Efficient Monitoring and Contact Tracing for COVID-19: A Smart IoT based Framework

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***Abstract*—The sudden outbreak of the *coronavirus disease* (also known as COVID-19 or colloquially just as *coronavirus*) has disrupted our lives in numerous ways. As the virus is spreading by leaps and bounds, the healthcare systems of even the most advanced countries have reached their capacity. This is primarily because a large fraction of people infected with COVID-19 are either asymptomatic or exhibit mild symptoms. This creates a large number of reasonably healthy *disease carriers*, which makes it easier for the virus to reach the more vulnerable population. Because of this, contact tracing and infection tracking are indispensable for containing the spread of this pandemic. Fortunately, this coincides with the emergence of Internet of Things (IoT), which is already being considered for healthcare applications but is a *match made in heaven* for contact/infection tracing because of its ubiquity. Inspired by this, we introduce a new IoT-based framework for contact and infection tracing, which specifically incorporates symptom based detection that has been ignored in the prior art on tracing models. The ability of this framework to meaningfully merge real-time symptom information (from the IoT devices) and the confirmed COVID-19 cases (from the medical tests) provides a fast and efficient way of tracking the disease spread, which is eventually useful for the effective utilization of the scarce resources (such as COVID-19 test kits). Simulation results corroborate the efficiency of our infection tracing method.**

I. Introduction

Despite going through multiple pandemics over the past century, we have been caught gravely unprepared by COVID-19. As evident from Bill Gates' 2015 TED talk titled, *"The next outbreak? We're not ready"*, the warnings of such an outbreak were loud and clear. Caused by the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2), the outbreak was first identified in Wuhan, China, in December 2019. However within the span of a few months, the pandemic engulfed almost the entire world, thereby forcing the World Health Organization (WHO) to declare it as a *Public Health Emergency of International Concern* on the 30^{th} January 2020, followed by a pandemic on the 11^{th} of March [1]. As of mid August 2020, a staggering 21 million cases are already reported across the globe with a fatality count standing at a whopping 0.75 million. The mammoth number of infected cases, hospitalizations and fatalities has overloaded the health-care systems of many developed countries, not to mention the agonizing condition of several developing and under-developed countries. The pandemic has also triggered a remarkable economic disruption, resulting in the largest global recession since the Great Depression, affecting hundreads of millions of people. Moreover, postponement or cancellation of major sports, religious, political, cultural and educational events is raising a question over the socio-economic future of the human civilization. Naturally, while grappling to cope up with such a deplorable situation, a paramount concern lies in thwarting or at least reducing any further spread of the virus.

While our understanding of COVID-19 is still evolving, it is well-accepted that physical proximity and contact are the primary reasons behind the transmission and spreading of this disease [2]. Furthermore, it is known that the major carriers of this disease are the small droplets produced by coughing, sneezing, and even talking. Recent studies have shown that the loud speech can generate thousands of such droplets per second, which may remain suspended in the air with time constants that may be higher than 10 minutes in confined environments [3]. This increases the likelihood of airborne transmission of COVID-19 in indoor spaces. Moreover, these droplets also contaminate surfaces, which spreads the infection further [2]. Although most contagious during the first three days after the onset of symptoms, the virus is capable of spreading even before symptoms actually show up. Major symptoms of COVID-19 include fever, cough, fatigue, shortness of breath, and loss of sense of smell, with further complications, like pneumonia and acute respiratory distress syndrome. The time from exposure to onset of symptoms generally range from two to fourteen days. In the absence of a vaccine and effective antiviral treatments, we are only left with symptomatic and supportive therapies.

While coping up with any viral pandemic, the popular notion of *Prevention is Better than Cure* still prevails and COVID-19 is no exception [4]. Recommended preventive measures include washing of hands with sanitizers or soaps, covering of mouth while coughing, maintaining a certain distance from other people, wearing a face mask in public as well as isolation of the infected people. While many regions have increased their testing capacity, significant importance is given to tracing the contacts of infected individuals. This is especially important in the case of COVID-19 because of the majority of the infected people being reasonably healthy (either asymptomatic or exhibiting mild symptoms), which makes it easier for the virus to spread to the more vulnerable population. In a typical contact tracing process [5], the health workers will talk to the infected (COVID-19-positive) individuals and alert anyone they might have exposed, while maintaining their confidentiality. As such, following a process that involves monitoring symptoms, timely testing, self-isolation

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if exposed, and medical care if infected has the potential to unveil spread patterns and contain infection rates. More importantly, contact tracing and monitoring helps in keeping the utilization of healthcare infrastructure below capacity and helps in gradually reopening the businesses. Naturally, the burning question to our current digital age is: *how to efficiently use advanced communication and Internet technologies to combat this pandemic? [6]*

In order to effectively address the above question, we need a communications solution that can monitor, trace, and wirelessly report infections, thereby providing detailed view of the infection spread to the decision makers. Quite incredibly, this is exactly the type of problem for which the Internet of Things (IoT) is being developed [7], [8]. The IoT comprises of a collection of interconnected physical objects or "things", typically equipped with sensing and software capabilities for autonomous information processing. Massive growth in smart devices as well as the gradual penetration of 5G wireless and advanced WiFi technologies have already set the stage for the next industrial revolution based on IoT. The advent of IoT is also introducing a gradual change in health care systems. The current emphasis in this direction is mostly confined to remote health monitoring and tele-health, which is increasing the reach of health-care professionals from the hospitals to the private environments, such as the patients' home. However, the future Healthcare Internet of Things (HIoT) [9] and Internet of Medical Things (IoMT) [10] envision a wide variety of features, starting from the maintenance of healthcare equipment to efficient tracking of patients and health-care providers. Continuing in these directions, it is expected that the future IoHT and IoMT devices will unveil the concept of *connected and smart hospital*, imbued with intelligent communication technologies under the aegis of the next generation wireless technologies.

In this article, we propose a novel IoT-based real-time solution for the contact tracing and monitoring of COVID-19 infection spread. The specific novelty of this approach lies in the use of IoT devices to identify *potentially infected* COVID-19 individuals. More specifically, our major contributions are:

- We propose contact tracing of people based on their handheld IoT devices using a graph theoretic approach applied to wireless networks.
- The information obtained from the IoT devices is merged with a *contact tracing graph*, created by a healthcare server, along with the *infection detection graph*, developed using information about the confirmed COVID-19 cases. This helps in developing an *infection tracing graph*, which provides key insights into how this infection spreads in a community.
- At the heart of this solution is the ability of wearable devices to share vital information about the individuals (such as temperature) with the healthcare server. We propose to do this by establishing device-to-device (D2D) communication links over 5G/4G wireless to share this information with the user's mobile phone, which will then act as a relay to share it with the healthcare server.
- Infection tracing of people in close proximity of individuals with high symptoms, and prompt identification of possible virus carriers aids in fast isolation and quarantining of possible infections. This information is also useful for the decision makers to properly route and dimension scarce resources, such as the COVID-19 testkits.
- Another novelty of our proposed scheme lies in the symbiotic merger of the information about symptoms with the contact and infection detection graphs, which is aided by the IoT network and is in stark contrast to the existing work on contact tracing, such as [11]–[13], which just uses contact and infection information (but not the symptom information).

Given the devastating impact of the pedantic, it is natural that many contact tracing and self assessment mobile applications have already been developed, such as the *Aarogya Setu App*[1] of the Indian Government and the *Self-Check App*[2] of the South Korean Government. It should be noted that different from these existing solutions, our proposed method uses IoT-based wearable devices to notify not only when a person comes in contact with an infected person, but also when a contact is made with a person exhibiting high symptoms. Moreover, if someone has come in contact with infected individuals (or those exhibiting high symptoms), the proposed scheme generates a notification including a probability of getting infected in two cases: whether or not everyone is wearing a mask. Furthermore, compared to both *Arogya Setu App* and *Self-Check App*, our proposed scheme considers symptoms and contact over a relatively longer period of time.

II. Role of IoT in Healthcare

With a general increase in life expectancy and onset of a variety of chronic diseases, the health-care and medical systems are poised for a drastic change in many countries. In order to alleviate the burden on healthcare infrastructure, while simultaneously maintaining affordability, in-home telemedicine systems are quickly gaining importance and popularity. Originally designed for achieving a small set of clinical objectives, today's telemedicine applications require higher sophistication and scalability. Lately, this necessity has spawned *Internet of Medical Things (IoMT)* [10], which fuses the safety and integrity of traditional medical devices with dynamic, scalable and generic features of the IoT. Indeed, rapid technological advances in wireless communications, specifically IoT, are considered as a panacea of the inherent shortcoming in our age-old healthcare systems.

Personalized, proactive, and cost-effective healthcare demands wide deployment and availability of IoT devices in almost all aspects of health management, thereby giving birth to the notion of *Healthcare IoT (HIoT)* [9]. Typically HIoT devices are of two broad types: (1) Personal HIoT devices, such as smart watches, which have already gained significant popularity across a diverse range of consumers in many countries. (2) Clinical HIoT devices, such as glucose monitors, which need explicit intervention and regulation from physicians and health-care professionals. Internet connectivity is enabling the healthcare institutions to explore emerging 5G

[1]https://www.mygov.in/aarogya-setu-app/

[2]http://ncov.mohw.go.kr/en/baroView.do?brdId=11&brdGubun=111

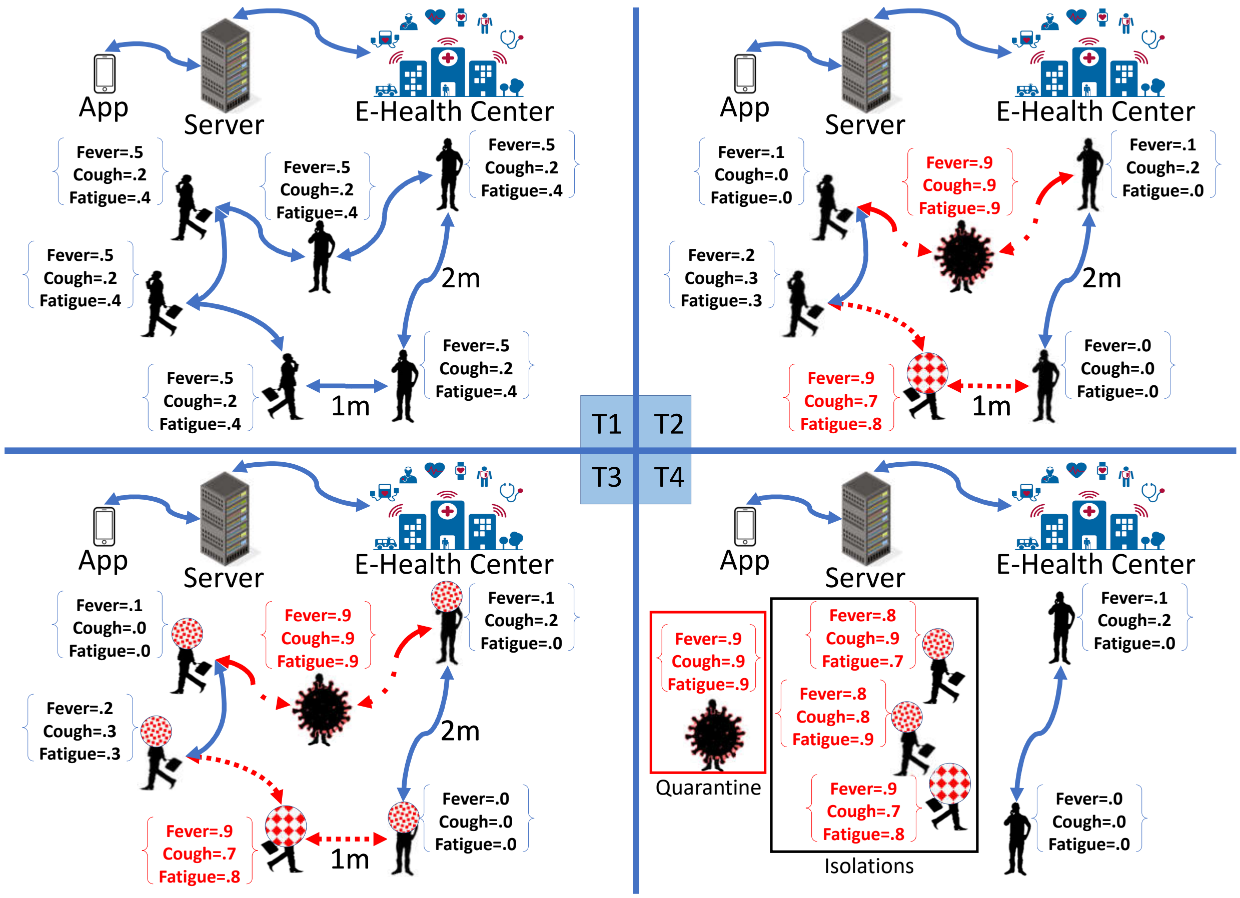

Fig. 1. Contact tracing using IoT and D2D communications.

wireless, cloud technologies, and large-scale data analytics for providing efficient health diagnosis, to provide improved yet affordable healthcare.

Unfortunately, the sudden emergence of the COVID-19 pandemic has disrupted the gradual creation of the HIoT ecosystem by putting unprecedented timelines for finding effective solutions. As stated already, contact and infection tracing is our best bet until effective medical interventions are available on a large scale. Analysis of the existing contact tracing models, e.g., see [13], originally developed for similar epidemics, like Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS), has pointed out the necessity of fast and efficient data collection and closed-loop communication between health administration, researchers, and infected as well as exposed individuals. This necessitates the need for novel solutions that collect almost real-time information about health vitals using IoT devices and merge it with the medical records in order to develop effective infection tracing solutions.

Besides the healthcare system, IoT is also converging with the social networking. The popularity of social networking has invigorated the importance of social awareness in emerging IoT applications and D2D communications, thereby giving birth to the notion of Social IoT (SIoT) and Social D2D (SD2D) networks [14]. The existing social relationships in SIoT mimic the human social networks, where a relationship is used as a sign of reliable connection, e.g., siblings and co-workers. Interestingly, social relationship and communications could also play a significant role in contact tracing, required for the pandemic control, as there is always a higher possibility of contact and proximity of persons belonging to the same social network in a given area (especially the same family or office). Equally importantly, the tools developed to incorporate such relationships in the analysis of wireless networks, such as [14], are useful templates for developing new contact tracing tools as well.

III. Proposed IoT-based Solution

Before we describe our proposed solution in detail, it must be noted that there are many sensors, such as the one in [15], that are being developed specifically for detecting COVID-19. While this would make the pandemic management easier, none of these will be ready for mass deployment any time soon, because of which we will not assume the availability of such sensors in our proposed solution. Instead, we just assume that the IoT devices, such as wearables, are used for monitoring the vital information (such as temperature) of their owners. This information is then sent to a dedicated smart healthcare server used for contact and infection tracing. One way to enable this information transfer is to utilize the user's mobile phone as a D2D-based 4G/5G wireless relay, which collects information from the IoT devices and sends it to the healthcare server. If the

Algorithm 1: IoT-based Contact Tracing Algorithm

Initialize $\mathtt{Dist_{th}}$, $\mathtt{Sm_{th}}$, $\mathtt{Time_{th1}}$, $\mathtt{Time_{th2}}$;
$\mathtt{Dist_{th}}$: Social distancing threshold allowed;
Symptom Flag $\mathtt{SF}$, $\mathtt{Sm_{th}}$: Symptoms threshold;
$\mathtt{Time_{th1}}$: Minimum contact duration for spreading infection from person with high symptom;
$\mathtt{Time_{th2}}$: Minimum contact duration for spreading infection from infected person;
if *distance* $<$ $\mathtt{Dist_{th}}$ *and person is confirmed infected* **then**
    immediate notification for quarantine;
    notify medical authorities;
end
if $\mathtt{SF} > \mathtt{Sm_{th}}$ **then**
    notify symptom carriers;
    self isolation;
end
if *distance* $<$ $\mathtt{Dist_{th}}$ **then**
    for *all persons in proximity* **do**
        if *persons with symptoms* $>$ $\mathtt{Sm_{th}}$ **then**
            if *contact duration* $>$ $\mathtt{Time_{th1}}$ **then**
                Notify infection probability with and without masks;
            end
        end
        if *persons with confirmed infection* **then**
            if *contact duration* $>$ $\mathtt{Time_{th2}}$ **then**
                Notify infection probability with and without masks;
            end
        end
    end
end

hand-held or wearable IoT device is unable to establish a D2D connection with the the mobile phone, it can use any form of capillary communications, like WiFi, Zigbee, Bluetooth, and so on, to establish communication with the mobile phone.

Note that social networking also plays an integral part in such contact tracing, as individuals within the same soci group have a high probability of being in proximity fo longer period of time. Moreover, knowledge of the social re tionships also aids the devices to find other devices belongi to the same owner, thus increasing the possibility of commu cations and contact tracing. On the device level, our propos framework ensures integrity by assuring communication o among the devices of the same owner. However, at network level, the wireless operator as well the server need guarantee the integrity and privacy of all the individuals. Fig highlights the proposed contact tracing and infection detecti framework. The overall system is composed of four differ stages. T1 represents the initial stage of the system. At every individual is checked for (1) symptoms, like fever, cou and fatigue with their corresponding infection rates and individuals with confirmed infection. At this stage, individuals showing high symptoms are identified. At stage T3, individuals exposed to the infected patients or individuals showing high symptoms are identified depending on their proximity. Finally, in stage T4 the infected patients are quarantined and the exposed individuals are isolated. The wearable IoT devices establish fast and efficient communications with the server by exploiting D2D 4G/5G communications or WiFi/Bluetooth, while preserving data integrity. As noted already, the ability of identifying individuals with high symptoms is where the proposed approach significantly diverges from the state-of-the-art contact tracing methods. Algorithm 1 outlines the high-level flow of our IoT-based contact tracing framework.

Our proposed scheme explores an underlying *Contact Tracing graph* $G_1(V_1, E_1)$. Every node in G_1 represents a person with his/her mobile or wearable device, with associated data and two major pieces of information: (1) mobility in the form of geographical location, i.e. (x, y) coordinates over time and (2) dynamics of symptoms over time, using either wearable or handheld devices or medical equipment. On the other hand, every edge in G_1 between two nodes actually represents the human-to-human contact or proximity information between two individuals. The wearable devices will utilize D2D-based 5G or 4G wireless communications to report this information to a centralized server, by using mobile phone or handheld device as the relay node. The centralized server is dedicated to keep track of each node in the network. At time t, the server can estimate and identify which person has been in contact with whom.

Given that a node is identified as a confirmed case, the server can mark and form *Infection Detection graph* $G_2(V_2, E_2)$. The information required for this operation includes (a) Contact Tracing Graph $G_1(V_1, E_1)$ and (b) Confirmed infection detection, either by getting information from hospitals or testing centers. Note that the edges in the *Infection Detection graph* inherit human-to-human contact or proximity information between the two individuals from the Contact Tracing graph G_1. Finally, given that the server has complete information of nodes and current active cases, the potential victims can be identified. One easy approach is to check if at time t a node v_x is within a distance threshold of an infected

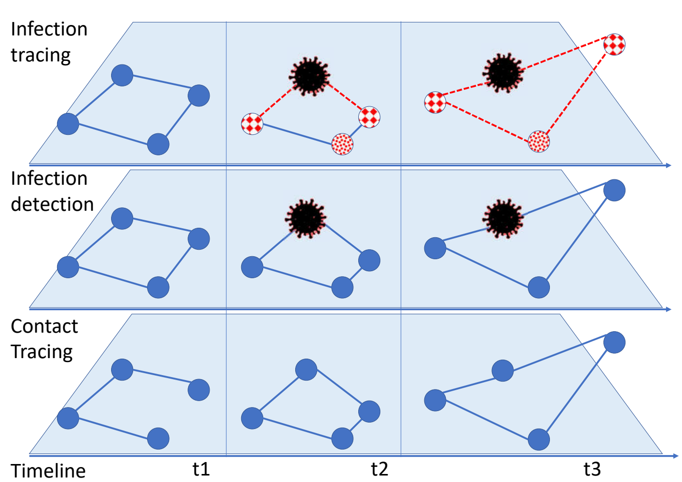

Fig. 2. Graph-based contact tracing model.

(COVID-19 positive) node for a specific duration. This forms the *Infection Tracing graph*, where every infected person is marked or colored based on its disease. Two different colors or patterns could be used: one to mark confirmed COVID-19 cases (black *coronavirus icon* in Fig. 1) and another to identify the *potentially infected* people (*red-white pattern* in Fig. 1). The set of edges now represent traces of infection transmission. It is interesting to investigate the likelihood with which each of these potentially infected people (i.e., nodes marked with the red-white pattern) will have COVID-19. Naturally, key parameters, such as the distance threshold, infection rate, contact duration and symptoms induce dynamics in this solution.

Considering mobility and physical contacts, infection detection and tracing could be periodically updated to represent dynamic connections between users. Random graph models are explored to capture these dynamics, where the probability of proximity between any two users is represented as dynamic appearance and disappearance of the corresponding edges. Such a graph-theoretic model efficiently abstracts continuous histories of users' proximity and contacts. Assuming that the proximity and contacts between any two users at any time instant depend on the corresponding proximity and communications at previous time instances, such a contact tracing graph can be analyzed using a Markov Process of a particular order. The proximity and contacts are updated at specific rates, thus resulting in the appearance and disappearance of edges. While the specific order of the model depends on the set of previous time instances considered, complex, higher-order Markov models generally contain more information than the corresponding lower-order models. As IoT devices are typically low power and the contact tracing calls for fast action, a suitable compromise between model optimization and implementation feasibility needs to be considered.

Using this model, we can analyze the contact tracing graph with varying density and degree distribution. As the rate of change in user-specific contacts (appearance and disappearance of edges in the Contact Tracing graph) is lower than the rate of model observation instances, the consecutive snapshots of the graph will be correlated. For example, there is a strong effect of a user's previous contacts or proximity on the probability of future contacts. Independent analysis using a simple memory-less model at individual time instants often ignores the underlying internal dependencies and fails to capture the rich correlations. Our graph theoretic model gains over most of the existing methods in this respect. Using suitable graph traversal across all the vertices, representing the (potential) infected persons and updating the edges, representing the infection transmission, this model provides an effective way of contact tracing.

IV. Simulation Experiments and Results

We have conducted representative simulation experiments to mimic the COVID-19 virus spread in Python. The simulation generates a population density of 250 to $1,500$ per square km, with each individual having properties, like a global unique identifier, current location, a disease flag (DF), and a symptom flag (SF). The initial positions are generated as per a binomial point process, where a relatively sparse and dense population densities are simulated using 250 and 1500 points per square km, respectively. The simulation area is chosen as 1 square km. Note that, as our interest is in understanding the underlying trends, the absolute values are not of much interest and the simulations could be scaled to a larger population size, with more computational power. $\texttt{DF} \in [0, 1]$ is a binary identification of a person, having COVID-positive status, set by a designated health center. The $\texttt{SF} \in [0, 1]$ is our contribution, which is calculated using a weighted sum of the symptoms. A symptom for a particular person is estimated using smart wearable devices or diagnostics by a health apparatus. We include programmable parameters related to the COVID-19 spread. Considering that a person is exposed to an infected individual, the infection probabilities with and without masks are set to 0.3 and 0.6, respectively. Since our understanding of the infection probabilities is still evolving, these are reasonable choices to study performance trends. Furthermore, the virus does not infect on momentary interaction but requires some time. We programmed the time as 10 time units (equivalently, epochs) to contract the virus by staying in the proximity of an infected person. The absolute time units are again not important because of our interest in the trends. The symptoms are monitored continuously and a warning is triggered if symptoms are higher than a predefined symptoms threshold for more than 60 time units. The simulation also observes each individual's movement and health vitals, using a random-walk mobility model over an area of 1 square km for up to 300 time units. Assuming that a person is at position (x, y) at a given epoch, his/her position is updated at the next epoch by first randomly selecting a direction from 9 possibilities (8 directions and 1 staying at the same position) and then moving him/her in that direction using a random speed between 0 and 10 meters per epoch. The entire simulation is repeated 100 times with different random seeds and the average results are reported. The contact tracing process is triggered in three steps, as mentioned below:

TABLE I
Key Simulation Parameters

Total People	250 – $1,500$
Total Area	1 km^2
Mobility Model	Random Walk
Speed	[1 – 10] meters/time unit
Distance Threshold	5 meters
Symptom Threshold	0.9
COVID Patients	[10 – 20]
Infection probability without mask	0.6
Infection probability with mask	0.3
Contact duration with infected individual	10 time units
Symptoms persistence duration	60 time units

1) *Social distancing violation*: Continuous monitoring of inter-device distances identifies the initial trigger when two or more devices come in close proximity of each other. The immediate detection of distancing violation is followed by further checking.

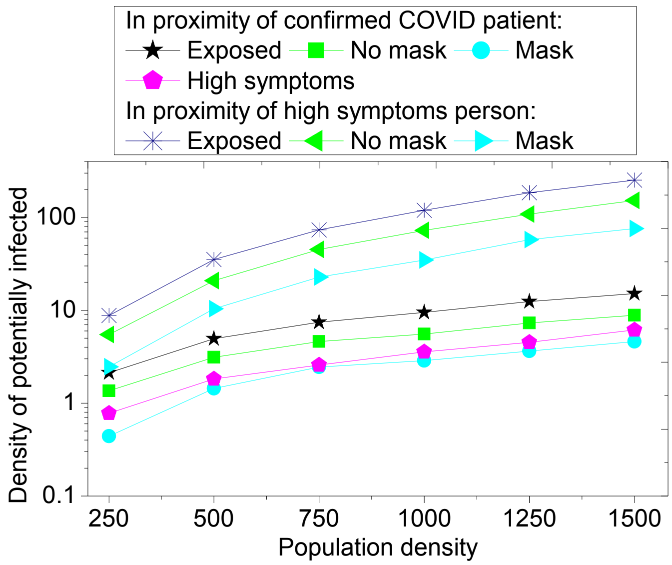

Fig. 3. Infection as a function of population density.

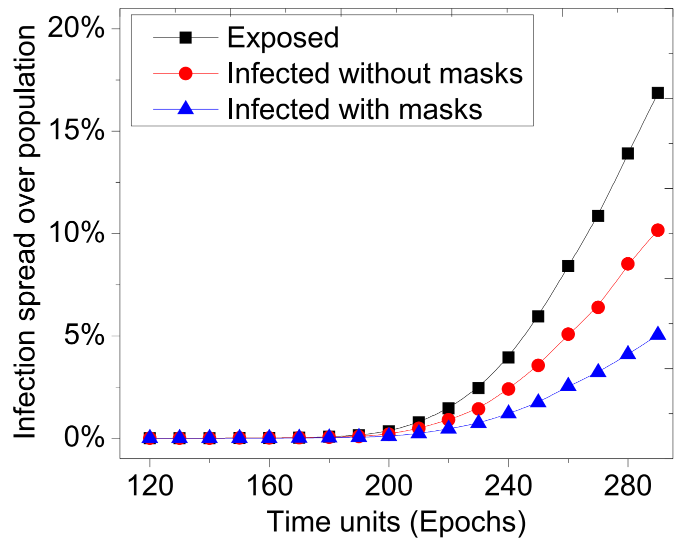

Fig. 4. Illustration of infection spread over time.

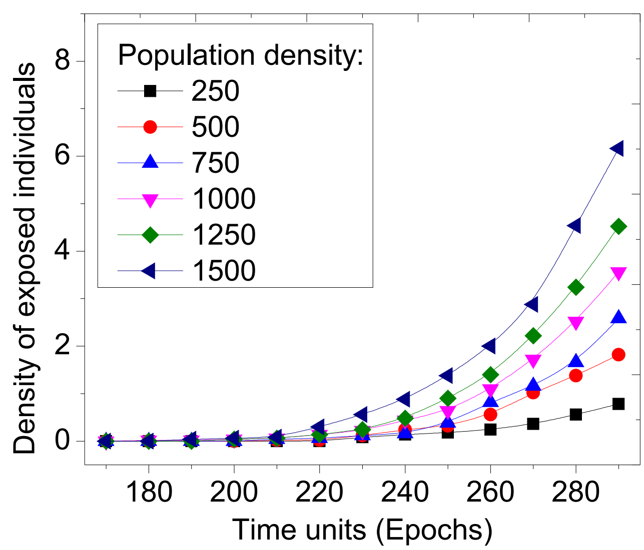

Fig. 5. The density of exposed individuals as a function of time.

2) *Possible disease spread infections*: Given that the devices have been in close proximity, the $\mathtt{DF}$ and $\mathtt{SF}$ are measured to identify potential carriers.
3) *Potential infected cases based on symptoms*: If any device owner has contracted the disease ($\mathtt{DF} = 1$) or has symptoms higher than the threshold ($\mathtt{SF} > \mathtt{Sm_{th}}$), an immediate alert is sent out to the health authorities and the infected individual without disclosing their identity.

We evaluate our solutions using the following metrics:

- (i) Number of people exposed (based on proximity) to a confirmed (infected) COVID-19 patient, (ii) potentially infected individuals in two cases: either everyone is wearing a mask or no one is wearing a mask, and (iii) the number of individuals showing high symptoms after coming in contact with an infected person. We ignore temporal dependence for the development of symptoms because of which the last metric does not truly depend upon whether the masks were used or not. However, this can be generalized by running a more realistic simulation with temporal dependence of symptoms. The trends are, however, expected to remain similar.
- Same as (i) and (ii) above, but now our focus is on counting persons exposed to individuals exhibiting high symptoms (instead of confirmed COVID-19 patients that was the case above).

Fig. 3 demonstrates the dynamics of people exposed to an infected person or a person with high symptoms. The density of people exposed to the infected individual increases with the increase in the number of individuals. Out of all the exposed individuals, assuming everyone is wearing a mask, the density of potentially infected individuals reaches up to three. On the other hand, with no masks, this count reaches to almost five. A different, *albeit* interesting information is an individual having high symptoms after getting exposed to an infected person. This is the set of people having high probability to have contracted the disease. Our framework also considers that a person with high symptoms can also transmit the infection to other exposed persons. The number of exposed people increases beyond 300 (per square km) for a population density of 1500 per square km. Around 100 people (per square km) could be potentially infected even after using masks. Without masks, however, this number increases to more than 200.

Over an observation window of 300 time units, we identify the percentage of potentially exposed and infected people with and without masks, by considering people having high symptoms. Fig. 4 shows that without appropriate intervention, the percentage of infected people increases to as much as 15%. Therefore, it is important to promptly isolate exposed individuals to reduce further spread. In the proposed solution, the IoT-based wearable devices can drastically reduce the disease spread with timely actions. Fig. 5 illustrates that number of individuals exposed to the infected person increases with the increase in the number of people considered in the mobility model. This directly translates to the smart lock downs and reduced outdoor activities. Nevertheless, with the passage of time, the virus spreads if no other interventions are put in place. Our proposed scheme not only identifies and tracks the infected individual but also traces back all exposed individuals to restrict the disease spread.

V. Conclusions and Discussion

The year 2020 will always be remembered as the year of the COVID-19 pandemic. Since every cloud has a silver-lining, this has also presented an almost perfect global use case for the IoT that has the potential of making it the most pervasive technology on the planet. With the COVID-specific sensors years away from mass deployment, current IoT devices, such as wearables, can be used to detect key symptoms of COVID-19, which can then be fused with contact tracing graph and information about confirmed COVID-19 cases to identify the potentially infected individuals. In this paper, we have developed the first framework to achieve this using the presently available IoT technology. The proposed framework facilitates real-time identification of potentially infected individuals, which is absolutely vital at the time when the healthcare infrastructure is reaching its limits even in the most developed countries. Specifically, this information can be used to identify infection clusters, which is useful for the decision makers to properly distribute scarce healthcare resources, such as protective equipment and COVID-19 testkits. This work can be extended in may directions, like incorporating the indoor location information and the privacy and protection of the health data. Moreover, we used simple mobility and symptom evolution models for our simulations to demonstrate the proof-of-concept. However, our framework is general and similar results can be easily obtained for the actual mobility traces and related COVID-19 data, whenever it becomes available. Most importantly, the evaluation of our proposed scheme is currently confined to simulation-based experiments. Therefore, a natural next step is to develop prototypes and refine them into products that could be used on a large scale.

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