Contactless Smart Screening in Nursing Homes: an IoT-enabled solution for the COVID-19 era

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***Abstract*—In the COVID-19 era, the provision of health indicators seamlessly and without contact, in groups at risk such as the elderly, is crucial due to the fast spread of the disease and the need to act quickly to contain its evolution. Continuous monitoring of vital signs, such as body temperature and cardio-respiratory rates, can be vital in early detection and prediction of COVID-19, which rapidly progresses and particularly affects the elderly population in nursing homes. Conventional clinical methods used for monitoring vital signs are contact-based, require contact sensors that need to be precisely attached by a trained health professional, are less convenient for repeatable measurements, and not practical for long-term monitoring. On the other hand, contactless vital signs monitoring using radar-based techniques, or IR-thermal imaging, do not require the attachment of physical electrodes and can be of great value in health screening of patients and help health professionals in early detection of the COVID-19 in the elderly population, in the specific context of nursing houses. This work describes the design and specification of a low-cost contactless health screening system for nursing homes, and includes the design of an IoT Edge device that can be placed above the beds where patients rest, allowing the continuous acquisition of health information and its processing without any type of contact and invasiveness.**

***Index Terms*—COVID-19, screening, vital signs, Doppler radar, teletermography, IR imaging, IoT**

I. Introduction

In the context of a pandemic situation such as the one we are currently experiencing with COVID-19, the need for continuous, accurate, and real-time monitoring of the health conditions in groups at risk, such as the elderly, is crucial, due to the fast spread of the disease and the need to act quickly to contain its evolution. COVID-19, specifically, has two characteristics that make it difficult to control: 1) the first symptoms appear on average 5-6 days after the onset of the infection and 2) most infected people remain asymptomatic or have mild symptoms. These two characteristics together, contribute to the fast spread of the COVID-19 disease, making it difficult to monitor and control its progression in the active population. However, the effective screening of suspected cases and their prior isolation have been used with success to reduce the number of infections.

In Portugal, recent data has shown that the impact of COVID-19 in the elderly population (70+) has a higher lethality rate, between 10% to 20% [1]. Another relevant indicator is the ratio of deaths of citizens with 70+ years old when compared with the total number of deaths, which, taking into account data from the Portuguese Health Authorities Daily Report of 11/5/2020 [2], results in a ratio of 87% of the deaths in Portugal correspond to citizens with 70+ years old. In addition, continuous monitoring of vital signs, such as body temperature and cardio-respiratory rates, can be of great importance in early detection and prediction of COVID-19, which rapidly progress and particularly affect the elderly. Conventional clinical methods used for monitoring vital signs require contact-based sensors that need to be precisely attached by a healthcare professional. Nevertheless, contact-based sensors are less convenient for repeatable measurements and not practical for long-term monitoring. On the other hand, contactless vital signs monitoring using radar-based techniques or teletermography-based systems do not require any type of physical attachment, which eliminates the possibility of skin irritation and not constraining the movement of the patient [3]. Moreover, the use of contactless health screening is of great value for the elderly population in the specific context of nursing houses, because it removes the need of using wires, being more comfortable and less invasive for the patients.

This paper describes the design and specification of a low-cost contactless IoT edge device for real-time vital signs monitoring (cardio-respiratory rates and body temperature) using a multimodal approach based on state-of-the-art Doppler radar techniques and IR thermal imaging. The proposed architecture includes an IoT Edge device that can be placed in nursing homes, above the beds where patients rest, allowing the continuous acquisition of health information and its processing without any type of contact and invasiveness.

II. Vital Signs Monitoring

Vital signs, including body temperature, heart rate, respiratory rate, and blood pressure, are of extreme importance to the early detection of clinical deterioration of patients, predicting the need for treatment, and monitoring clinical course. Moreover, several studies indicate that either, poor vital signs monitoring or, not acting on-time to abnormal vital signs detection, has been implicated in many preventable deaths worldwide [4]. Further, Brekke et al. refer that the importance of vital signs is not limited to their values. Vital

TABLE I
VITAL SIGNAL ELECTRICAL CHARACTERISTICS. ADAPTED FROM [10] AND [11].

Vital sign	Measurement range	Frequency range (Hz)	Sampling rate (Hz)	Resolution (bits)
Temperature	36.5°C to 37.3°C, average 37°C	0...0.1-1	0.2-2	12
Respiratory Rate	12 to 18 breaths per minute	0.1...10	20	12
Heart Rate	60 to 100 beats per minute	0.4...5	10	12

signs trends increase the probability of detection of early clinical deterioration [5].

The novel COVID-19 global pandemic increases the need for remote vital signs monitoring at home or nursing homes to improve early detection of COVID-19 positive patients. In this context, our proposal will assist healthcare professionals in detecting abnormal vital signs values or trends in the elderly.

A. *What to measure and why?*

The signs and symptoms experienced by patients with COVID-19 are vast and depend on the severity of the disease. Several studies have shown that, in most cases, initial symptoms include fever, cough, dyspnea, and diarrhea [6] [7]. Besides, an elevated respiratory rate could be an important indicator of respiratory dysfunction and be a prognostic associated with poor outcomes [8] [9]. Based on this evidence, we consider paramount to monitor the patients' body temperature and respiratory rate to support health care professionals screening patients for COVID-19 disease. Additionally, a recent review, [6], including 16 studies and 7706 participants point out the need to investigate the role of heart rate on the COVID-19 diagnoses, therefore, since the technology that is being addressed allows its measure, we decide to include the heart rate.

B. *Vital signs characterization*

Vital signs are objective measures of a patient's physiologic functions, providing relevant information to the early diagnosis of COVID-19 disease. Therefore, vital signs screening to detect abnormalities or suspicious trends is a relevant tool to help the healthcare team to decide about the need for further evaluation of potential COVID-19 positive patients.

We propose to monitor the body temperature, the respiratory rate, and the heart rate to detect values outside the normal range or a consistent trend that could result in out-of-range values, according to Table I.

C. *Conventional vs. Contactless Approaches*

Typical vital signs monitoring systems are contact-based, requiring the use of several contact sensors and wires to connect them to the monitoring devices. Moreover, such sensors need to be carefully attached to the patient's body by qualified healthcare professionals. Therefore, the use of contact-based vital signs monitoring systems requires close person-to-person contact. Hence, regarding the actual COVID-19 pandemic scenario, the use of such devices is not suitable for long-term use in the context of residential care for the elderly.

Unlike the previously mentioned contact-based vital signs monitoring systems, the use of contactless sensors to detect vital signs does not require person-to-person contact, neither the use of on-body sensors or wires attached to the patient. Therefore, these characteristics make these systems ideal for vital signs monitoring in nursing homes regarding the actual pandemic scenario. Our approach involves the use of different contactless technologies to detect vital signs, namely, a thermal camera to detect body temperature and a radar to detect respiratory and heart rates.

The healthcare community regularly uses thermal cameras to detect patients' body temperature in hospitals and other scenarios. Moreover, this technology has proven its utility in the context of previous pandemics, such as H1N1 and Ebola. Indeed, based on previous experience, it's clear that thermal cameras can be a great asset in the context of the actual COVID-19 pandemic [12].

Regarding the use of radar technologies, it has been successfully used for years to monitor heart and respiratory rates. According to [12], radar technology can achieve 80% accuracy for heart rate detection and 94% accuracy for the detection of respiratory rate. Moreover, radar technologies can be used not only to monitor the respiratory rate but also to detect abnormal respiratory patterns, including tachypnea (i.e., a medical condition that occurs when the respiratory rate exceeds the normal range, cf. Table I), a symptom present in many COVID-19 patients.

III. TECHNOLOGIES FOR CONTACTLESS VITAL SIGNS MONITORING

Conventional clinical methods for detecting vital signs require the use of contact-based sensors, which may not be practical for long-term monitoring and less convenient for repeatable measurements. Moreover, they require precise and *in-situ* attachment that need to be performed by a trained healthcare professional, not guaranteeing the recommended social distance, and increasing the risk of spreading COVID-19 among the at-risk elderly population. In the next subsections are introduced the techniques adopted in this work for contactless vital signs monitoring, namely radar-based approaches and teletermography-based systems.

A. *Radar-based Approaches*

A Doppler radar working in the microwave band or even in the millimeter-wave band, can be implemented in a small sized board containing both transmission and reception circuitry and the processing unit used to extract the vital signs from the radar signals. This type of radar allows, in a discreet way, to send an electromagnetic pulse towards the patient's chest, regardless of whether or not he has any protection in terms of clothing. Upon reaching the rib cage, the same signal is reflected and modulated in phase due to the movement induced by breathing. The signal is also affected by the heartbeat that induces micro-Doppler in the reflected signal. The signal received by the radar thus contains information that will allow assessing the patient's condition, not only by estimating the state of his breathing but also by sending real-time indications of the possible change in the breathing pattern, thus making it possible to follow the evolution of the disease.

The most common radar architectures used to achieve this goal are based on continuous wave (CW) Doppler radars [13] [14] or frequency modulated continuous wave (FMCW) radars [15] [16]. The CW Doppler radars are simpler and have lower power requirements. However, this type of sensor is only able to detect relative displacements. In contrast, the FMCW radars have more complex architecture and have higher power requirements, but are able to simultaneously detect the absolute displacement. This can be important in the present application to discard interfering echoes from other movements besides the ones coming from the subject of interest. Table II summarizes the advantages and disadvantages of each of the types of radar.

TABLE II
COMPARISON BETWEEN CW AND FMCW RADARS.

Parameter	CW	FMCW
Architecture	Simple	Complex
Power consumption	Low	High
Phase detection	Yes	Yes
Range detection	No	Yes

The methods typically used to detect the heartbeat and chest movements depend, in one way or another, on the phase shift of the echoed signal, relatively to the transmitted one. Therefore, a higher operating frequency leads to higher sensitivity. On the other way, the signal attenuation along the path also increases with the signal frequency.

Table III lists some commercial available radar boards/Evaluation Modules (EVM) which may serve the purpose of detecting heartbeat and chest movements. Besides the system price, other important parameters are the operating frequency, radar architecture (CW/FMCW) and development tools.

A good compromise regarding characteristics and price are the Texas AWR1443B and Texas AWR1642B which have FMCW architecture and are able to show high sensitivity due to the operating frequency interval. Moreover, FMCW permits simultaneous detection of absolute displacements which, as previously mentioned, allows discarding interfering echoes coming from other targets besides the subject of interest. Additionally, these evaluation modules contain everything required for fast solution development being supported by Texas mmWave Studio and mmWave software development kit.

B. *Teletermography for Adjunctive Diagnostic Screening*

Telethermography (TT) is a technique that uses an infrared camera to capture infrared or caloric energy from a distant object to generate video images, without any contact [17]. The resulting image has a correspondent thermal (infrared) relation of the source that radiates heat. TT is therefore a contactless technique that allows to overcome the limitations of traditional thermometric methods, such as thermometers, thermocouples, and thermistors. A major advantage of using this technique is that it enables the visualization of thermal gradients on the skin surface under observation, and to check their modifications over time [18].

Methods based on TT are able to determine surface skin temperature, which can then be used for initial temperature assessment at a reference body site (e.g., oral, tympanic membrane) [19]. There are two major advantages of using TT systems for temperature diagnostic screening: i) the technique is contact-less, i.e. no wires and no touch is needed; and ii) can be used in high throughput areas, such as airports, warehouses, and factories, where other temperature assessment methods have shown to be unreliable.

Recently, due to the COVID-19 pandemic, several governamental organisms, notably US FDA, is helping to promote the availability of TT systems by taking a risk-based approach and clarifying the policies that FDA intends to apply to TT systems during the COVID-19 pandemic.

TABLE III
CHARACTERISTICS OF COMMERCIAL RADAR EVALUATION BOARDS.

Board Name	Frequency Band [GHz]	Radar Architecture	Price
AWR1443BOOST	76 - 81	FMCW	$299
AWR1642BOOST	76 - 81	FMCW	$299
AWR6843ISK	60 - 64	FMCW	$149
OPS241-A	24 - 24.25	CW	$169
OPS241-B	24 - 24.25	FMCW	$169
EV-TINYRAD24G	24 - 24.25	FMCW	$1800
EV-ADF5902SDIZ	24	FMCW	$500
POSITION2GO	24 - 24.25	FMCW	$286

The most common symptom of COVID-19 is fever typically appearing 2-14 days after exposure [20]. The use of TT systems as an adjunctive diagnostic tool to assist caregivers and health professionals in the detection of elevated body temperature, which may indicate the presence of fever, can effectively reduce the physical contact between the elderly and the health professionals. Moreover, there is available scientific literature that supports the use of TT systems for adjunctive diagnostic screening [20] in the context of initial human temperature assessment for fever triage during the COVID-19 pandemic. For clarification, in april 2020, FDA classified TT systems into [19]:

- **General purpose**: not intended for medical purposes, and normally used in construction and other industrial applications;
- **Medical purpose**: specifically designed for medical purposes, such as measurement of the self-emanating infrared radiation that reveals the relative temperature variations of the surface of the body.
- **Adjunctive Diagnostic Screening**: designed to provide an initial body temperature measurement for triage use, that in a case of elevated body temperature confirmed, a secondary evaluation method (e.g., non-contact infrared thermometer (NCIT) or clinical grade contact thermometer) must be used for clinical diagnosis.

In the context of this work we will focus on TT systems intended for Adjunctive Diagnostic Screening, which means that we are pursuing the goal of designing tools that will provide an initial body temperature estimate that is not intended to replace the conventional methods (e.g., non-contact infrared thermometer (NCIT) or clinical grade contact thermometer), normally used for clinical diagnosis. In the context of nursing homes, what is of great value in using TT systems to continuously monitor the body temperature of the elderly, is the consequent reduction of the physical contact between the elderly and the health professionals, and, the reduction of the coexistence of both in the same physical space, which, as a consequence, results in the overall reduction of the likelihood of COVID-19 infections inside the nursing home.

In 2020, due to the COVID-19 pandemic, efforts have been made by the scientific community to put forward effective health screening systems based on thermal imaging. In [21], Jiang et al. present a portable health screening device for detecting respiratory infections. The proposed system uses a commercial thermal image camera (FLIR one) and a smartphone to obtain a thermal imaging video of human faces that are then used to extract relevant health indicators (body temperature and respiration state). These indicators are then used by an health assessment module to obtain the screening result. Preliminary experiments have shown that the system can offer an accurate screening result within 15 seconds. Other example is the work presented in [22], were a combination of low-cost thermal sensors are used to implement an array of sensors that give better coverage for wide area monitoring, shape detection and object tracking. The IR thermal sensors used are based on the AMG8833 chipset and the adopted computational platform is the Raspberry Pi. In [23], Farady et al. present a head temperature assessment and mask classification method based in a real-time deep learning model. They use a deep learning object detection method to create a mask position and head temperature detector using a popular one-stage object detection. An RGB camera and a thermal imaging camera are used to generate the input images used by the deep learning model. The system outputs information about head temperature and assesses whether the mask is correctly positioned. The tested model is light and achieves a confidence level of approximately 80%.

Table IV presents a comparative analysis of low-cost IR sensor arrays based on the following criteria: resolution, field of view, accuracy, refresh rate, and price. Resolution is related with the image size measured in pixels, i.e. the acquired data points that will be used for thermal measurement. The field of view defines the area that the sensor responds with higher sensitivity at a given moment, being determined by the combination of the IR detector size, lens, and the distance to the radiating object. This means that, for a given field of view, if more data points are provided, a higher visual resolution is obtained and smaller details can be identified

TABLE IV
LOW-COST IR SENSOR ARRAYS COMPARATIVE ANALYSIS

Chipset	Resolution	Field of View	Accuracy	Refresh Rate	DevKit	Price
AMG8833	8x8 pixels	60º	±2.5ºC	0.5∼10 Hz	Sparkfun Adafruit	\$41 \$45
MLX90640	32x24 pixels	55º / 110º	±1ºC	0.5∼64Hz	Grove Sparkfun Waveshare	\$39 \$70 \$175
FLIR Lepton 3.5	160x120 pixels	57º	±0.05ºC	8.7 Hz	Sparkfun Groupgets	\$239 \$288

in the thermal image, resulting in a more accurately measured temperature. The accuracy criterion is relevant for comparison with the *clinical accuracy*, whose maximum permissible error shall not exceed +0.2ºC when operating in the interval 35.5ºC to 42ºC [24]. Finally, the refresh rate is the rate at which the IR sensor generates images, not being, in this work, a priority criterion for component selection.

IV. Conceptual Architecture

Figure 1 illustrates the proposed architecture which includes: 1) IoT Edges deployed in nursing homes; 2) Cloud AI Engine with Context Broker and Storage; and 3) Client Apps. The system automatically generates health indicators that can be used for patient screening. These health indicators do not intend to substitute a clinical diagnosis, but instead, to assist caregivers and health professionals in their work, operating as an adjunctive screening tool, that may be of great value for COVID-19 early symptoms detection. Complementarily, and in order to assess the Indoor Air Quality (IAQ) in the nursing home, several indoor environmental parameters will be acquired by the IoT Edge device, namely air temperature and relative humidity, CO_2, Volatile Organic Compounds (VOC) and Particle Matter (PM). These parameters were selected due to its known relationship with allergic and respiratory pathologies. For example, CO_2 is known to cause respiratory problems, eye irritation, flu and allergic rhinitis [25]; VOC is known to affect the nervous system, cause headaches, liver problems and lack of memory [26]; and PM2.5/PM10 are known to be responsible for breathing problems, such as asthma and bronchitis [27].

In the proposed architecture, for each bed, an IoT Edge device is installed in a position that is in line-of-sight with the chest of the patient. This way, real-time contactless health screening can be performed locally at a specific room in the nursing home. The collected signals (body temperature, cardio-respiratory rate and IAQ parameters), are then transmitted through a backhaul network (Wi-Fi/4G) to a context broker that dispatches the data, based on its relevance, to an intelligence layer — to search for specific patterns that may be related with symptoms associated with COVID-19 — and to a context provider that contextualizes the data before storage.

A. IoT Edge Specification

Figure 2 depicts the IoT Edge architecture specification. The computational system selected for the IoT Edge is a Raspberry Pi 4 Model B, which has a 1.5 GHz 64-bit quad core ARM Cortex-A72 processor, an on-board 802.11ac Wi-Fi, Bluetooth 5, gigabit Ethernet connectivity and four USB ports. The choice of this computational system allows, in the development phase, a faster integration of all elements, e.g. sensor interfacing, edge processing and backhaul communications. In addition, since low-power is not a mandatory requirement in the IoT Edge design, in this proof of concept, energy will be ensured by the power grid.

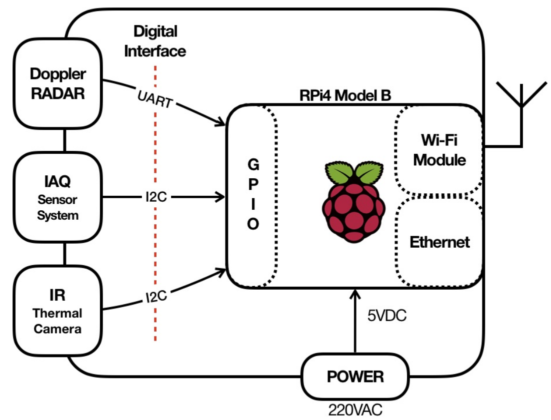

Fig. 2. IoT Edge Device Specification.

Regarding the Doppler Radar, we opted to evaluate two models AWR1442B and AWR1443B. For this, we considered the evaluation boards provided by Texas Instruments,

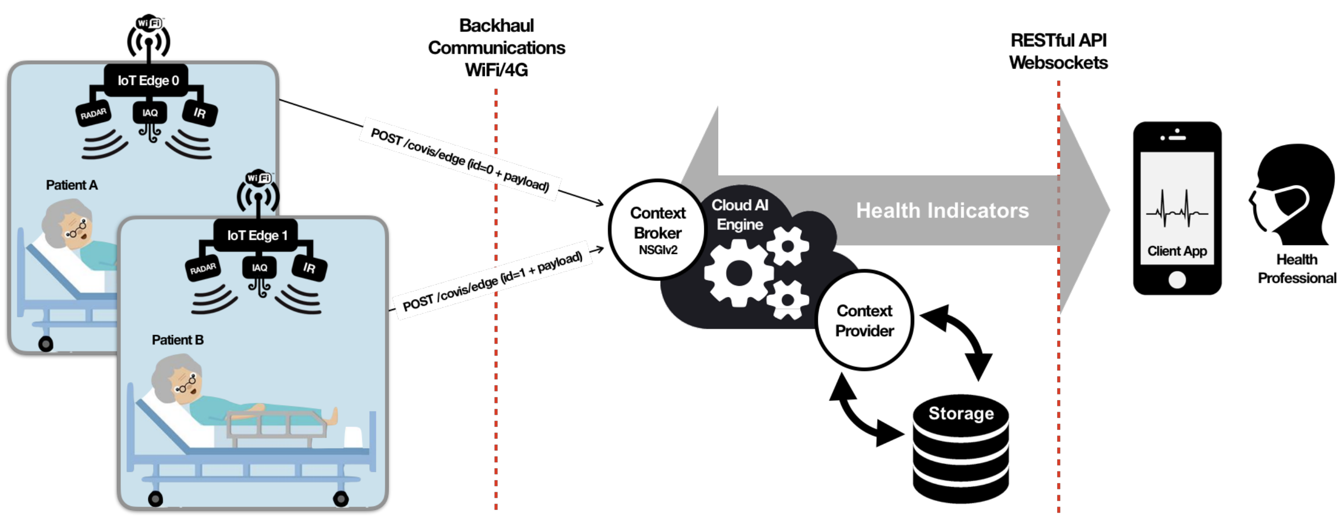

Fig. 1. System Architecture: 1) IoT Edges deployed in nursing homes; 2) Cloud AI Engine with Context Broker and Storage; 3) Client Apps.

cf. Table III, having both an FMCW architecture and an high sensitivity due to the operating frequency interval in the band 76 - 81 GHz. The interface with the RPi is guaranteed by a serial UART that is used to transmit an ASCII encoded message with both cardio and respiratory rates.

The IAQ sensor system includes a low-cost DHT22 sensor to measure the relative humidity and temperature of indoor air, that interfaces with the RPi through a 1-wire interface [28]. Additionally, a SGP30 gas sensor is included to detect a wide variety of volatile organic compounds (TVOCs) and the carbon dioxide equivalent (eCO_2), an indirect measure, that although not highly accurate, after calibration turns out to be a very reliable estimate that allows to effectively infer the CO_2 trend on a budget. The SGP30 interfaces with the RPi throught I2C interface [29]. To measure particle matter we used the SPS30 optical sensor that can interface with the RPi throught I2C or UART [30].

Regarding the Thermal Camera selection, at this stage, we opted to evaluate two models, the Melexis MLX90640 IR sensor and the FLIR Lepton 3.5 thermal camera. For this, we considered the evaluation boards presented in Table IV, both provided by Sparkfun.

B. Cloud AI Engine

The cloud engine must be able to collect data from several IoT devices, in a secure and efficient way. Since the number of IoT Edge devices is unknown, the data collect and storage technologies must allow scalability and robustness to be able to process large amounts of IoT devices. One approach would be to develop a custom API capable of handling the incoming data and computing the health indicators. However, this would restrict the cloud engine to those specific IoT Edge devices and would imply major changes in the API when other IoT device types would be added to the system. Furthermore, the effort required to develop a cloud system from scratch would be too high and costly, making its implementation unfeasible in the time available. Taking these factors into consideration, we opted to use some components of FIWARE, an open source platform to accelerate the development of smart applications, as our cloud engine.

This approach allows to add versatility and integrability of the IoT Edge devices to other contexts and also use the cloud engine to integrate other standardized devices.

The Context Broker centralizes and provides context to data coming from different sources. Additionally, it allows modeling and gaining access to context information in a way that is independent of the source of that information. By keeping the information centralized and organized, external entities can collect, process and display the information without needing to directly interact with data sources.

In this application, we need to perform health screening of patients in beds (that can be identified by specific geographical coordinates), after measuring their vital signs, each IoT Edge device generates a specific data payload for each patient/edge. The way in which the vital signs of a given patient are obtained may vary, depending on the IoT Edge device usage. Thus, vital signs of a given patient may be measured through an IoT Edge device deployed above the bed of a room in a nursing home, while in another situation they may be obtained through authenticated users, such as health professionals, that can manually perform the screening using standard methods and report them using their smartphone or tablet. Moreover, by using a Context Broker, the client application will be able to query the health condition of a patient associated with a specific IoT Edge device or subscribe to changes in its patterns.

C. Client App

The client application will be based on responsive web technologies that will include spatial context inside the nursing home, i.e. floor > room > bed. Visual analytics tools will also be provided to health professionals through Grafana, an open-source software that provides a powerful interface for metric display and time-series data analysis and exploration.

V. Discussion

The proposed architecture includes the design of an IoT Edge device that can perform real-time health screening, in nursing homes, without any type of contact and invasiveness. However, there are some challenges that must be addressed in order to obtain a set of reliable measurements. In relation to the radar, three main drawbacks have been identified: 1) the maximum line-of-sight working distance from the radar to the subject chest must be evaluated; 2) the frequency band in use impacts the radar sensitivity; and 3) multipath and fading effects may negatively impact the cardio-respiratory rate detection accuracy. Given this, it is crucial to design an experimental procedure to evaluate the cardio-respiratory rate obtained using the radar-based techniques. This way, it will be possible to evaluate in a controlled environment the impact of the problems identified before and to compare its performance with reference instruments, e.g. BIOPAC BSLBSC-W and SS5LB for cardio and respiratory rates evaluation, respectively.

With respect to the teletermography component, a careful evaluation should be implemented in order to guarantee the effectiveness of the proposed solution. Problems such as the patient's position in relation to the thermal sensor must be analyzed with caution, and a procedure must be devised to validate the results obtained, always in comparison with a reference instrument, such as the FLIR E54-EST a handheld thermal camera used for non-contact screening. In our specific case, we will explore the usage of low-cost thermal sensors to obtain relative measurements of the body temperature, i.e. the short-term tendency, to assess elevated or diminished body temperatures, which may indicate a change in the health condition of the patient, not being intended to replace conventional diagnostic methods used by caregivers and health professionals.

VI. Conclusion and Future Work

In this work we present the architecture and specification of a low-cost real-time contactless health screening system for nursing homes that is of great value in the COVID-19 era. The proposed architecture includes the specification of an IoT Edge device that can be placed in nursing homes, above the beds where patients rest, allowing the continuous acquisition of health information and its processing to obtain health indicators, without any type of contact and invasiveness.

Next steps include the development of the testbed with all building blocks that will be used as a basis for experimental validation. The testbed will include the development of the Edge IoT prototype and the cloud engine that will be validated with users a real scenario. The experiments that will be held during the testbed validation process will be carried out with a set of users in a controlled environment by comparison of all measured variables with reference measurement instruments.

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