Edge Computing For Smart Health: Context-aware Approaches, Opportunities, and Challenges

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Edge Computing For Smart Health: Context-aware Approaches, Opportunities, and Challenges

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***Abstract*—Improving efficiency of healthcare systems is a top national interest worldwide. However, the need of delivering decent healthcare services to the patients while reducing healthcare costs is a challenging issue. One of the promising approaches for enabling smart healthcare solutions is adopting next generation mobile and wireless networking technologies to provide real-time and cost-effective healthcare services. In this paper, we present our vision for the benefits of exploiting edge computing within the field of smart health (s-Health). The main advantages of leveraging edge computing have been investigated through discussing the benefits of in-network processing concept and context-aware approaches for satisfying s-health requirements. Finally, we discuss several challenges and opportunities that edge computing could facilitate for s-Health to inspire more research in this direction.**

***Index Terms*—Edge computing, Internet of Things (IoT), context-aware optimization, heterogeneous network, in-network processing.**

I. Introduction

The evolution of computational intelligence systems and Wearable Internet of Things (WIoT) devices, along with the advances of next-generation wireless technologies, has boosted the development of traditional healthcare processes into smart-healthcare services. Smart-health (s-health) can be considered as the context-aware evolution of mobile-health, leveraging wireless communication technologies to provide healthcare stakeholders with innovative tools and solutions that can revolutionize healthcare provisioning. Part of the s-health concept is also remote health monitoring, where patients and caregivers can leverage mobile technologies for providing healthcare information remotely. This will significantly reduce hospitalization and enable timely delivery of healthcare services to remote communities at low costs.

In s-health systems, besides WIoT devices, various wireless sensors, cameras, and controllers play an important role: they allow patients' automatic identification and tracking, correct drugpatient associations, and intensive real-time vital signs monitoring for early detection of clinical deterioration (e.g., seizure detection, heart failure, etc.). All these *things* will report an impressive amount of data that need to be transported, swiftly processed, and stored, while ensuring privacy protection. Such requirements make the conventional cloud computing paradigm unsuitable for s-health, since the centralized approach cannot provide a sufficiently high level of scalability and responsiveness while causing a heavy network load. A new approach has therefore emerged, known as Mobile Edge Computing or Multi-access Edge Computing (MEC), defined as the ability to process and store data at the edge of the network, i.e., at the proximity of the data sources. The advantage of MEC in a smart heath environment is multifold as it can provide short response time, decreased energy consumption for battery operated devices, network bandwidth saving, as well as secure transmission and data privacy. Furthermore, it can be applied to various network scenarios, including cellular, WiFi and fixed access technologies. This paper paves the way for MEC usage in smart heath environment through answering the following questions:

- What are the motivations and main expected benefits of leveraging the MEC architecture in s-health systems?
- What are the s-health requirements, solutions of MEC, and open challenges?

In what follows, Section II introduces a MEC-based system architecture that meets the s-health requirements, highlighting the benefits of pushing data processing and storage toward the data sources including. Section III presents possible solutions for implementing in-network processing, event-detection, and network-aware edge computing so as to make a MEC-based system architecture able to fulfill all s-health requirements. Section IV then discusses some challenges that MEC poses and further opportunities that such a paradigm offers, including the use of device-to-device (D2D) communications for improved energy and spectrum efficiency, the need and benefit of combining heterogeneous sources of information, as well as privacy and security issues. Finally, Section V concludes the paper.

II. MEC-based Architecture for Smart Health

We now give a brief description of the proposed MEC-based architecture for e-health applications, and discuss the benefits that it offers to s-health systems.

A. MEC-based S-Health System Architecture

The proposed system architecture, shown in Figure 1, stretches from the data sources located on or around patients to the service providers. It contains the following major components:

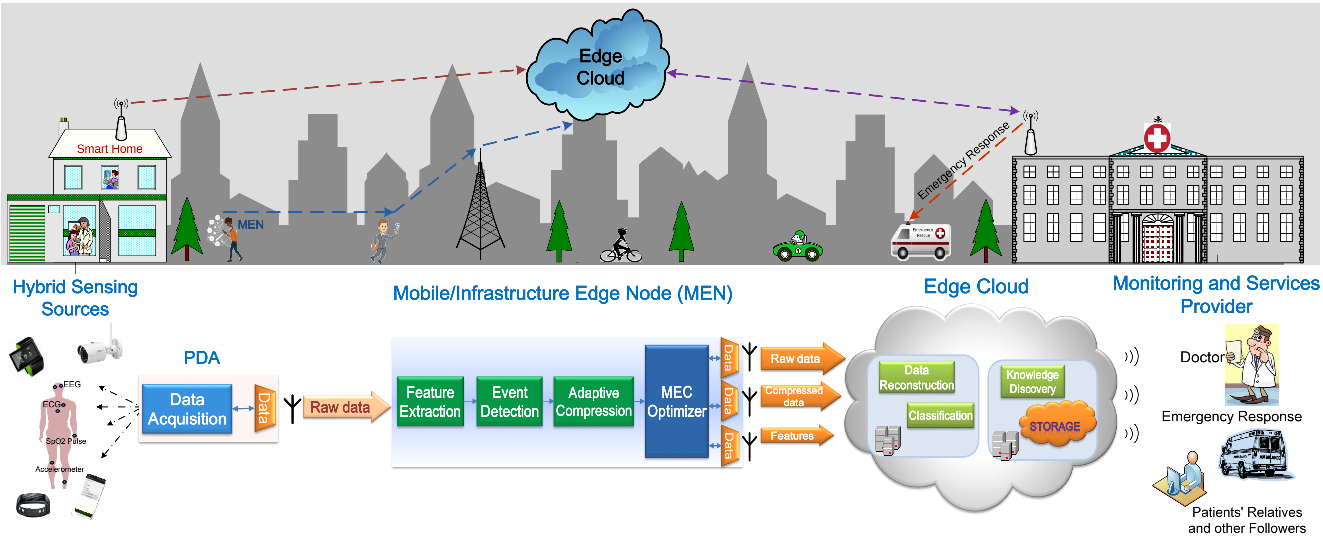

Fig. 1. Proposed smart health system architecture.

Hybrid sensing sources: A combination of sensing devices attached/near to the patients represent the set of data sources. Examples include: body area sensor networks (including implantable or wearable medical and non-medical sensors), IP cameras, smartphones, and external medical devices. All such devices are leveraged for monitoring patients' state within the smart assisted environment, which facilitates continuous-remote monitoring and automatic detection of emergency conditions. These hybrid sources of information are attached to a mobile/infrastructure edge node to be locally processed and analyzed before sending it to the cloud (see Figure 1).

Patient Data Aggregator (PDA): Typically, the Wireless Body Area Network (WBAN) consists of several sensor nodes that measure different vital signs, and a communication hub or PDA which aggregates the data collected by a BAN and transmits it to the network infrastructure.

Mobile/Infrastructure Edge Node (MEN): Herein, a MEN implements intermediate processing and storage functions between the data sources and the cloud. The MEN fuses the medical and non-medical data from different sources, performs in-network processing on the gathered data, classification and emergency notification, extracts information of interest, and forwards the processed data or extracted information to the cloud. Importantly, various healthcare-related applications (apps) can be implemented in the MEN, e.g., for long-term chronic disease management. Such apps can help patients to actively participate in their treatment and to ubiquitously interact with their doctors anytime and anywhere. Furthermore, with a MEN running specialized context-aware processing, various data sources can be connected and managed easily near the patient, while optimizing data delivery based on the context (i.e., data type and supported application) and wireless network conditions.

Edge Cloud: It is a local edge cloud where data storage, sophisticated data analysis methods for pattern detection, trend discovery, and population health management can be enabled. An example of the edge cloud can be a hospital, which monitors and records patients' state while providing required help if needed.

Monitoring and services provider: A health service provider can be a doctor, an intelligence ambulance, or even a patient's relative, who provides preventive, curative, emergency, or rehabilitative healthcare services to the patients.

B. Which Benefits for S-health

Given the characteristics and requirements of e-health applications, Table I summarizes some of the e-health systems that can benefit from the above architecture. It is not the objective of this paper to provide an in depth technical comparison on the different proposed e-health systems. However, we investigate the practical benefits of leveraging MEC in such systems. In what follows, we will discuss the advantages of the proposed MEC architecture in the light of these systems.

1) Monitoring Systems Using Wearable Devices: Heart monitoring applications are the most common type of remote monitoring applications. Monitoring vital signs related to the heart reveals many types of diseases, e.g., Cardiac arrhythmia, chronic heart failure, Ischemia and Myocardial Infarction [1][2][3]. In [1], authors present a real-time heart monitoring system, where the extract medical data of the patients are transmitted to an Android based listening port via Bluetooth. Then, this listening port forwards these data to a web server for processing. Also, [2] exploits Android smartphone to gather patients information from wearable sensors and forward it to a web portal in order to facilitate the remote cardiac monitoring. However, in these systems, the smartphone is used only as a communication hup to forward collected data to the cloud. Hence, continuous data transmission is not viable due to the high energy toll it implies. The proposed MEC architecture is efficient in such systems in threefold. First, managing the devices operational state and their data transfer at the MEN allow for a better usage of the devices' battery; also, the proximity between sensors

TABLE I

SUMMARY OF THE E-HEALTH RELEVANT SYSTEMS.

Application	Collected Data	Description	Limitations	MEC Benefits
Cardiac disorder detection [1]	ECG	Heart monitoring system is developed for detecting status of the patient and sending an alert message in case of abnormalities *Requirements*: long lifetime for the battery-operated devices	All data processing tasks are performed at a web server	Data reduction and BW saving
Remote Cardiac monitoring [2]	Heart rate blood pressure body temperature	A location based real-time Cardiac monitoring system is developed *Requirements*: long lifetime for the battery-operated devices	Fewer number of subjects participated in the experiments	Location Awareness and energy saving
Detection of Ischemia and Myocardial Infarction [3]	ECG and Electronic Health Records (EHR)	Presenting different methods leveraged ECG signal with EHR information to detect Ischemia and MI *Requirements*: low computational complexity	Majority of the reviewed literature did not exploit contextual information	Data reduction and BW saving
Parkinsons disease (PD) detection [4]	Voice signal	A PD monitoring system over the cloud is proposed using feature selection and classification of a voice signal *Requirements*: Reliability and high classification accuracy	All data processing tasks are performed at the cloud	Data reduction and BW saving
Contactless heart rate measurement [5]	Heart rate	Heart rate measurement from facial videos using digital camera sensor *Requirements*: Reliability and high measurement accuracy	Illumination variance, motion variance, and motion artifacts	Data reduction and BW saving
Prediction of Bradycardia in preterm infants [6]	ECG	Leveraging point process analysis of the heartbeat time series to predict infant Bradycardia prior to onset *Requirements*: Fast prediction of emergency situations	Using single-channel ECG data to predict Bradycardia	Low latency
Real-time epileptic seizure detection [7]	EEG	Automatic epileptic seizure detection system using wavelet decomposition is proposed *Requirements*: Fast seizure detection	Requiring large amount of data for training to improve specificity of the detector	Low latency
ECG change detection [8]	ECG	A centralized approach for the detection of abnormalities and intrusions in the ECG data is developed *Requirements*: Fast detection of abnormalities	Using one type of data for detecting abnormality and emergency situations	Low latency
Remote monitoring of chronic obstructive pulmonary [9]	Pulmonary Function Test (PFT)	Real-time tracking system of chronic pulmonary patients comfortable in their home environment is developed *Requirements*: Fast detection of abnormalities	Relying on one type of data	Low latency

and MEN further reduces the energy consumption due to data transmission. Second, with regard to the data transmission from the MEN toward the cloud, data compression and the selection of the most convenient radio interface to be used, can significantly decrease the energy consumption at the MEN. Third, the network edge can be fruitfully exploited to extract context information and apply localization techniques, which allows matching the patients geographical position with the nearest appropriate caregivers (e.g., hospital or ambulance).

2) Contactless Monitoring Systems: Along with the evaluation of remote sensing, contactless monitoring has attained much focus recently. The main motivation of using contactless sensors is enabling ordinary life as much comfortable as possible to all patients, since the patients are required only to be present within a few meters from the sensors [4]. Heart rate measurement from facial videos using digital camera sensors is one of the rapidly growing directions to extract physiological signals without affecting patient's activities [5]. However, transmitting large volumes of data generated from these camera sensors using conventional cloud-based architecture is not advisable and may deem some of these applications impractical given the limited bandwidth availability. For instance, the amount of digital data generated from a single-standard camera can reach to 40 GB per day. Accordingly, processing, compressing, and extracting most important information from the gathered data at the MEN greatly reduce the amount of data to be transferred toward the cloud, hence the bandwidth consumption, and even makes it possible to store the data locally.

3) Disorder Prediction/Detection Systems: One of the promising applications of s-health, is the predictive monitoring of high-risk patients. The aim of these techniques is improving prediction/detection of the emergency to implement preventative strategies for reducing morbidity and mortality associated with high-risk patients. For instance, [6] presented a simplistic framework for near-term prediction of Bradycardia in preterm infants using statistical features extracted from ECG signal. Also, [7] proposed a quick seizure detection algorithm using fast wavelet decomposition method. In such real-time prediction/detection systems, the swift delivery of data to the server is a necessity. In many cases, this requires that data are analyzed and even a diagnosis is made as close as possible to the patient. However, detecting the changes of the physiological signals (e.g., changing in ECG values) in continuous health monitoring systems is not an easy task. It can be an indication for an emergency situation (e.g., occurrence of a heart attack) [8][9]. This abnormality detection task becomes even more challenging during wireless communication transfer of patients data to the cloud due to the erroneous communication and security attacks that could introduce errors or makes changes in the patients data. Hence, quick detection of the changes in the gathered medical data at the MEN is essential for real-time abnormal event detection. In a nutshell, the implementation of MEC architecture addresses all these issues, and the ability of the MEN to perform event detection/prediction fulfills these requirements even in the case of emergency applications.

III. Implementing the Edge Node Functions

In our vision, the evaluation of e-health systems toward s-health can be achieved through moving intelligence to the network edge, while accounting for the characteristics of gathered data and applications. Thus, the ultimate goal of our MEC architecture is to fulfill the different requirements of e-health systems mentioned above and enable s-health services through implementing the following main functionality at the network edge. This will also lead to lowering emergency response time, reducing energy consumption at battery-operated devices, and saving network BW, while having a reliable performance. In particular, we present two case studies to show the improvement in data delivery and QoS for s-health systems using MEC architecture.

A. Multimodal data Compression Using Deep Learning

In this case study, we illustrate the importance of implementing a multimodal data compression scheme at the edge for reducing amount of transmitted data, hence, energy consumption and network bandwidth, as requested in Section II-B1, B2. The conventional approach of transmitting the entire medical data wirelessly to an external server or the cloud implies the transmission of a massive amount of data. For instance, in brain disorder monitoring systems, biomedical data such as EEG, Electromyography (EMG), and Electrooculography (EOG) is required to be stored and accessed remotely along with video recording patient's activities for correlating these activities with EEG pattern, which results in generating 8-10 GB per patient per day. A promising methodology to deal with this issue in s-health systems is to perform local in-network and data-specific compression on the gathered data before transmission taking into consideration the applications' requirements and characteristics of the data. This allows, on one hand, reducing the amount of transmitted data, hence saving consumed network bandwidth and transmission energy, on the other hand, implementing compression techniques with high compression ratio and low signal distortion.

In what follows, we investigate the EEG-EOG monitoring system as a case study to illustrate the advantages of implementing deep learning approach for multimodal data compression at the MEN. The multimodal dataset in [10] is used, which contains EEG and EOG signals of 32 participants watching to 40 music videos. Herein, we emphasize that deep learning can be a good candidate for multimodal data compression, due to its ability to efficiently leverage not only the intra-modality correlation, which allows extracting hierarchical representations of data, but also inter-correlation among different modalities. In particular, we exploit Stacked Auto-Encoders (SAE), i.e., special type of neural networks allowing for the hierarchical extraction of data representation.

SAE consists of three main layers: input layer, hidden layer, and output layer. In hidden layers, the layer with the least number of neurons is called the bottleneck layer. At the MEN, SAE's encoder converts the input data x into a compressed representation z at the bottleneck layer through learning the different order features from the input data layer by layer. At the server side, SAE's decoder obtains the reconstructed data $\tilde{x}$ using the compressed representation z, where

$$z = Wx + b \tag{1}$$

$$\tilde{x} = \tilde{W}z + \tilde{b}. \tag{2}$$

W, and $\tilde{W}$ are the encoder and decoder weights matrices, respectively, while b and $\tilde{b}$ are the bias vectors. The objective of SAE is to find the optimal configuration of the weights matrices and bias vectors that minimizes the reconstruction error. Meanwhile, we constraining the neural network by reducing the number of hidden neurons in order to turn the neural network to learn from compressed version of the data. Hence, we adjust our compression ratio by adopting the number of neurons in the bottleneck layer. We also remark that although our compression scheme requires first training the neural network, this process can be conducted offline at the server side to obtain the optimal configuration (i.e., weights matrices and bias vectors), after that the compression is done at the MEN using this configuration with simple matrix multiplications.

The main advantages of using multimodal data compression over single modality compression is considering inter-modality correlation during compression, which results in obtaining a better representation of the data. Also, it enables encoding the multiple modalities in a single-joint representation. This joint representation is obtained by concatenating the two modalities (i.e., EEG and EOG signals) into one single stream z. In Figure 2, we compare the proposed multimodal SAE with Single Modality (SM) compression scheme, where we applied compression on each signal separately, to show the benefit of multimodal compression for obtaining better distortion. As shown, for the same compression ratio, we could obtain up to 50% reduction in EEG distortion using multimodal SAE compression compared to SM compression.

B. Edge-based Feature Extraction and Classification

In what follows, we consider epileptic seizure detection as a case study to show the advantages of implementing feature extraction and classification at the edge for fast

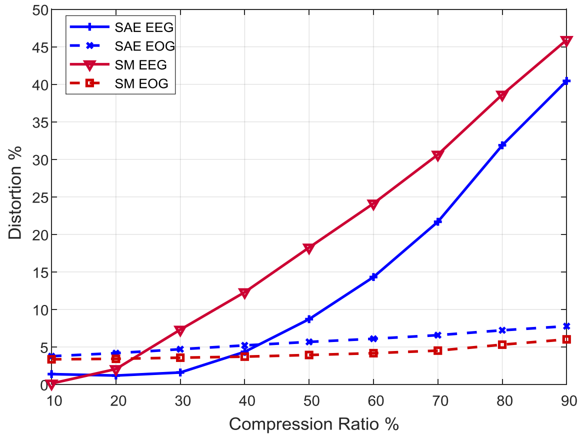

Fig. 2. Distortion and compression ratio variations for EEG and EOG signals using SAE and SM compression schemes.

detection of abnormalities, as requested in Section II-B3. It is assumed that a MEN gathers EEG data from the patient using an EEG Headset, processes, and forwards it to the cloud. The EEG dataset in [11] is used with three sets, denoted A,B, and E, each containing 100 EEG records of 23.6-sec duration and sampling rate 173.61 Hz. Sets A and B represent healthy subjects with eyes opened (A) and closed (B), respectively, while set E contains seizure activity.

1) Feature Extraction : Many neurodegenerative diseases detection methods, such as Parkinsons, Epilepsy, Alzheimers, and Huntingtons, have been reported in the literature based on extracting some features from the patients' vital signs, voice, or captured videos. Such features are used to differentiate a potential patient from a healthy person, or to identify emergency situations. For instance, [4] proposed a method to detect Parkinson's disease (PD) leveraging certain features of a voice signal. However, this proposed healthcare monitoring system for PD patients is built using cloud computing, where the voice signals are transmitted and processed at the cloud server, then the results are sent to registered doctors for a proper prescription. Instead, using our MEC architecture, the voice signals can be processed at the MEN, instead of transmitting them to the cloud, and sent directly to doctors, which significantly saves network bandwidth and guarantees data privacy.

Another important use of such statistical features is to remotely monitor the health of individuals through supervising their daily activities. These features describe characteristics of individuals' daily activities, hence they can be used for training machine learning techniques to predict individuals' status. Thus, implementing such feature extraction techniques at the MEN is a promising solution to offload part of the network load to the edge, hence improving network performance and QoS.

In our case study, we aim to optimize the EEG data transmission based on the detected patient's state at the edge. Feature extraction is at the basis of event detection at the MEN. The first step in this procedure is extracting a set of epileptic-related features from the gathered EEG data. To this end, there are two possible approaches for extracting these feature: time-domain and the frequency-domain feature extraction. Herein, we consider frequency-domain feature extraction scheme due to its immune to signal variations resultant from electrode placement. By transforming the gathered EEG data into the frequency domain, the normal/abnormal EEG classes under study exhibit different mean, median, and amplitude variations. Also, Root Mean Square (RMS) and Signal Energy (SE) are good signal strength estimators in different frequency bands. Hence, to distinguish between seizures and non-seizure events we select the following five Frequency Features (FF): mean (μ), median (M), peak amplitude (P), RMS, and SE.

2) Event-detection at the edge : The second step in our procedure is developing a reliable, edge-based classification technique for seizure detection leveraging extracted features. A number of machine learning techniques, including supervised, unsupervised and reinforcement learning, have been investigated for the purpose of classification, for a variety of application. In a nutshell, supervised learning algorithms leverage a labeled training data set to learn the relation between inputs and outputs. In contrast, unsupervised learning algorithms classify the provided data sets into different clusters by discovering the correlation between input samples. The third category includes reinforcement learning algorithms and exploits online learning, which involves the exploration of the environment and the exploitation of current knowledge, in order to classify the data [12]. However, some limitations should be considered when applying machine learning techniques in s-health, namely, (i) the trade-off between the algorithms' computational complexity and the obtained classification accuracy, (ii) the need to process large datasets so as to ensure high accuracy, (iii) it is not straightforward to mathematically formulate the learned model, or to have the full control over the knowledge discovery process.

In the considered case study, we define an IF-THEN classification rule using generated FF to detect abnormal variations in sensed EEG data due to Seizure as follows

$$S = \begin{cases} \text{Normal}, & \text{if } \sum \mu + M + P + RMS + SE \leq \gamma \\ \text{Seizure}, & \text{if } \sum \mu + M + P + RMS + SE > \gamma \end{cases} \quad (3)$$

where S is the status of the patient, and γ is a classification threshold that is obtained during an offline training phase. Using this swift classifier, we could achieve 98.3% classification accuracy for seizure detection.

Applying this classification to estimate the patients state at the edge has two additional advantages. First, it enables a selective data transfer scheme that adopts the most convenient transfer mode depending on the detected patient's conditions (see Figure 3). As an example, if no emergency is detected, the collected data can be further processed to extract and transmit only those features of the signals that are fundamental to the patients state assessment. While in case of emergency, all gathered data from a patient have to be frequently reported to the cloud for high-intensive monitoring. This could obtain 98% reduction in transmission energy consumption in the case of no emergency (normal class). Second, a quick emergency notification system can be implemented at the edge to notify patient's caregivers in case of emergency, as well as doctors at the remote site. Thus, it is important to implement a highly accurate classification technique at the MEN that, leveraging some features extracted from the gathered data, allows for a reliable detection of the patient's state while requiring low computational resources.

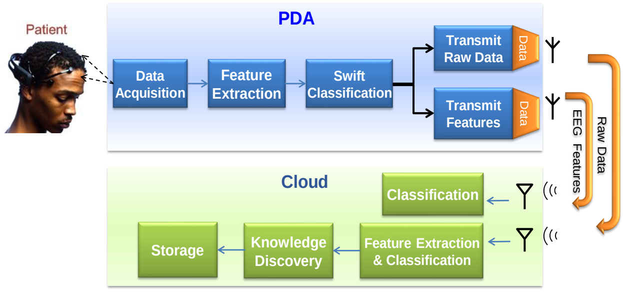

Fig. 3. Efficient class-based data transmission for s-health systems.

IV. Challenges and Opportunities

Here, we discuss three main challenges and opportunities that characterize MEC-based s-health systems and represent interesting lines for future research.

A. Collaborative Edge

Healthcare requires data sharing and collaboration among different stakeholders in multiple domains. However, sharing of data owned by a stakeholder rarely happens due to privacy concerns and the high cost of data transfer. In this context, collaborative edge, which connects the edges of multiple stakeholders that are geographically distributed (such as hospitals, centers for disease control and prevention, pharmacies, and insurance companies), is beneficial in treefold. First, it provides distributed data sharing among different stakeholders at low cost issues, thanks to computation and processing at the participant edges. Second, in the case of remote monitoring, it enables patients to forward their medical data to the cloud through other users/edge nodes by exploiting D2D data transfer. This also improves spectrum and energy efficiency and allows data transferring even in geographically remote areas [13]. Third, it enables a patient's edge node to directly connect to the nearest hospital's edge in the proximity for continuous monitoring, without the need of going through the cloud. This helps to increase monitoring efficiency, reduce energy consumption and operational cost, as well as improve high-quality services.

B. Combining Heterogeneous Sources of Information

Various sources of information are used in S-health systems for efficient monitoring, hence, leveraging advanced multimodal data processing techniques for combining these sources of information at the edge is a promising trend toward automating supervision and remote monitoring tasks. However, several challenges remain open when we come to the s-health systems with hybrid sensing sources. First, in terms of multiple modalities, it is not straightforward to incorporate multiple active and passive data streams in s-health systems, where power consumption is a limiting factor; indeed, transmission of highly informative biosignals (e.g., EEG, EMG, and electrocardiogram) is an energy hungry process for battery-operated devices. Second, artifacts arise from internal sources, e.g., muscle activities and movements, as well as from external sources related to noise, interference, and signals offset, which have critical implications on data quality [14].

In this context, adopting a MEC-based s-health system architecture would be beneficial in two ways. First, it permits to address system complexity associated with such heterogeneous and variable data-stream inputs. This is done through implementing multimodal in-network processing techniques that yield the correlation between different modalities, in addition to the temporal correlation within each modality. Moreover, a MEC-based architecture enables extracting high level application-based features at the edge rather than the cloud. By doing so, a MEN can send a limited number of the extracted features, or the obtained correlations, instead of transmitting either the original or the compressed data. Second, advanced signal processing for artifact removal can be incorporated at the edge, in order to improve signals quality before data transmission.

C. Privacy and Security

Great potential of s-health system can only be achieved if individuals are confident in the privacy of their health-related information and providers are confident in the security of gathered data. However, ensuring privacy and security is not straightforward. Wireless medical devices are typically susceptible to various types of threats, such as information harvesting, patient tracking and relaying, as well as denial of service attacks, which violate confidentiality and integrity of the devices. Data processing algorithms and data storage may also be subject to attacks. Below we discuss some challenges and opportunities that MEC poses in this respect.

First is the ownership of the collected data from the patients. Storing the data at the patients' proximity, where it is collected, and enabling the patients to fully own the data is a better solution for privacy protection. Also, the patient will be able to control if the data should be stored at the edge or transmitted to the cloud after removing or hiding some of the private information from the data.

Second is the trade-off between increasing security level and QoS. Increased security through strong cryptographic algorithms or long sized encryption keys, adds more processing and additional overhead at the edge, which may have a significantly adverse impact on QoS [15]. This imposes an essential need to design joint QoS and security mechanisms for s-health applications that maximize QoS while meeting the application security requirements.

V. Conclusion

In this paper, we presented our vision of an s-health system leveraging the multi-access edge computing paradigm. Such an approach can indeed boost the system performance by efficiently handling the enormous amount of data generated by sensors and personal as well as medical devices at the edge of the network, and addressing the limited energy capabilities of such devices. In particular, edge-based processing like compression and event detection can greatly reduce the amount of data transferred toward the cloud, thus removing one of the major bottlenecks in s-health systems. Furthermore, processing data at the edge will ensure better user privacy than when raw data is uploaded to the cloud. In this context, we identified some computing tasks that can be implemented at the edge and presented effective approaches to implement them, so as to ensure short response time, efficient processing and minimal energy and bandwidth consumption. Finally, we highlighted some challenges and opportunities of edge computing in the s-health filed that are worth further research.

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