Wireless Technologies for Social Distancing in COVID-19 Pandemic

Subjects: Computer Science, Information Systems | Computer Science, Hardware & Architecture | Computer Science, Interdisciplinary Applications
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So-called “social distance” refers to measures that work to prevent disease spread through minimizing human physical contact frequency and intensity, including the closure of public spaces (e.g., schools and offices), avoiding large crowds, and maintaining a safe distance between individuals. Because it reduces the likelihood that an infected person would transmit the illness to a healthy individual, social distance reduces the disease’s progression and impact. During the early stages of a pandemic, social distancing techniques can play a crucial role in decreasing the infection rate and delaying the disease’s peak. Consequently, the load on healthcare systems is reduced, and death rates are reduced. The concept of social distancing may not be as easy as physical distancing, given the rising complexity of viruses and the fast expansion of social interaction and globalization. It encompasses numerous non-pharmaceutical activities or efforts designed to reduce the spread of infectious diseases, including monitoring, detection, and alerting people. Different technologies can assist in maintaining a safe distance (e.g., 1.5 m) between persons in the adopted scenarios. There are a number of wireless and similar technologies that can be used to monitor people and public locations in real-time.

Keywords: COVID-19 ; pandemic ; social distancing ; wireless technologies

1. Introduction

Because of COVID-19, worldwide perceptions of the pandemic disease have been transformed, having clear implications for global health and the economy. Within six months of starting in Wuhan, China (from January to June 2020) [1], a total of 210 nations and worldwide have confirmed more than ten million infected people, including more than five hundred thousand deaths, according to the world health organization (WHO) [2], COVID-19 has caused significant economic losses in addition to the worldwide health catastrophe (e.g., a potential 25% rate of unemployment inside the U.S [3]. In March 2020, one million Canadians lost their jobs [4], 1.4 million jobs were lost in Australia in the year 2020 [5], in addition to an estimated global Gross domestic product GDP loss of 3% [6], an economic downturn, as many experts had expected [6][7][8]. Solutions are urgently needed to stop the spread of the disease, lowering its harmful effects and buying more time for pharmaceutical solution development in such a situation. Severe Acute Respiratory Syndrome (SARS), Influenza A virus subtype (H1N1), and COVID-19 are examples of contagious diseases where social distance can be an efficient non-pharmaceutical way to limiting the spread of disease [9][10][11].

So-called “social distance” refers to measures that work to prevent disease spread through minimizing human physical contact frequency and intensity, including the closure of public spaces (e.g., schools and offices), avoiding large crowds, and maintaining a safe distance between individuals [9][12]. Because it reduces the likelihood that an infected person would transmit the illness to a healthy individual, social distance reduces the disease’s progression and impact. During the early stages of a pandemic, social distancing techniques can play a crucial role in decreasing the infection rate and delaying the disease’s peak. Consequently, the load on healthcare systems is reduced, and death rates are reduced [9][10][11].

It was shown that the effects of social distancing techniques on the number of instances as reported, on a daily basis [13]. It can be seen that social separation can help minimize the highest number of cases [11] not overburden public healthcare resources. In addition, social isolation can help lower the number of affected people in the long run [11].

The earlier social separation is put into place, the more powerful the effects will be [13]. A number of countries have introduced social distancing measures, including travel restrictions during the current COVID-19 outbreak, shutting public areas and making public warnings they should retain a spacing of 1.5–2 m once they walk outside [14][15][16]. Such strong and large-scale initiatives, however, can be difficult or even impossible to undertake, e.g., individuals still need to go outside to get food, health care, or important work because not all public spaces can be blocked. In such context, technologies play a key role in helping social distancing procedures. For example, they work by sensing the distances between people and notifying them when they get too close to each other. Methods of social distancing could be divided into two categories: public and individual. For the public, this means closing or restricting entry to educational institutions and workplaces, cancelling large gatherings of people and placing travel restrictions on them as well as border control and quarantining structures. As far as personal precautions are concerned: isolation, quarantine, and encouraging people to maintain physical boundaries between them [12]. A country's social distancing policy usually takes effect after it has been implemented (e.g., lockdown at diverse stages) for 13–23 days; as observed in the second graph, the daily number of new cases begins to decline as social distancing is enforced (i.e., flattening the curve) [17][18]. Considering the enormous possibility, social distancing is ultimately successful when it is used appropriately. However, as demonstrated in **Figure 1**, it is not an easy task to implement because of several challenges.

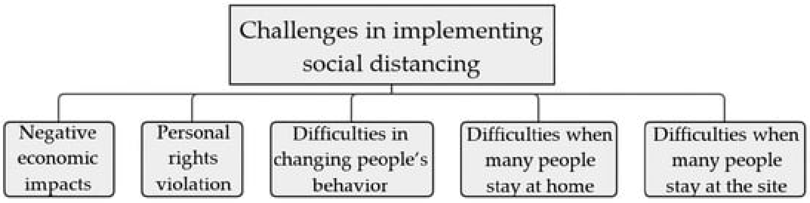

Figure 1. The biggest obstacles to implementing social distancing.

Travel restrictions, border controls, and the closing of public spaces are among the social distancing measures that negatively affect the economy. This could lead to the authorities removing restrictions too soon, e.g., Iran, South Korea, China, Germany have to re-impose limitations after lifting restrictions too early [19][20]. Restrictions like quarantines, cancelling mass meetings, and solitary may contradict cultural and moral precepts, e.g., Iran locked religious amenities throughout lockdown [21]. Aside from that, tracking people's movements and tracing their contacts is essential, e.g., contact tracing in Singapore [22], also violate people's privacy. As a result, people may not adhere to these rules. People find it difficult to cope with social distancing, even when they desire to. There are many challenges, such as determining and keeping a safe distance of 1.5–2 m between people all the time, health care and food must still be obtained from other sources, and working from home is not always feasible (essential workers). Many individuals will be forced to work or study remotely due to the closure of schools and companies, which will result in a massive rise in Internet usage and online service needs, e.g., Zoom users [23] and Microsoft Teams users [24] have increased up to 1270% and 775%, respectively, while there is a lockdown. Some systems may have issues when implementing social distancing strategies in specific contexts. Examples include tiny system capabilities and small space systems designs. Accordingly, many strategies and concepts have been presented in the literature deploying several types of wireless technology in various settings to combat COVID-19 dissemination through social distancing techniques.

2. Wireless Technologies for Social Distancing

2.1. Background

The concept of social distancing may not be as easy as physical distancing, given the rising complexity of viruses and the fast expansion of social interaction and globalization. It encompasses numerous non-pharmaceutical activities or efforts designed to reduce the spread of infectious diseases, including monitoring, detection, and alerting people. Different technologies can assist in maintaining a safe distance (e.g., 1.5 m) between persons in the adopted scenarios. There are a number of wireless and similar technologies that can be used to monitor people and public locations in real-time.

To collect valuable data, such monitoring is necessary (e.g., records of people inside buildings, contacts, symptoms, crowds, and social distancing measures violations) to facilitate social distancing. Technologies like Bluetooth, Ultra-wideband (UWB), Global Navigation Satellite Systems (GNSS), and thermal sensors allow you to track the movement of infected persons, as well as the contacts that they established. They can take precautionary measures if they've been exposed to infected individuals (e.g., self-isolation, limit access, and test for the disease).

Furthermore, technologies such as Wireless Fidelity (WiFi), Radio frequency identification (RFID), and Zonal Intercommunication Global-standard (Zigbee) can be used to schedule access to a specific building. It's possible to acquire pandemic data using the latest technologies. Infected and susceptible people can be predicted based on the data. **Figure 2** shows the applications of technologies to specific social distancing scenarios introduced and discussed in [25][26].

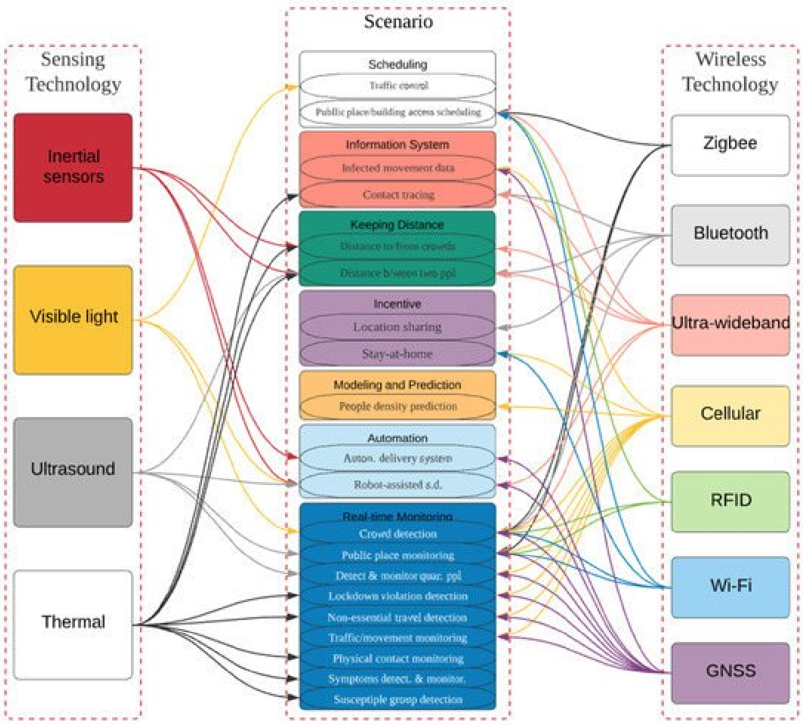

Figure 2. Applications of wireless technologies to different social distancing scenarios.

As shown, some technologies, e.g., Cellular, Global navigation satellite system (GNSS), Artificial intelligence (AI) and Thermal, can be used in various scenarios, while technologies such as Zigbee, RFID, Visible Light (VL) and Ultrasound are appropriate to fewer scenarios. Scenarios that belong to the same group are all the same colour. Same-coloured arrows connect one technology to multiple scenarios. Here, the researchers will discuss the features and characteristics of the models and designs, which consist of deploying various wireless technologies used for making successful social distancing scenarios. The focus will be on issues and challenges in terms of system building/or system functionalities.

2.2. Taxonomy

A taxonomy of relevant articles from the literature is presented in this section for the first time in the social distancing research area. The taxonomy classifies all social distancing studies into many vital categories. The researchers taxonomy consists of vital aspects that are important to review and clarify the details that are required for creation of any sort of social distancing research using wireless technology.

Many types of social distancing scenarios were employed in various situations. Real-time monitoring and keeping distance were the most scenarios used so far, while scheduling and incentive are the least. Specifically, the research [27] temperature and saturation level monitoring using Message Queuing Telemetry Transport (MQTT) was designed. Here covers the use of MQTT to classify patients based on temperature and saturation levels measured.

The study [28] looked at how to interpret body-induced thermal signatures for physical distancing and temperature screening. A statistical model was used for the proposed framework to capture body-induced thermal signatures from noisy data, and a mobility model is used to detect multi-body activities and minimize erroneous target detection. Furthermore, body-induced impacts fade practically exponentially with the range between the Infrared sensors and the person. Whenever the user is in close proximity to the Infrared radiation (IR) sensor array, the temperature is automatically detected. The study presented a stochastic method for thermal indicators that is less susceptible to such flaws. The suggested screening approach is based on a mathematical model and Bayesian decision concept, and it allows the user to navigate during the screening procedure whereas its location is estimated (constantly) by using Bayesian framework. This approach can be used as a general framework for multi-sensor installations and big IR arrays.

An Internet of Things (IoT) solution for social distancing in smart cities relying on multi-sensor was described in [29], and here was to offer an IoT system founded on an IoT, wireless sensor network (WSN), and algorithms (Neural Network (NN), and Shortest Path First (SPF)) that can distinguish warnings, accessible exits, gathering points, safest and shortest routes, and congestion based on real-time data collected by sensors and cameras using computer vision. The IoT system was used to tackle two distinct problems: an urgent scenario and a surveillance situation. Data, both raw and processed, is transmitted to a platform interface for further live monitoring of environmental and architectural factors.

The authors of [30] utilized AI and a mass surveillance system, as well as a Beyond fifth-generation (B5G) framework that takes advantage of the 5G network's low-latency, high operability, to diagnose COVID-19 using chest X-ray or computerized tomography (CT) scan images, and to establish a mass surveillance system to monitor social distancing, mask wearing, and body temperature. A user layer, an edge layer, and a cloud layer form the framework. The COVID-19 detecting approach suggested here could be applied to any contagious diseases. As a result, it will aid in reducing hospital overcrowding, verifying non-COVID-19 patients, and processing critical personal data at the edge to preserve privacy.

Research [31] focused on the assessment of technology-assisted distance estimation for safe aircraft boarding. It proved the normal COVID-19 distance estimation's vulnerability to faults, which could also lead to huge inaccuracies in distance calculation and the impracticability of typical tracking methodologies during passenger boarding/deboarding. It reviewed and assessed the limitations of received signal strength indicator (RSSI)-based distance estimate in difficult circumstances, and it proposed the use of additional signal measures and to optimize technology-assisted social distancing effectiveness. The optimized consideration of passenger groups in the context of a pandemic boarding scenario significantly contribute to a faster process (reduction of boarding time by about 60%) and a reduced transmission risk (reduced by 85%), which reaches the level of boarding times in pre-pandemic scenarios. The associated cabin and the linked position sensing paradigm will be a major enabling technology in this regard. Path-loss (PL) modelling in these circumstances is highly reliant on the propagation environment and must frequently be calculated empirically. The PL exponent is the sole tuning parameter available, and it is very volatile for diverse scenarios and cannot explain propagation processes in different contexts in a universal way.

The study [32] proposed a model for spotting violations of distance. The paper introduced an IoT edge-based solution focused on model transformation and an entire weighted graph for detecting breaches of social distance standards in indoor public settings. The system configuration allows for the capture of the status of individuals in a group based on predetermined distance measurements. The system examines the distances among group members and determines how much the social distancing metric is being violated in a given area. The proposed IoT edge-based architecture of the system is made up of numerous elements, each of which is in charge of accomplishing and administering a variety of duties. Wearable instruments and WSN infrastructure (sensor layer), data handling at edge points (middleware layer), and a cloud graph repository are among the elements (data storage layer). The suggested system includes a notification delivered to an authorized person alerting them of the status of physical distancing measures at a specified moment and recommending when immediate intervention is required. The mathematical basis of the described system is a comprehensive weighted graph model with a limited network capacity made up of groups of persons representing a real-world crowd in an indoor context. Indoor tracing, positioning, localization, and observation systems are a set of networked devices that are used to locate or track items. Individuals inside buildings, train stations, airports, basement garages, and other sites sharing characteristics of systems that identify violations of distance measures are included.

The study [33] featured surveillance and prediction for mass gatherings (MGs) throughout geographic borders. An integrated platform of this type may assist in the early detection of infectious disease risks of global value, as well as offer information into which diseases are more likely to expand into the MG, support with anticipatory monitoring at the MG allow mathematical modelling of infectious illness transmission to and from MGs, simulating the impact of community health actions directed at various local and global stages, serving as a foundation for scientific study and development in MG health, and improve interaction between the scientific sector and stakeholders on a national, international, and worldwide scale. MGs are conceptualized as global-to-local-to-global occurrences since they consist of a reasonably balanced global-to-local convergence followed by a local-to-global separation of people from all over the world.

The study [34] primarily utilized AI for prediction. It processes users' medical data in real time to forecast COVID-19 infection by watching their symptoms, and it promptly sends an emergency alert, medical reports, and major warnings to the user, their guardian, and doctors/experts. It gathers sensitive data from hospitals/quarantine sites via patient IoT devices in order to take the required actions/decisions. Furthermore, it broadcasts a warning message to official health organizations in order to limit the spread of chronic illnesses and take rapid and timely action.

On the other hand, the studies that considered keeping distance have similar factors but different scenarios. Specifically, the study [35] introduced an intelligent wearable device, Suraksha, that may be worn when walking outdoor and will aid sustain social distance. Some exist devices cannot capture motion in all directions; however, the suggested gadget can recognize motion in all directions in 360 o up to 1.5 m. As a result, the user does not have to be concerned about their surroundings at all times. It is a small gadget that is uncomplicated to operate and is constructed using basic electronic parts. The device can also connect to health applications through Bluetooth and allow contact tracing. The effort is motivated by the necessity to develop a gadget that allows people to keep a safe distance from others during the transmission of contagious diseases. The design is tailored towards every individual. The described system is a low-cost, effective, and lightweight means of assisting individuals in maintaining social distance by sensing close movement between individuals and activating an alarm in case of tight proximity.

The research [36], created a system for measuring social distancing in university campuses leveraging microcomputer modules, with mobile hubs provided to students as entry permits. The data gathered by mobile nodes is forwarded to a monitoring center. The node can be worn around the neck with the help of a neck strap. Distances among students are calculated by transmitting and receiving Bluetooth low-energy (BLE) advertising packets between nodes on a regular basis. The findings revealed that using average or median RSSI data, it is conceivable to approximate distances generally, and RSSI varies based on the direction of the person who wears the device, and also the sender-node battery power has no effect on RSSI.

A protocol for physical distancing on another wearable device proposed in [37] named “6Fit-A-Part”. The study focused at on the creation of a wearable gadget that generates an alarm if another sensor of a similar type is identified within a certain distance. It makes use of off-the-shelf UWB wireless technology to estimate distance with others in the area in real time. They created a one-to-all ranging mechanism that can reliably estimate distance to surrounding devices and alert the user if the distance drops below a predefined threshold in a minimal period of time. Whenever physical boundaries occur between devices, the equipment may adapt for human occlusions and eliminate unwanted cautions.

The research [31] conducted an assessment of technology-supported distance gauging approaches in an aircraft cabin setting by means of a radio propagation simulation constructed on a three-dimensional aircraft model. It has revealed the conventional COVID-19 distance estimation’s sensitivity to mistakes, which can lead to massive mistakes in distance calculation and the difficulty of typical tracing methodologies during passenger boarding/deboarding.

The study [38] investigated the feasibility of using indoor localization technology to determine the distance between users in indoor areas. The research also investigated how information about people’s connections obtained can be leveraged at three stages: beforehand, during, and post individuals access a service, as well as several concerns that concretely deal with the real-world deployment of an Indoor Localization System (ILS). A standard design for an ILS with three illustrative use-cases was also proposed. The authors offered a framework for evaluating the functionality of the proposed architecture.

Various kinds of implementation were used in the literature using different tools and settings. On one hand some studies have made their implementation using real experiments such as [27][30][35][36][39][40][41], while some studies have conducted a simulation-based implementations, such as [29][31][32][33][34][42][43][44][45]. On the other hand, few studies made both implementation, simulation based and real experiments, such as [28][37], while the study [38] did not present implementation method.

Some of the systems and techniques in the literature as shown in the taxonomy, require internet access to be fully functional; for example, internet connection is needed when using a web-based indoor navigation system in [41], while using a low-cost portable device to maintain distance as in [35] or using video surveillance for real-time distance estimation in [40] do not need internet access to store or retrieve information for further processing; however, the researchers found the almost equivalent number of studies used both approaches.

Another factor taken into account by the researchers taxonomy is the usage of systems and techniques found in the literature, specifically, some approaches are compulsory to follow at the location and others are not, for instance, when utilizing certain scenarios such as contact tracing in [43], individuals must follow the procedures imposed by the system at the site and take action by interacting with some components included in the system such as smartphone, while in [45] using machine learning for COVID-19 cases prediction, it is not compulsory for people to take action or to be a functional part of the system components.

Location of the existing systems is another important factor, whereas some studies considered the indoor area while others focused on outdoor. Utilizing social distancing systems inside buildings and in close areas found to be easier and more controllable, and more important than outdoor social distancing approaches because it is harder to minimize physical contact and monitor in confined areas and small size rooms such as aircraft cabins. The study [35] proposed solution makes use of passive infrared sensor (PIR sensor) sensors which detects humans and animal bodies and not arbitrary objects, the proposed wearable device is more suitable for outdoor area, and the study [41] presented an efficient and cost-effective indoor navigation system for driving people inside large smart buildings to preserve distance among people, whereas the study [40] presented a simple real-time method for distance estimation with any kind of camera between people applicable either in close quarters or open spaces. On the other hand, it is hard to determine the suitability of location for some studies.

It is worth notice that smartphones are essential for some approaches such as contact tracing, Bluetooth-based and WiFi-based systems, while others do not require users to have a smartphone such as temperature screening or distance monitoring using a thermal camera. The most important factor in the researchers taxonomy is the type technology used by previous studies, including sensing components, wireless components, and other components. Various wireless and other technologies have been used in the previous social distancing systems and scenarios; however, some systems consist of using specific technology as the main component, for example, using IR to detect the distance between two people, while others use additional wireless technology as a secondary component as supplementary for other functions included in the system such as for uploading data for backup. For wireless and sensing technologies, the most technologies were used in the literature are WiFi and Bluetooth, authors [42] used WiFi as main component in their study, whereas other studies have used the WiFi technology as secondary component for their proposed system, such as [35][36]. The Bluetooth technology has taken a significant role in many studies as main component such as the indoor navigation system in [41]. Moreover, only few studies have considered the use of other technologies as main component in their systems, such as UWB, RFID, Cellular, thermal and IR. In addition, for other types of technologies such as Cloud, IoT and video surveillance, were the most used in the literature, followed by Machine learning and Artificial intelligence, and finally indoor navigation was considered by one study. All the abovementioned factors and studies are summarized in the taxonomy as shown in **Figure 3**.

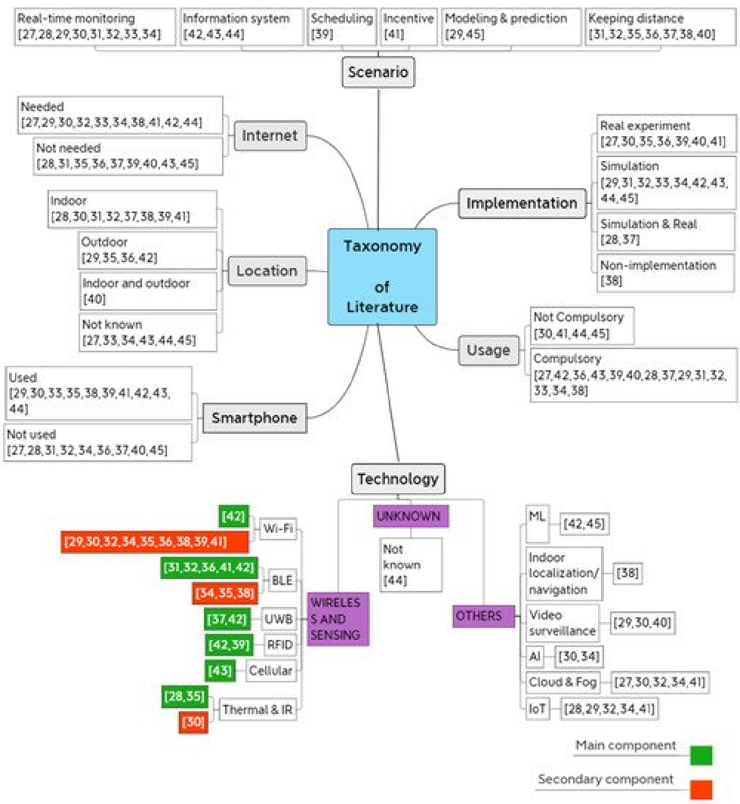

Figure 3. Taxonomy of literature.

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