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Medical Digital Twins for Elderly Care: Human-Centered Technologies for Continuous Health Monitoring

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Abstract—The healthcare sector is experiencing a profound transformation, fueled by the rapid evolution of sixth-generation (6G) cellular networks and Internet of Things (IoT) technologies. At the heart of this shift lies the concept of medical digital twins (MDTs), which serve as dynamic virtual representations of physical systems or biological processes. MDTs offer a secure environment to simulate and evaluate therapeutic strategies, leading to reduced costs and more informed clinical decision-making. They also enable real-time support and in-depth data analysis, setting new standards for patient care. Nonetheless, realizing the full capabilities of MDTs remains challenging due to the inherent complexity of human life cycles. Crucial aspects include selecting appropriate data sources and defining robust communication protocols between the physical and digital realms. In particular, integrating wearable technologies with edge computing and WiFi-based Channel State Information (CSI) can significantly enhance health monitoring and activity recognition for elderly individuals within indoor settings. The synergy of IoT advancements and 6G networks paves the way for improved data exchange and continuous synchronization between digital and physical counterparts. This paper, part of the HIPPOCRATES project, presents an IoT-driven architecture for MDTs that incorporates wearable sensors and CSI data to strengthen health monitoring and early intervention strategies, with a focus on elderly care.

Index Terms—Digital twin, IoT, CSI, Edge Computing, Elderly care, Assistive technology.

I. INTRODUCTION

Advanced technologies, including the Internet of Things (IoT), Cyber-Physical Systems (CPS), Digital Twin (DT), and Artificial Intelligence (AI), are transforming healthcare by facilitating real-time health data monitoring and analysis [1]. Leveraging this technological trend, the Medical Digital Twin (MDT) emerges as an innovative model, offering an in silico representation of a person's body, dynamically mirroring their molecular, physiological, emotional, and psychological states alongside lifestyle changes, thus heralding major improvements in personalized healthcare [2]. Fig. 1 shows some possible applications of MDTs with an emphasis on targeting elderly people. Although MDTs hold promise for personalized services, they encounter major challenges. These include the

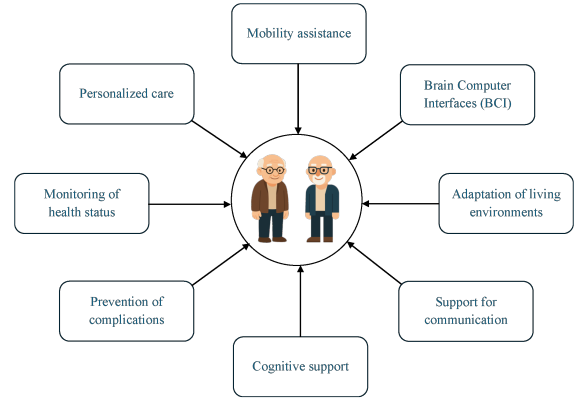


Fig. 1: Possible applications of digital twins to support elderly people.

demand for comprehensive, high-quality individual data collection, the intricacy of building and validating advanced AI models that can precisely predict complex human behaviors, and the imperative to secure and protect vast amounts of sensitive personal information [3]. Hence, precise parameter selection is vital for high-fidelity virtual twin modeling, while efficient data transfer is key for real-time physical-cyber synchronization, which is crucial for effective MDTs and personalized healthcare [4].

A comprehensive medical DT that utilizes wearable devices such as smartwatches and smart rings combined with edge computing can monitor vital metrics such as electrocardiogram (ECG), oxygen saturation (SpO₂), and blood pressure. Furthermore, particularly for elderly individuals, channel state information (CSI) can be used as a non-intrusive means to collect spatial data crucial for fall detection and activity recognition (*e.g.*, standing, sitting, walking), thus improving monitoring via MDT and facilitating timely home interventions. The advent of sixth-generation (6G) technologies, including IoT, advanced AI, machine learning, 3D networks, and extended reality (XR) applications, has the potential to

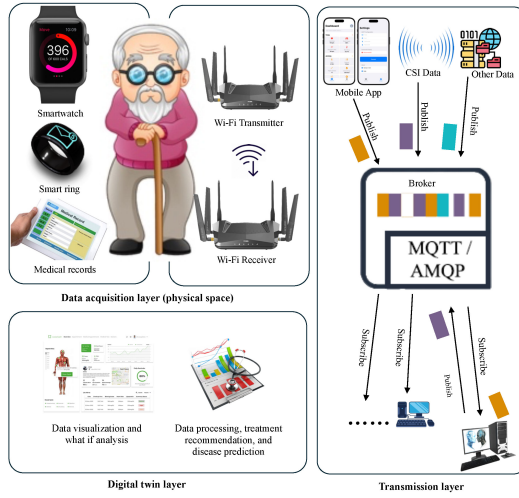


Fig. 2: System architecture of Medical Digital Twin.

significantly enhance the integration and interaction between physical entities and their digital counterparts, thereby enabling a smoother exchange of information and functionality between the physical and digital domains. Message queuing telemetry transport (MQTT) and advanced message queuing protocol (AMQP) are some widely adopted IoT protocols to facilitate real-time data exchange that could be used to optimize the creation of MDT to support cutting-edge healthcare applications [5] [6].

Main contributions

The main objective of this work, developed within the HIPPOCRATES project, is to propose a novel system for the implementation of MDTs, by integrating information from CSI and wearable devices, and utilizing IoT protocols for efficient data transmission. Beyond monitoring vital signs through wearable technology, CSI can also enable approximate indoor localization, distinguishing, for example, whether an individual is in the kitchen or living room, and recognizing the activity being performed. This capability is particularly valuable for detecting critical situations like falls, allowing immediate notification to caregivers or emergency services. The collected data provides a detailed overview of an individual's health and activity, offering significant benefits especially for elderly people, individuals with chronic conditions, or those recovering at home. Real-time analysis and communication of this information to healthcare professionals enable the early identification of potential problems and prompt interventions. As illustrated in Fig. 2, the proposed system is based on a multi-layered architecture, where data are captured from the physical environment and transmitted via MQTT/AMQP to a DT, which acts as a centralized platform for storage, access, and further analysis. In addition to supporting caregivers, the system offers direct benefits to elderly users themselves. For instance, auditory feedback based on CSI positioning data can assist elderly people with reduced spatial awareness, enhancing their ability to navigate home

environments safely, reducing accident risks, and improving overall quality of life.

II. RELATED WORK

The implementation of MDTs is gaining ground in personalized healthcare, particularly in the context of elderly care. Digital replicas of patients can be created by aggregating data from wearable devices and environmental sensors in MDTs. This enables personalized, continuous, and preventive health interventions geared toward the elderly.

The authors of [7] introduced a privacy-aware DT framework to support and facilitate the autonomous living of the elderly. Their solution is based on a network of non-invasive sensors deployed in home environments to monitor daily activities and generate a real-time digital profile of the elder. The system was tested over a two-month period in two homes, which led to promising results indicating that the solution is viable and technically feasible. However, the authors acknowledge limitations in terms of scalability and user engagement over extended periods.

Other studies have focused on the integration of wearable technologies into DT systems. A review of methods, applications, and challenges related to human DTs is provided in [8]. The authors of the paper also explore how biometric data from smartwatches and other wearable devices can improve the accuracy of patient replications, enable early detection of health problems, and support remote monitoring. Despite the several benefits, the authors emphasize that significant obstacles must be faced, such as the complexity of accurately modeling the human body, the need to use many sensors (which can be complicated for elderly users), limited Internet access in disadvantaged areas, high equipment costs, and concerns about data security and patient privacy.

AI-guided DTs have been proposed to support rehabilitation and decision making in physical therapy in [9]. According to the authors, DTs can simulate therapy outcomes, dynamically adapt rehabilitation plans, and enable remote monitoring. In addition, they can support professional training and increase patient motivation through visualization of progress.

The work in [10] is interesting in terms of the challenges presented by the authors in using DTs for personalized medicine, including: the need for high-quality data; the lack of interoperability between health systems; the complexity of modeling dynamic physiological systems; and ethical concerns regarding privacy, consensus, and equity. In addition, high computational requirements and the absence of standardized protocols limit large-scale deployment and integration into clinical workflows.

As mentioned above, DTs can be fed by data from a variety of sources, including CSI. With respect to CSI, it has enabled a wide range of wireless sensing applications, offering richer data by capturing detailed multipath effects [11]. In particular, CSI has been widely used for indoor localization [12], [13] and movement detection or activity recognition [11], [14]. Machine learning approaches, including Random Forests, support vector machines (SVMs), convolutional neural networks

(CNNs), and long short-term memory (LSTM) networks, have been employed to classify human activities from CSI data, enabling accurate recognition of daily movements and falls, critical features for elderly monitoring [14]–[16]. Additionally, CSI has proven effective in non-invasive health monitoring, particularly for respiratory analysis. Breathing-induced changes in signal amplitude and phase allow the estimation of respiratory rate and detection of conditions such as sleep apnea [17], [18]. Compared to early received signal strength indicator (RSSI)-based approaches like UbiBreath [19], CSI-based methods offer greater stability and sensitivity. Techniques to refine phase information, such as differential processing between antennas, further enhance system robustness [20]. These capabilities make CSI a promising tool for elderly care, providing real-time, contactless monitoring of both movement and vital signs, and enabling proactive interventions that can significantly improve safety, autonomy, and overall quality of life.

III. THE HIPPOCRATES PROJECT

A. Channel State Information (CSI)

CSI captures detailed characteristics of a wireless communication channel, reflecting effects like scattering, fading, and attenuation. Introduced with IEEE 802.11n in 2009, CSI allows WiFi systems to adapt dynamically to changing conditions, improving communication reliability. Unlike simpler metrics such as RSSI, CSI provides a high-resolution view of the channel's frequency response across transmitting/receiving antennas and subcarriers, organized into a three-dimensional matrix ($N_{tx} \times N_{rx} \times S$). Its granularity has enabled diverse applications, from localization and motion detection to unconventional uses like fire or concealed object detection [11]. In this study, CSI data was collected using two PCs placed at opposite ends of an empty room. Participants performed activities such as standing, sitting, walking, and running within line-of-sight. Additional tests included a second person remaining stationary to evaluate the system's robustness. Data was processed through LSTM neural networks after filtering. Three models were trained: one for individual activity recognition, one with an additional passive subject, and one on the combined dataset. Testing demonstrated that CSI-based classification achieved an average accuracy of 94%. The results confirm that CSI, integrated with IoT communication protocols, is an effective tool for transmitting real-time activity to a digital twin, supporting detailed health monitoring and continuous assessment even when another person is present inside the same room.

B. Healthcare IoT

IoT constitutes an expanding network that unifies various components, including software, hardware, physical entities, and computing devices, facilitating communication, data acquisition and exchange, thus offering a unified platform for interactions, especially in personalized healthcare contexts [21]. The ISO/IEEE 11073 Personal Health Device (X73-PHD) standards [22], inherently integrated with the IoT, have

attracted substantial interest within IoT-based healthcare. With the rising demand for effective healthcare for the elderly, the integration of IoT technologies facilitates advanced remote monitoring and custom wearable devices designed to enhance the health and daily support of older individuals [23]. The growing dependence on IoT for home monitoring of older adults raises significant privacy issues, mainly related to the collection, storage, and possible misuse of their personal and health information [24]. Therefore, employing these technologies should focus on strong privacy and security measures to maintain the confidentiality and integrity of sensitive health data, thereby building user trust [25].

C. Edge computing

To create a thorough and dynamic model, digital twins necessitate varied real-time data streams. Edge computing, an innovative advancement in the IoT domain, enables efficient data generation and instantaneous processing. This technology is optimal for time-critical uses, such as health monitoring, by ensuring low-latency communication and immediate data management. It also enhances data security and privacy, supporting rapid analysis and decision-making [26].

Hence, once data has been collected through wearable devices, a mobile app, Health Twin (HT), installed on a user's smartphone, retrieves health data from the user's primary health app. This mobile app centralizes permissions, handles data, and stores it directly on the device. Refer to Listing 1 for pseudocode on its operation. HT processes the data locally also to provide the most immediate real-time alerts, health trend analysis, and anomaly detection. Securely, HT transmits the refined data to an external system via an integrated MQTT interface. In real time, the data are published to the main digital twin system using an MQTT broker. To give more control to the user, the app provides the option to choose a reliable MQTT broker that offers data encryption while transmitting.

```

1 // Mobile App (HT)Pseudocode
2 Initialize MobileApp
3 Load MQTTConfig (brokerAddress, credentials, QoS=1)
4
5 Loop while App is running:
6     if Platform == "iOS":
7         healthData = fetchFromAppleHealth()
8     else if Platform == "Android":
9         healthData = fetchFromGoogleHealthConnect()
10
11     if isValid(healthData):
12         if not isConnected(brokerAddress):
13             connectToMQTTBroker(brokerAddress)
14             if connection fails:
15                 log "Broker connection failed"
16                 sleep(refreshInterval)
17                 continue
18             publish(mqttTopic, healthData, QoS=1)
19     else:
20         log "Invalid health data retrieved"
21         sleep(refreshInterval)
22
23 Work in background until the user terminates the
    connection

```

Listing 1: Mobile App Pseudocode for Health Data Publishing.

IV. NETWORK ARCHITECTURE AND FUNCTIONAL DESIGN OF AN IOT-ENABLED MEDICAL DIGITAL TWIN

The network architecture presented in this work is aimed at real-time data transfer from the physical twin to its digital counterpart by leveraging the MQTT and the AMQP protocols, streamlining the creation and continuous updating of the MDT. This section outlines the key features of the DT that can be realized through the proposed framework and details the underlying architecture supporting IoT-based communication.

A. Procedure for the realization of the digital twin

The DT is constantly fed with data related to its physical counterpart. This includes critical physiological parameters, such as heart rate, blood pressure, and blood oxygen saturation, which are constantly monitored through wearable sensors. At the same time, environmental sensors provide real-time data on movement and detect potential obstacles. However, despite the undoubted importance of data, the efficient functioning of any DT depends on its interaction with the physical entity. The adoption of lightweight but robust IoT communication protocols such as MQTT and AMQP can ensure the rapid transmission of data from the physical to the digital domain. The integration of sensor-derived data is performed to provide a holistic representation of the monitored person. The latency associated with this integration process is minimized using edge computing strategies, which provides a substantial advantage for elderly support applications that require low latency, such as those involved in fall detection, providing mobility support, and assisting indoor navigation. The data aggregated in the DT can be converted into an interactive, three-dimensional representation of its physical counterpart. For this purpose, sophisticated software such as Unity or Unreal Engine 5 can be used. These platforms generate high-fidelity simulations, enabling dynamic visualization of data and behaviors. Such advanced visualization is particularly beneficial in the areas of healthcare, education, and accessibility technologies for the elderly. The ability to run “what-if” scenarios on the DT gives users a mechanism to simulate different circumstances and predict potential outcomes without incurring real risks.

B. The IoT protocols

The infrastructure underlying MQTT revolves around three main elements: the publisher, the broker, and the subscriber. In the proposed framework, the publisher corresponds to the physical entity to be digitalized. The MQTT broker acts as an intermediary between the publisher and the subscriber. Its main role is to accept the data transmitted by the client and manage its dissemination to all associated subscribers. The broker is responsible for maintaining various levels of quality of service (QoS) to ensure that the data are delivered with maximum reliability and accuracy, which is well suited to the use case discussed in this paper given the high sensitivity of personal medical data. In our architecture, the MQTT subscriber is deployed on a separate machine equipped with specialized software dedicated to the realization of the DT.

By obtaining real-time data from the broker, the subscriber updates the DT, ensuring that it accurately reflects the current physiological condition of the corresponding physical entity.

MQTT is compared, in this paper, with another protocol used to enable real-time communication between the physical and digital twins, namely AMQP. The architecture of AMQP, similarly to MQTT, is built around three components: the publisher, the AMQP broker, and the subscriber. The publisher collects the data from the physical twin and sends them to the broker. The AMQP broker, unlike the MQTT broker, is designed to provide more features such as message acknowledgment, guaranteed delivery, and flexible exchange types (direct, topic, fanout, headers), enabling more sophisticated communication patterns. The subscriber, running on the DT system, receives the data from the broker and updates the virtual representation. AMQP is particularly suited for scenarios that necessitate robust delivery guarantees and seamless interoperability with mission critical systems, as it ensures secure and reliable real-time data transmission.

V. EXPERIMENTAL RESULTS

In the context of CSI data collection, three neural networks are employed following a filtering step. Each network is trained independently: the first one focuses on recognizing four specific activities performed by a single person; the second one does the same thing but when another person is present in the same room, to test whether it is still possible to infer movement information from CSI data if another person is physically “interfering”; the third one combines the two datasets. Data acquisition is carried out using the Intel 5300 CSI Tool [27], a platform specifically designed for CSI data experimentation. To perform the measurements, two PCs equipped with three antennas each are positioned on opposite sides of a room, approximately five meters apart, functioning as the transmitter and receiver, respectively.

SIMO measurements are taken on channel 64, centered at 5.320 GHz, and data is collected. The resulting information is organized into variable-sized blocks with dimensions $N \times 1 \times 3 \times 30$, where N denotes the number of data samples, 1×3 represents the number of antenna pairs ($TX \times RX$), and 30 corresponds to the subcarriers. These data blocks are then processed and classified using an LSTM neural network.

After the training phase is complete, the system is tested using data that matches the defined activity. The input provided to the network consists of blocks containing several seconds of measurements.

The results confirm the viability of leveraging CSI data for activity classification even when another person is present in the same room as the target. The approach achieves an average accuracy of 94%, with specific percentages shown in Figs. 3,4.

To test the network architecture described in section IV, we have set up a testbed to quantify the performance of the MQTT and AMQP protocols used to transmit data from the physical twin to the DT. In this work, the MQTT broker *test.mosquitto.org*, which is a test server provided by

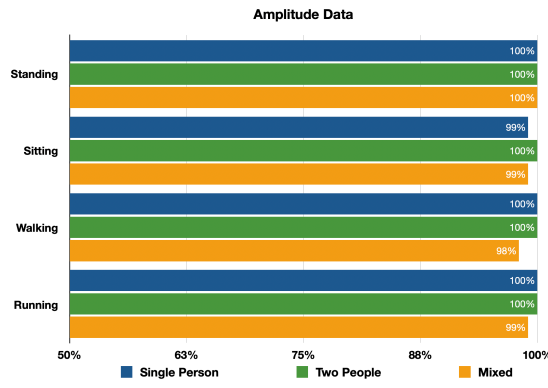


Fig. 3: Results for movement classification using amplitude information.

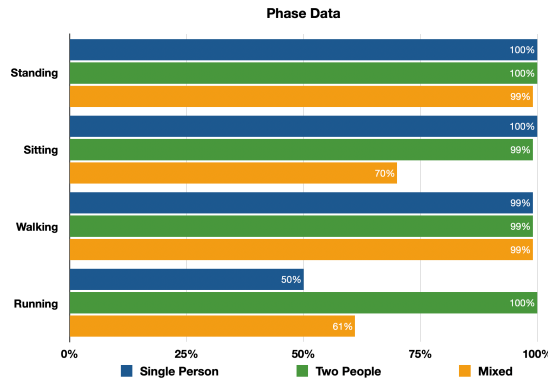


Fig. 4: Results for movement classification using phase information.

the Mosquitto project foundation, has been used. Instead, to thoroughly evaluate the efficiency and effectiveness of the AMQP communication protocol, we used the publicly available broker service hosted and managed by CloudAMQP. The following metrics have been measured:

- *Average (Avg) Throughput*: expressed in kilobit per second (kbps), is useful to provide information on the effectiveness of the proposed architecture for transmitting data, since it is calculated as the ratio between the amount of data transmitted and the time taken to complete the transmission. In our case, the throughput was averaged over the transmissions made in a given time interval.
- *Avg Latency*: expressed in milliseconds (ms), represents the time elapsed between the transmission of a message from the physical twin to the MDT. Measuring latency allows us to assess system responsiveness, which is critical for real-time monitoring applications. In our tests, latency was measured under different packet loss conditions to evaluate the robustness of the protocols.

Looking at Fig.5, for all packet sizes sent during testing, MQTT QoS 0 produces the highest throughput due to its low overhead and the absence of acknowledgment mechanisms.

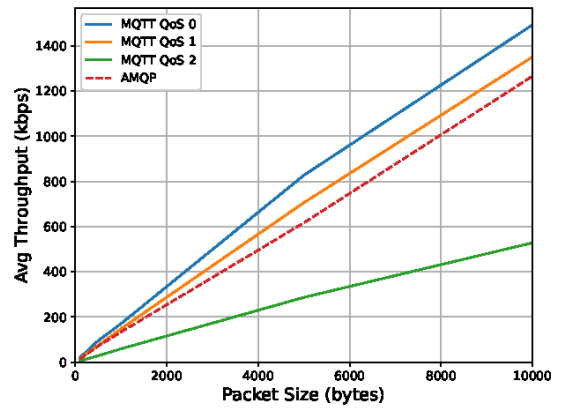


Fig. 5: Average throughput obtained as the size of the transmitted packets varies.

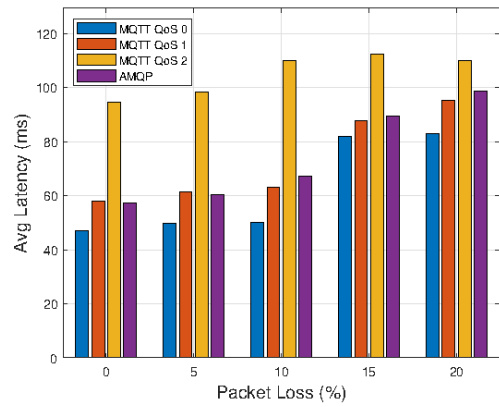


Fig. 6: Average latency under varying packet loss percentages.

As reliability levels increase (QoS 1 and QoS 2), the avg throughput decreases. In particular, the lowest throughput is observed with QoS 2, since this level guarantees delivery exactly once, requiring handshaking in four stages (PUB, PUBREC, PUBREL, PUBCOMP). Thus, each message generates multiple exchanges between the client and the broker, increasing overall latency and reducing transmission efficiency compared to QoS 0 and 1. The avg throughput for AMQP shows a similar trend to MQTT QoS 1 but with slightly lower values. This is to be expected, as AMQP adds protocol overhead through message encapsulation and additional features.

The average end-to-end latency is shown in Fig. 6 as packet loss levels vary from 0% to 20%. Due to its low overhead and lack of delivery guarantees, MQTT with QoS 0 has, in general, the lowest latency. However, it is worth underlining that, as packet loss increases, its performance deteriorates dramatically, indicating a greater susceptibility to unstable network conditions. MQTT with QoS 2 adds more overhead and causes higher latency. Its robustness in lossy situations is evidenced by the fact that it exhibits more consistent behavior as packet loss increases. Interestingly, as the packet loss

rate increases, AMQP achieves latency values slightly lower than MQTT QoS 2 and comparable to QoS 1. This result shows that, despite its complexity, AMQP can provide reliable delivery with modest latency, making it a good substitute in situations that require stringent delivery guarantees.

VI. CONCLUSIONS

The implementation of Medical Digital Twins (MDT) using cutting-edge technologies such as Channel State Information (CSI), Internet of Things (IoT) and edge computing represents a profound leap forward in healthcare, especially in the care of the elderly. As a product of the HIPPOCRATES project, this paper presents an innovative architecture designed to collect data through IoT wearable devices and the CSI, with the overall goal of monitoring the elderly in indoor environments. The wearable devices are responsible for obtaining vital health indicators, while the CSI is used to acquire data related to the person's location and movement. These data are transmitted to the individual's MDT using the IoT protocols MQTT and AMQP. Experimental results obtained by comparing the performance in data transmission with the two protocols are provided. The purpose is to highlight the trade-offs between efficiency and reliability for MQTT and AMQP in different scenarios, specifically by varying the size of packets sent and the percentage of packets lost due to unstable network conditions. This work demonstrates that the integration of wearable sensors, CSI data, and IoT protocols allows effective real-time monitoring for elderly care.

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