A-WEAR PROJECT: A network for dynamic WEarable Applications with pRivacy constraints

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Short Report "Proposed wearables network architecture"

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1 Abstract

This document comprises the Milestone 10 – Proposed wearable network architecture published at the webpage. This document covers the main networking architectures for wearables, the workflow for wearable data handling, and the related enabling technologies. This document also reports an overview of the proposed framework for wearables built upon the identified enabling technologies. Parts of this deliverable are taken from the results of ESRs and supervisors of H2020 Marie Sklodowska-Curie Innovative Training Network/European Joint Doctorate, A-WEAR Project [1, 2].

2 Disclaimer

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3 Architectures for wearable networks

This section discusses the main networking architectures for wearables and the related enabling technologies.

3.1 Wearable architecture development

Wearable architectures significantly evolve over the last years (as shown in Fig. 1 [1]). They started with eHealth systems, which were based on a few specialized devices, such as biomedical sensors, worn by the patient, and on some storage and computation facility, either locally or remotely located in the Internet [3]. Therefore, the first architecture of wearables is represented by a separate device (Fig. 1A, Step 1).

At the next step of the architecture evolution, wearables were connected to more powerful external devices via wired links for data processing tasks that could not be executed on the wearables due to their form factor limitation (Fig. 1A, Step 2). Such architectures, mainly applied in healthcare-related applications, restrict user mobility, which is considered an obstacle to expanding wearable solutions. As a result, traditional wired health monitoring systems have been replaced with wireless wearable systems (Fig. 1A, Step 3).

Due to the mass adoption of smartphones being a part of the personal wearable cloud, manufacturers started to aim at other consumer wearables as supplements in a personal ecosystem rather than standalone devices. It resulted in a new architecture where personal smartphones act as relays or gateways to transmit the data to the cloud either directly or after a pre-processing in the custom applications (Fig. 1A, Step 4). This architecture is supported by Internet of Things (IoT) technologies capable of bridging in the proximity of the users to a multitude of general-purpose smart devices. These IoT devices allow to gather further information concerning the environment surrounding the user and adapt it to the user's needs.

According to the IoT architecture provided in [4], the gateways are also called monitoring stations that are part of the perception layer for people with disabilities. Logically, the development of personal wearable clouds prompted the star-like topology communications (Fig. 1B). However, due to the broad adoption of Bluetooth technology as a leading connectivity enabler, wearable devices started to communicate purely in a centralized way using the gateway devices as masters.

Most fitness, sports, and healthcare wearable applications follow the fourth evolution step in Fig. 1A, while sharing their data with applications installed on the smartphones. This option implies several situations where wearables cannot connect to the network, such as the non-existence of a smartphone nearby, non-installed applications on the smartphones, or an outdated phone software [5]. Considering such possible scenarios and the end-users ever-increasing expectations and needs, device manufacturers consider equipping wearables with short-range and long-range connectivity chipsets. As a result, these standalone wearables can function independently from other devices (Fig. 1A, Step 5).

Although this standalone wearable-based architecture provides a way towards separating wearables from other personal devices and an opportunity to communicate directly with the cloud, it brings some challenges in terms of network design and dimensioning. For instance, additional loads on the wireless networks are expected due to the lack of pre-processing, usually performed by the gateway devices. Another challenge is related to the deployed communication technologies optimized for low-power operation, thus, long battery life and reduced device complexity.

Today, most wearable devices have at least two wireless interfaces on board (Fig. 1A, Step 6). The trend of unifying the operation is expected to push vendors to add more wireless modules, with the possibility of intelligent technology selection mechanisms based on improved situational awareness.

The evolution of wearable architectures would surely benefit from recent advancements in the 5G and beyond research arenas, like software-defined networking (SDN), network functions virtualization (NFV), edge/fog/cloud computing, advanced air interface technologies, as well as from trends in the IoT realm, such as Social IoT (SIoT) and object virtualization.

3.2 Enabling Technologies

Before discussing the main enabling technologies for the collection, delivery and processing of wearable data, the workflow for their handling is first specified.

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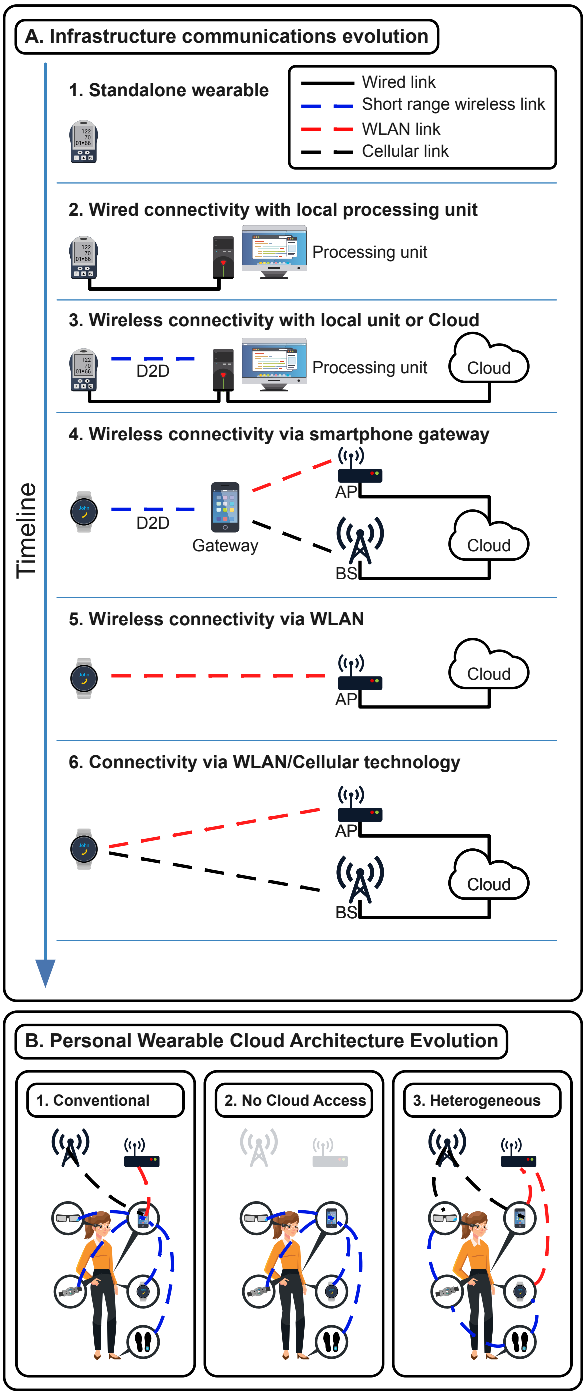

Figure 1: The development of wearable architectures [1].

3.2.1 Workflow of wearable data

The stages of wearable data handling are as follows: data collection (sensing), data transfer, data pre-processing, data processing, data computing, and data storage.

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Data Collection: Given the popularity, low cost, and size of wearable devices, they have become one of the most used devices to collect information in different domains such as health and fitness tracking. For instance, wearable devices are widely used to collect medical information from patients; thus, some of the common measurements obtained from the users are glucose levels, blood pressure, and other relevant information. This primary data is also known as raw data.

Wearable devices primarily collect and process user-generated data, and collective data retrieval is commonly referred to as crowdsourcing, a powerful tool for collaboratively retrieving a large amount of data. Crowdsensing is a way to enable crowdsourcing by coordinating the data gathering from the devices. In other words, crowdsourcing needs to gather data, whereas crowdsensing explores the possibilities of leveraging users as sensing nodes to collect and share their data for multiple purposes. Standard sensing techniques are as follows [6]:

- *Participatory (active) sensing* refers to obtaining information through the user's action, such as measuring one's exercise on their smartwatch.
- *Opportunistic (passive) sensing* describes periodic action to gather information, determined by elapsed time, distance, or other metrics from the last data gathering.
- *Opportunistic mobile social networks* refer to self-organizing, point-to-point networks of devices sharing the information between themselves.

Data Transfer: The data transfer phase is an essential part of the wearable device data chain. The main technologies for transferring wearable data are further discussed in subsection 3.2.2. At this point, we only note that many wearable solutions limit the amount of power spent during the data transmission by pre-processing it to decrease the actual amount. For example, it is achieved by applying compression schemes to the data before transmission [7]. Additionally, the power constraints usually limit the transmission's security, as proper data encryption is often computationally demanding.

Pre-Processing: Although the central part of data processing takes place in different computing layers [8], the early pre-processing stage is essential for wearable devices since they do not have enough computational and storage resources to process "unnecessary" data. Collected data contain incomplete and duplicate information, errors, inconsistencies, etc. It requires early preparation before the data processing (locally or in the Cloud). Thus, once the data is collected, it should be filtered, structured, cleaned, and validated to improve the data's quality. The cleaning and validation are then essential to detect the quality issues, including duplicate values, outliers, missing values, and inconsistencies. Once these issues are detected, multiple techniques can be used to remove missing values, delete outlier samples, merge duplicate data, etc. As a result, the data processing step takes less time.

Data Processing: During the data processing phase, different techniques and methods are applied to the input data to obtain meaningful information. Nowadays, Machine Learning (ML) techniques, such as clustering, regression, classification, among others [9], are broadly used to analyze and process the data. Additionally, these ML techniques can be run by using batch processing, real-time processing, and online processing.

Generally, the most significant part of the data collected by wearables is time series [10]. This kind of data could be typically used for classification purposes, anomaly detection, or forecasting. However, there are few challenges connected to the analysis of time series, i.e., the limited amount of data, computation capacity, and power resources.

The recorded time series gathered by wearables contain a special pattern. The pre-processing steps are also needed to obtain the final expected results. In terms of architectural choices, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (BLSTM), Multilayer Perceptron (MLP), Gated Recurrent Units (GRU), and transfer learning are robust techniques for wearable data [11, 12].

Data Computing: Computation and operation on bulky and raw data is a challenging task. Thus, during the first steps of the architectural evolution, wearables were mainly utilized as data collectors. After that, the devices were connected to a personal computer with a wire for post-processing. This phase could be treated as the introduction of edge computing for wearables, i.e., moving heavy computations to the closes network device instead of local computations.

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With the smartphone's introduction as a gateway, wearable data processing on it was adopted swiftly. Following the vendors' footprints, most application developers aimed to save battery-constrained wearable lifetime by moving the smartphones' computations. The Edge operation hardened. Simultaneously, some virtual reality (VR) / augmented reality (AR) devices still do not have the required processing power or tend to overheat. Thus, the only option is to utilize a powerful edge device for computing in trade-off to transmission overheads.

Nowadays, wearable devices mainly rely on Edge and Cloud computing paradigms, as well as Fog Computing [13, 14] to complement their typically constrained capabilities. Cloud, Fog, and Edge computing are three levels that simplify the Internet of Wearable Things (IoWT). However, there are many more paradigms suitable for integrating with wearables in reality [15], and the whole cloud system is much broader and more complex. The actual classification also covers Mist Computing, Mobile Computing, Mobile Cloud Computing, Mobile ad hoc Cloud Computing, Multi-access Edge Computing, Cloudlet Computing, and Transparent Computing [16]. Indeed, the variety of options to efficiently execute computing between mobile nodes is vast. To date, the most promising paradigm being driven by the industry is Multi-Access Edge Computing (MEC) [17].

With reference to wearables, task offloading to the edge has been investigated in [18] for ML-based smart healthcare applications. The role of fog computing to process data provided by wearable devices is investigated, for instance, in [19].

Data Storage: After the data processing stage, the useful information is exposed to the user through reports, graphics, tables, etc., and then available for further storage, applications, and development. At data storage stage, the altered data is stored for further analysis, which is then used by recommendation systems for marketing purposes and collective intelligence to improve the decision-making process.

3.2.2 Communication Technologies

The wide range of wearable devices and related technologies allows for various supported connectivity solutions, defined by the wearable's requirements for range, data rate, power restrictions, mesh types, developer's preferences, and numerous other aspects. Data transfer specifics, including encryption level, coding and transmission schemes, modulation, and cyclic prefix, are also individually defined depending on the utilized technology.

The most commonly used data transmission technologies in wearables include Near Field Communication (NFC), Bluetooth Low Energy (BLE), Wireless Fidelity (Wi-Fi), ZigBee, Low-Power Wide Area Network (LPWAN), and other cellular or non-cellular IoT transmission technologies.

According to the coverage area they can be classified as short-range and long-range communication technologies.

Short-Range Communication Technologies: Generally, wearable devices can communicate with each other in a Peer-to-Peer (P2P) manner and with the gateway nodes using short-range technologies.

Bluetooth (and its currently broadly adopted version, Bluetooth Low Energy, BLE) is a short-range communication protocol for Personal Area Network (PAN) working at a maximum transmission distance of 100 m and the 2.4 GHz unlicensed Industrial, Scientific, and Medical (ISM) band. A piconet is the most straightforward pattern of a Bluetooth network, and it is composed of the *master* of the connection (commonly, a gateway node), and a maximum of seven served active *slaves* (clients) [20].

The second primary wireless short-range technology is defined by the IEEE 802.11 standard, also known under the market name of Wi-Fi, which aims to provide connectivity to mobile devices within the Wireless Local Area Network (WLAN). A direct connection between devices is allowed by the ad-hoc mode foreseen by the standard. Nonetheless, the lack of efficient power saving and enhanced Quality of Service (QoS) has pushed the Wi-Fi Alliance to make a move towards the Wi-Fi Direct option, which handles the P2P communications more efficiently [21].

Moreover, the current development of immersive technologies, such as AR/VR, dictates higher throughput and lower delays. Developers are opting for technologies that operate in high and ultra-high frequencies, e.g., IEEE 802.11ad, IEEE 802.11ay, and IEEE 802.11ac, which provide Gigabit data rates in millimeter-wave (mmWave) band. Moreover, high frequencies have propagation limitations, which is an advantage for dense packing scenarios, where human bodies act as a natural barrier and allow better use of spatial reuse.

The Terahertz (THz) frequency band ranging from 100 GHz to 10 THz offers substantial bandwidth, theoretically enabling capacity in the order of terabits per second at negligible latency. Currently, the THz frequency band is a subject of exploration for point-to-point communication among regulators, operators, and manufacturers. Visible Light

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Communications (VLC) is among the connectivity solutions that operate in the THz frequency range, more precisely from 400 and 800 THz (780–375 nm). This technology can simultaneously achieve illumination and communication between two or more devices in proximity, thus improving energy efficiency using existing lighting infrastructure [22].

The wearable communication technologies with the shortest range correspond to Radio Frequency Identification (RFID)/NFC systems. RFID nodes can be worn to provide them with hands-free operations and allow flexible and mobile asset tracking by being attached to gloves or helmets, and operating on the same 13.56 MHz frequency [23].

Multiple works propose to support wearables through Device-to-Device (D2D) communication to increase the wireless networks' capacity and coverage by enabling immediate communications between the users. Using the mmWave link is a tempting approach to achieve high data rates in wearable networks. The industry recognizes the importance of mmWave technology for high-quality wearable devices [24]. For example, the IEEE 802.11 working group is looking at high-performance, mmWave-based wearables in public places as a possible use case. As pointed out in [25], mmWave is an ideal candidate for D2D in very dense scenarios because it requires directional transmission to overcome high path losses, which in turn reduces interference between adjacent lines [26]. D2D is also beneficial for mmWave picocells due to its high attenuation, especially for users at the cell's edge.

5G wireless communication systems utilize New Radio (NR) sidelink for D2D communication [27]. The new NR sidelink use cases require low-latency, high-reliability, and high-throughput transmissions, as well as a high connection density. To this end, four new designs are introduced to sidelink (Rel-16) [28, 29]: (i) in addition to broadcast, also unicast and multicast are supported; (ii) the performance in terms of latency is improved by grant-free transmissions adopted in NR uplink transmissions; (iii) it improves the channel sensing and resource allocation procedures to mitigate collisions among different sidelink transmissions initiated by various terminals; (iv) high connection density is achieved by supporting congestion control and QoS management.

Long-Range Communication Technologies: More advanced opportunities are brought to wearables by long-range technologies. In contrast to short-range communications (with short-range technologies enabling a longer battery life, cheaper and less complex devices), long-range communications allow wearable devices to communicate directly with an access point (AP), a base station (BS).

Motivated by the increased popularity of these solutions, the 3rd Generation Partnership Project (3GPP) introduced its Massive Machine Type Communications (mMTC) technologies for low-power operation and reduced-complexity devices, namely Narrowband Internet of Things (NB-IoT) and Long Term Evolution (LTE)-M [5]. The introduction of these technologies paved the way for the usage of cellular modems in standalone wearables. First introduced in 3GPP Release 13 specifications, both technologies are optimized to communicate small amounts of infrequent data with minimal power consumption and maximal coverage. Taking into consideration the traffic requirements of wearable applications that might be higher in comparison with smart city or other more common Low-Power Wide Area (LPWA) use cases, several enhancements to the NB-IoT and LTE-M standards are suggested in 3GPP Release 14 specifications to offer higher data rates while still consuming less power.

Nonetheless, presently deployed in cities, LPWA technologies are already utilized for cases of long-range communications and low energy consumption requirements [30]. The first target of these technologies was low-end IoT devices such as sensors. However, LPWA connectivity solutions have started attracting other application scenarios used in wearable systems. An example of non-lincensed LPWA technology is Long Range LPWAN protocol (LoRa). It is a long-range wireless technology that operates in the license-free ISM radio band at 868 MHz and offers transmissions up to 25 km operational distances. Another alternative LPWA technology used by proprietary wearable devices is Sigfox, which, similarly to LoRa, operates at the sub-GHz ISM band and provides extended coverage. While LoRaWAN is based on a spread spectrum technology, Sigfox is a narrowband technology owned by the Sigfox company in charge of deploying networks.

3.2.3 Social-aware Communications

Beyond the conventional connectivity and interaction between heterogeneous IoT and IoWT devices, the concept of SIoT supports a plethora of socially-driven collaborations among objects [31]. The synergy of social networking and IoWT paradigms offers some benefits and allows devices to socialize, collaborate, and establish group communications according to the relationships. For instance, *Social object Relationship* is established when objects come into contact, sporadically or continuously, because their owners come in touch with each other during their lives. *Ownership object Relationship* brings together devices held by an owner, *Co-Work Object Relationship* integrates objects that work together to provide service for a common IoT application, *Parental Object Relationship* clusters objects belonging to the same production batch, whereas *Co-Location Object Relationship* combines devices in the same place. The concept of using elements of social networks in IoT has attracted an unprecedented amount of attention from the research community. Not surprisingly, most of the research contributions in this field focus on devices and their owners, their particular aims and needs, and trustworthiness.

The SIoT paradigm allows devices to interact, share, and exchange data by taking into account both their physical constraints and their "social" behavior. The combination of social networking concepts with the IoWT offers a number of advantages. First, SIoT enables effective discovery of the services offered by IoT objects, based on typical social network mechanisms. Second, it allows the exchange on a social basis of information associated with/generated by wearables. Third, it ensures scalability through social collaboration among nodes. A further remarkable beneficial aspect is the possibility to establish social relationships between objects that use different technologies; this allows device interoperability across different IoT platforms. Finally, SIoT can leverage the degree of interaction between objects to guarantee trusted connections between friend devices.

However, as wearable devices are typically resource-constrained, creating and managing social relationships would further challenge their design.

3.2.4 Object Virtualization

Virtual objects provide the semantic description of the related physical objects and of their resources (e.g., memory, storage, processing) and capabilities (e.g., sensing, actuation, computing), which are abstracted into a set of attributes. This abstraction allows performing an effective search of the capabilities/resources needed for creation and composition of IoT services at the application layer [32].

The virtualization has become a key component of many reference IoT platforms [33, 34] and commercial implementations [32], and the interest for it has been further boosted by the emerging concept of digital twins for IoWT [35, 36, 37]. The idea of DTs was first introduced in [38] and later formalized in [39], where the main elements of the DT concept are identified, namely, a real space (physical objects), a virtual space (virtual objects), and the link for the data flow between real and virtual domains. Further, digital twins have already been shifted from concept to reality [40].

3.2.5 SDN and NFV Technologies

In addition to defining more advanced air interface technologies, 5G networks will leverage programmable approaches to networking and use IT virtualization technology extensively for functions and applications within the telecommunications infrastructure. Core network design is expected to rely on virtualized network functions (VNFs) designed according to the NFV principles [41]. NFV is a network architecture concept that manages virtualization technologies to virtualize entire network functions, which can run as virtual machines over standard servers provided by Edge/-Cloud Computing environments, instead of being implemented in proprietary purpose-built hardware. SDN [42] can be leveraged to interconnect VNFs and physical NFs chained to create telecommunication services. By decoupling the data plane from the control plane and relying on a centralized network orchestration, SDN can flexibly implement sophisticated routing and traffic engineering policies.

SDN and NFV technologies offer tools and mechanisms to make networks flexible, programmable, and more manageable. Such features have been recognized in the literature as attractive also in wearable architectures, which may entail strict data delivery requirements [43, 44, 45, 46].

3.2.6 Network Slicing

The network slicing technology [47] can support multiple heterogeneous services, by logically isolating NFs and resources that are specifically tailored to a service's need on top of the same physical infrastructure. It can be realized through NFV and SDN technologies. NFV enables the network element function and physical entity to become decoupled and replaces the dedicated and shared hardware. SDN technology realizes the separation of the control plane and the forwarding plane to sense and dispatch the network resources using the network control plane from the global perspective.

In [48], network slicing technology-based 5G wearable architecture is presented to improve the network resource sharing and energy-efficient utilization. The data-driven network slicing management is introduced to adjust the

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network resources in accordance with the wearable service dynamics. Similarly, in [49], a data-driven resource management framework that includes the service cognitive engine, the resources cognitive engine, and the global cognitive engine is proposed in order to realize service-aware and efficient management of network slicing resources. In [50], an architecture based on network slicing is proposed to provide reliability for smart health applications.

4 A-WEAR Wearable Architecture and Main Functionalities

This section presents a general overview of the proposed framework for wearable communications built upon the previously discussed representative IoT and 5G enabling technologies.

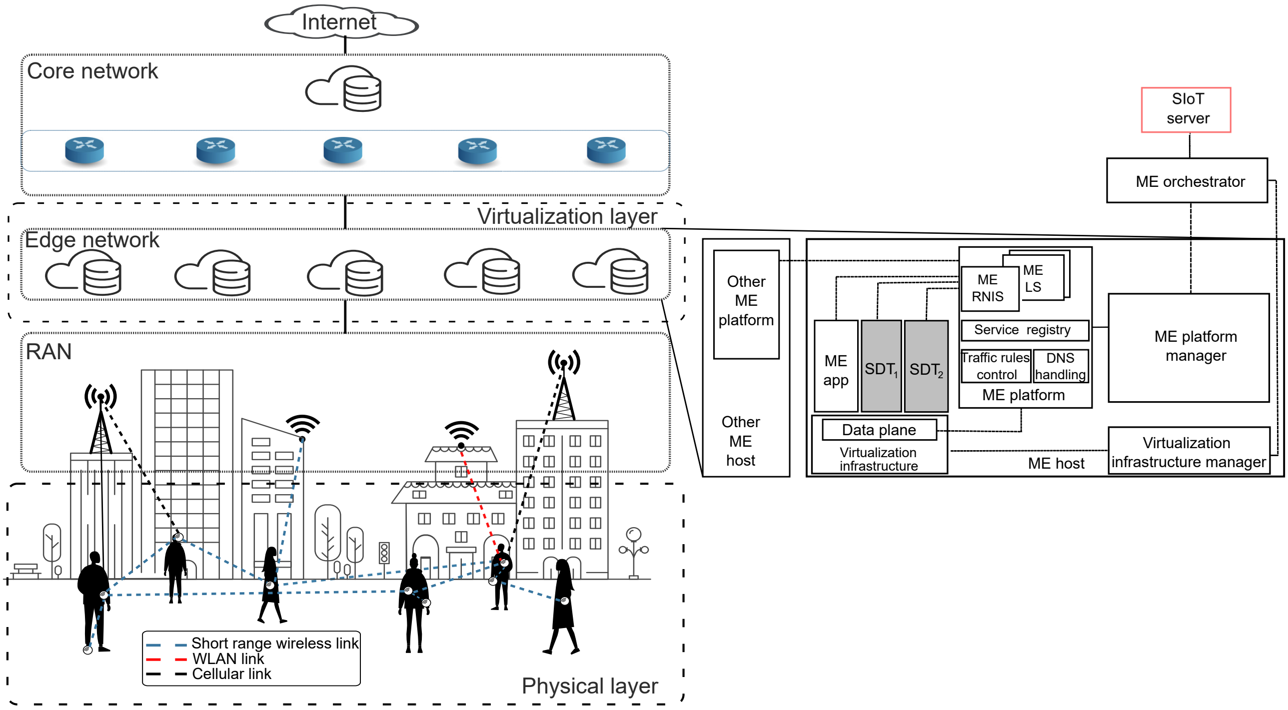

Figure 2: A-WEAR wearable architecture.

The architecture illustrated in Fig. 2 consists of the *real-world layer* and the *virtualization layer* [2].

The former one represents the physical world that accommodates wearable devices. They can be either connected with each other via D2D and/or with other remote entities, either through a gateway node (e.g., a smartphone) or directly through the connectivity facilities offered by the 5G/5G+ Radio access network (RAN) [51], as previously discussed.

The virtualization layer is responsible for hosting the digital counterparts of physical devices, i.e., Social Digital Twins (SDTs). The SDT, similarly to the DT, augments the physical device with storage and computing capabilities. It provides caching and preliminary filtering/aggregation of raw data streamed by the corresponding device before feeding IoT applications processing them [2].

In addition to the semantic description of the corresponding physical device, the SDT also keeps the information about all the social relationships established by the connected physical device according to the SIoT paradigm [31]. In particular, the SDT stores metadata describing the type of friend devices and the SIoT relationship type for each friend device. An IoWT device willing to query friend devices, discover services, and/or push data to them needs to read the friendship information stored in the SDT. Once such a piece of information is retrieved, the SDT itself can interact with its peers on behalf of the physical device. We assume that SDTs are deployed as virtualized applications, e.g., as containers [52], and instantiated in edge servers.

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The latter ones, referred to as ME hosts, in agreement with the ETSI MEC architecture [17], are associated to BSs/APs. Indeed, according to the 5G vision, the RAN may encompass both 3GPP and non-3GPP access.

The ME orchestrator has visibility of the resources and capabilities of the entire edge network, made of several ME hosts, and determines the most suitable ME hosts for instantiating the applications according to the application requirements (e.g., in terms of latency, processing requirements), available resources, and mobility conditions.

Backhaul links interconnecting BSs/APs and hence, ME hosts, can be orchestrated by an SDN controller.

In the envisioned framework, it is in charge of selecting the ME hosts where each SDT should be placed. Besides conventional performance requirements, the ME orchestrator may interact with the SIoT server to get information about social relationships of the physical devices to decide the most suitable SDT placement [2].

In particular, the SIoT server contains the database for the storage and the management of the data and the relevant descriptors. These record the social member profiles and their relationships, as well as the activities carried out by the objects in the real and virtual worlds. Data about humans (object owners as well as visitors) are also managed. Object's location information is updated its profile in the SIoT server so that an object can detect the co-location relationship with other objects. Also, the information about trustworthiness is uploaded to the SIoT server and thus is available to the whole community [31].

The types of interactions between the wearables and the corresponding SDTs (e.g., frequency of data exchange) as well as the capabilities of the wearable physical objects, can be further considered in the edge placement decision by the ME orchestrator.

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