (b) we achieved only 20% accuracy for detecting a cough and 83% accuracy for detecting a sneeze. The 80% miss-classifications for cough were detected as sneezing and the 16.67% miss-classifications for sneeze were detected as coughing. As mentioned previously, during the experiment, we followed CDC guidelines CDC (2020).

System Accuracy with Multiple People: Lastly, we conducted an experiment to see how well our system performs with multiple people, one male and one female. As mentioned previously, during the experiment, we followed CDC guidelines for CDC (2020) having individuals wash their hands, wear face masks, and practice social distancing. Before conducting the experiment, we had to calibrate our system, by collecting data for each person at their respective locations using our calibration process described previously in Fig. 8. We used the same environmental setup shown in Fig. 6, but only had one subject sit at 3 ft and the second subject sit at 9 ft from the radar in accordance with our IRB and CDC protocol for maintaining social distancing of 6 ft. These were the only two locations that we had the subjects sit at. For the initial data collection we had each subject start behind the radar and then enter the room and sit at one of the two locations. Each subject performed two activities each, taking turns between each activity: touching their face, sneezing, and coughing. Then each subject left the room walking towards the radar one at a time. Using this data set we adjusted the values for each membership function shown in Fig. 16(a) and (b), and (c). Then we conducted a second experiment where we had each subject stand behind the radar and enter the room one at a time. Each subject sat at the same locations as before, and performed each activity twice, taking turns between each set. Then each subject left the room walking towards the radar one at a time. Between each experiment we made sure to sanitize the area. We recorded a total of 16 activities performed. Then we applied the same *fuzzy* IF-Then rules defined in our previous control systems and achieved an overall accuracy of 95% shown in Fig. 16 (d). One of the sneezes was miss-classified as a cough.

3. Discussion

Our system is capable of monitoring activities at home including coughing, sneezing, face touching, and entering/leaving room shown in Fig. 13. In addition we evaluated our system in different scenarios showing that it can detect our set of activities at different distances shown in Fig. 14, through a wall shown in Fig. 15 (b), and with multiple people shown in Fig. 16 (d). Our system does not require a large historical data set for calibration, but can use a couple examples, three of each activity in our case, to define *fuzzy* IF-THEN logic rules capable of differentiating each activity from each other. In addition we identified two features, the IQR, and relative distance feature, to differentiate each activity. The IQR distinctly differentiates face touching from all other activities as observed in Fig. 9 (a). The relative direction feature we created distinctly differentiates enter/leaving a room from all other activities as observed in Fig. 9 (b). We observed that our system can miss-classify a cough for a sneeze or a sneeze for a cough when using the relative direction feature to differentiate the two activities. The relative direction feature does not distinctly differentiate the cough and sneeze from all other activities. In our implementation we expanded the set of linguistic variables for our second *fuzzy* control system and had to define a new set of *fuzzy* logic IF-THEN rules to differentiate coughing from sneezing. This is due to the similarity between the motion movements of the chest and head when sneezing versus coughing. Still our system can accurately detect that a sneeze or cough happened.

Our system also makes some assumptions used to detect and monitor each activity. The first assumption we make is in regard to the placement of the radar. We assume that when our system is used the radar will be positioned in such a way, that when a person enters the room, they will be walking away from the radar. In addition, we assume the radar will be in a position such that when a person leaves the room they will be walking towards the radar. The second assumption we make is that when a person is in a room, and in the FoV of the radar, they are assumed to be quasi-static and sitting on a chair. Quasi-static refers to people sitting still, watching TV, or typing on a laptop. If a person were to get up and starting walking around, then our system would assume the person would be leaving/entering a room, but when a person is sitting our system would assume the person would be performing motions related to coughing, sneezing, and face touching. We also make assumptions about the motion of the head when coughing and sneezing. The motion of the head, during inspiration, compression, and expiration, are assumed to start with the head moving backward and then start to move forward as the person coughs. Similarly we assume the head will move backwards when sneezing during inspiration, and more forwards in relation to a cough, as the person exhales. For arm motion we assume that the person's arm starts at the side of their body, swings up to touch their face, and then after touching their face, swings back down to their side. Lastly, we assume that when multiple people are in the room, they will be separated by some distance, in our case 6 ft for practicing social distancing. There could be cases when multiple people are sitting next to each other, such as on a couch, but we did not have a chance to test our system for this case as it violated social distancing practices.

Our system has some limitations which we describe next. The first limitation is that our system has to be calibrated for each person at different distances. This is because a set of collaboration data is needed to define the membership functions related to each activity. We argue that this approach works well when there are limited data sets or acquiring a set of training data for a system is unavailable or hard to achieve. In our case, we could not find any existing data sets that have captured motion data from activities related to coughing or sneezing. Also, acquiring data related to coughing and sneezing assumes some health risks, as people collecting the data could get sick from those performing the activities. In our present time, with the onset of COVID-19, acquiring data related to coughing and sneezing, is either not an option due to social distancing laws or highly risky. Thus, for our experimentation we performed data in a single family home with individuals who are healthy and voluntary performed coughing, sneezing, face touching, and entering/leaving activities. We followed our approved IRB protocol and CDC guidelines CDC (2020) to minimize risk during data collection by sanitizing areas before and after each experiment as well as washing hands, wearing face masks, and practicing social distancing. We also limited the number of people in the study to two, as to minimize risk and spread of COVID-19. A second limitation of our system is the detection range and FoV. During our experimentation, we showed that activities could be detected as far as 2.74 m from the radar. The OPS243–C radar that we used in our system is capable of detecting activities at further distances, (50 m–60 m), but we only evaluated distances based on the room size where our experiments were performed. Further research could be done to experiment and observe how far activities such as coughing and sneezing could be detected from the radar. The FoV is also limited, but can be increased by adding additional sensors. In regards to activity detection, our system is not limited to the set of activities we defined and can be extended to include others. Although, if additional activities were to be added, then new features may need to be created and a new set of *fuzzy* logic IF-THEN rules would have to be defined. Our calibration process can be used to collect data related to other activities. Lastly our system is limited to how activities are performed when multiple people are being monitored. If activities from multiple people are happening at the same time at the same distance from the sensor, our system will assume the motion is from one person. This limitation can be avoided by zooming into the FMCW reflections from each individual separately Adib et al. (2015, pp. 837–846). Although, we did not apply this method, our system can still detect activities from multiple people if they perform activities at the same time if they are separated by some distance. Again, we separated each subject by 6 ft to practice social distancing, but further research can be done to see how our system performs when two subjects are closer to each other. Given these limitations, our system is very capable of accurate monitoring, and to our knowledge the first smart home monitoring systems to use CW/FMCW radar to monitor activities including: coughing, sneezing, face touching, and entering/leaving a room. In addition, our mobile application, gives people a more detailed view of the activities performed in their household, allowing them to clean and practice better hygiene.

4. Conclusion

In this work, we present a new smart home monitoring system that can detect voluntary coughing, sneezing, face touching, and entering/leaving a room. Our system includes a mobile application with alert notifications for the type, time, and location of the activity detected. To detect, differentiate, and locate each activity, we use a combined CW/FMCW radar to capture the motion speed, direction, and range information. We used two features, the IQR of the velocity, and a relative direction feature, in-order to implement a set of *fuzzy* IF-THEN logic rules which can differentiate activities in different scenarios. We also defined a set of distances, (close, near, far), based on the RMS range values to locate each activity. With a single individual our system can detect activities with an overall accuracy of 96%. In addition, our system can accurately detect activities at different distances (0.91 m, 1.83 m, and 2.74 m), through a wall, and with multiple people. Our system can be used to track activities at home helping people maintain proper hygiene, knowing which areas to clean and aid in social distancing practices. We envision this system being used to help stop the spread of the devastating COVID-19 virus as well as support contact tracing efforts.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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