Smart Healthcare

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Contents

Abstract

Internet-of-Things and machine learning promise a new era for healthcare. The emergence of transformative technologies, such as Implantable and Wearable Medical Devices (IWMDs), has enabled collection and analysis of physiological signals from anyone anywhere anytime. Machine learning allows us to unearth patterns in these signals and make healthcare predictions in both daily and clinical situations. This broadens the reach of healthcare from conventional clinical contexts to pervasive everyday scenarios, from passive data collection to active decision-making.

Despite the existence of a rich literature on IWMD-based and clinical healthcare systems, the fundamental challenges associated with design and implementation of smart healthcare systems have not been well-addressed. The main objectives of this article are to define a standard framework for smart healthcare aimed at both daily and clinical settings, investigate state-of-the-art smart healthcare systems and their constituent components, discuss various considerations and challenges that should be taken into account while designing smart healthcare systems, explain how existing studies have tackled these design challenges, and finally suggest some avenues for future research based on a set of open issues and challenges.

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1

Introduction

A rapidly aging population and the dramatic increase in the cost of in-hospital healthcare have led to the recognition of the importance of efficient healthcare systems (Nia et al., 2015) and fostered several novel research directions at the intersection of healthcare, data analytics, wireless communication, embedded systems, and information security. Implantable and Wearable Medical Devices (IWMDs), which facilitate non-invasive prevention, early diagnosis, and continuous treatment of medical conditions, are envisioned as key components of modern healthcare (Ghayvat et al., 2015; Mukhopadhyay, 2015; Mosenia et al., 2017b). The computational power, energy capacity, and networking capabilities of IWMDs have improved significantly in the last decade while their sizes have decreased drastically. These technological advances have brought daily healthcare systems from a distant vision to the verge of reality. Furthermore, the emergence of Internet-of-Things (IoT) and the introduction of new computing/networking paradigms (such as Cloud computing and Fog computing), which make possible systems consisting of several heterogeneous sensing and computing devices, have revolutionized traditional healthcare and provided an opportunity to replace in-hospital medical systems with Internet-connected IWMD-based systems, thus bringing us to the dawn of a new era of smart healthcare.

Smart healthcare does not have a unique definition. However, *our broad interpretation of smart healthcare is that besides **clinical** usage, it also utilizes IWMDs to gather, store, and process various types of physiological data during **daily** activities.* Smart healthcare systems may rely on wireless connectivity to take advantage of external resources, e.g., computational/storage resources available on nearby devices or the Cloud, or inform a clinician about the patient's medical condition. Hence, smart healthcare offers a proactive approach to early detection and even prevention of medical conditions. It even enables physicians and clinicians to assist patients in their home environment where they can be continuously monitored with the help of numerous Internet-connected healthcare systems. This reduces the need for institutionalization and hospitalization, and is especially beneficial to the disabled and elderly. It also has the potential to reduce healthcare costs significantly and enhance the quality of life of patients.

Since the introduction of the first IWMD (an implantable pacemaker) in 1958, several types of IWMDs have been developed and introduced in the market, ranging from sweat-analyzing devices (Gao et al., 2016) to Internet-connected multi-sensor continuous long-term health monitoring systems (Nia et al., 2015; Pantelopoulos and Bourbakis, 2010). However, despite a rich body of literature on IWMD-based and clinical healthcare systems (see (Pantelopoulos and Bourbakis, 2010), (Mosenia et al., 2017b), and (Musen et al., 2014) for a comprehensive survey), the fundamental challenges associated with design and implementation of smart healthcare systems have not yet been well-addressed. The main goals of this article are to define the scope of smart healthcare and investigate state-of-the art smart healthcare systems, their constituent components, their design considerations, and how existing studies have tackled these challenges. In particular, we do the following.

- We present a novel framework for smart healthcare, which aims to support both in-patient and out-patient health monitoring and discuss and compare clinical and daily healthcare.

- We describe several emerging smart healthcare systems, including IBM Watson (High, 2012), Open mHealth (Estrin and Sim, 2010), Health Decision Support System (HDSS) (Yin and Jha, 2017), Stress Detection and Alleviation system (SoDA) (Akmandor and Jha, 2017), and an energy-efficient system for continuous health monitoring of a patient's medical condition over the long term (Nia et al., 2015).
- We discuss several considerations and challenges that should be taken into account while designing smart healthcare systems.
- We describe five research trends for addressing these design considerations, including compact deep neural networks and compressive sensing to drastically reduce computation energy and storage, and MedMon, OpSecure, and SecureVibe to enhance security of healthcare systems.
- Finally, we discuss several future research directions, including the need to obtain medical datasets and machine learning models for them, standardization and infrastructure, and the promising role that Fog computing can play in smart healthcare.

The rest of the article is organized as follows. In Chapter 2, we present a smart healthcare framework that enables exploitation of the rapid clinical-to-daily healthcare expansion. In Chapter 3, we analyze five emerging systems that act as enablers of smart healthcare. In Chapter 4, we discuss associated design considerations and challenges in these systems, including efficiency, security, accuracy, cost, responsiveness, maintainability, scalability, reliability, and fault tolerance. In Chapter 5, we describe five emerging research trends that address some of these challenges. In Chapter 6, we discuss open issues and future research directions. Finally, we conclude in Chapter 7.

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