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Mobile Technologies for Smart Healthcare System Design

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Wireless Networks

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Preface

Nowadays, people pay more attention to their physical health because the accelerated pace of life and increasing work pressure have compelled many people to adapt to a sedentary lifestyle. Such sedentary lifestyles often lead to many chronic illnesses (e.g., obesity), which negatively impact people's quality of life. Thus, it is important to continuously pay attention to people's health conditions and provide in-time actions. The traditional way of healthcare requires patients to perform hospital visits or wear dedicated devices, which are intrusive and costly. Consequently, solutions providing a low-cost, long-term, non-invasive health monitoring system are highly desirable. Mobile technologies have recently demonstrated success in many application domains, including pervasive computing, Internet of Things (IoT), smart homes, etc. The integrated sensor modalities and wireless communication capabilities make mobile technologies a promising way to address healthcare needs that traditional approaches cannot offer. This book intends to provide comprehensive analyses and state-of-the-art designs of low-cost, long-term, and non-invasive health monitoring systems from different perspectives by leveraging mobile sensing technologies.

In this book, we show how to utilize wireless signals and mobile technologies to facilitate smart healthcare in addition to their original capabilities. In particular, we introduce the identification of many kinds of activities exploiting the prevalence of WiFi infrastructure. We extract channel state information (CSI) in WiFi signals to achieve fine-grained activity recognition. Furthermore, a personalized fitness assistant system in home/office environments has been designed using the existing WiFi infrastructure. Since millimeter wave (mmWave) technologies have already been integrated into WiFi standards, they become a promising solution to enhance the resolution and accuracy of wireless-based smart healthcare systems. Along this direction, the personalized fitness assistant system has been further enhanced by using a single commercial-off-the-shelf (COTS) mmWave device to demonstrate its capability to handle more complex scenarios in indoor environments, including dynamic environment changes and multiple people. We then study another essential healthcare component, eating habit monitoring, which can facilitate dietary behavior analysis and nutrition study. The designed system provides environment-invariant eating behavior monitoring. Moreover, we find that mobile devices (e.g., smartphones and smartwatches) can be extended for smart healthcare in addition to their original usage. We again develop a personalized fitness assistant system for people carrying mobile devices to help them achieve fitness goals while minimizing the chances of injury. The system dynamically depicts comprehensive short-term and long-term workout pictures of the user's exercises using wearable mobile devices. In addition to its original usage of measuring physiological signals, photoplethysmography (PPG) sensors are exploited to facilitate advanced healthcare applications. Specifically, we demonstrate that built-in PPG sensors on wearables can enable finger-level gesture recognition, sign language interpretation, and continuous user authentication.

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Chapter 1
Introduction

1.1 Background

The advent of mobile sensing technologies has facilitated widespread connectivity among different devices, including smartphones, tablets, voice assistants, wireless sensors, and smart appliances. This integration has transformed many aspects of daily life and enabled a wide range of applications such as mobile healthcare monitoring, activity recognition, and user authentication.

In particular, long-term healthcare-related applications employing mobile sensing technologies are crucial in promoting personal well-being. Notably, the portability of mobile devices, coupled with their wearability around the clock, offers continuous monitoring capabilities. These applications are crucial for vulnerable demographics of young children and people suffering from chronic diseases such as obesity, paralysis, or respiratory illnesses. Therefore, sensing methodologies for long-term mobile health monitoring have become essential in diverse research spanning areas such as activity recognition, fitness assistance, dietary tracking, and vital signs monitoring.

To support these functions, various forms of techniques in mobile devices have been developed, each with unique usage potential. Traditionally, health monitoring was primarily conducted in hospitals. These institutions utilized specialized sensors like electrocardiograms or glucometers to track specific aspects of an individual's health, in order to provide comprehensive evaluations. In comparison, choices for home-based monitoring used to be quite limited. Nowadays, users can utilize personal devices such as smartphones or wearable devices to enable the wide adoption of long-term mobile health monitoring in their daily lives. This evolution has been enabled through the integration of diverse sensors. The proliferation of WiFi has interconnected numerous mobile devices, thereby conferring upon each device the ability to offer mobile sensing capabilities. Furthermore, inherent sensors like accelerometers and microphones within mobile devices can augment the sensing capabilities even further.

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1.1.1 *Advanced Mobile Sensing Technologies*

1.1.1.1 WiFi-based Technologies

Fine-grained Channel State Information (CSI) has been proposed as a more accurate wireless sensing strategy utilizing WiFi signals. Unlike Received Signal Strength (RSS), CSI not only indicates path loss over distance but also aggregates multipath effects such as scattering and fading. This makes CSI more sensitive to changes in signal propagation caused by human body movement, including subconscious motions associated with breathing [18, 24, 25, 30, 41, 42]. In comparison to RSS, CSI contains a larger set of values, including amplitude and phase information, for orthogonal frequency division multiplexing (OFDM) subcarriers. Separate subcarriers can span different frequency ranges and, thus, experience slightly different multipathing effects while propagating from the WiFi endpoint devices. This information provides more fine-grained details of the wireless channel than RSS. Consequently, CSI has enabled WiFi signals to become a promising sensing modality for healthcare applications.

1.1.1.2 mmWave-based technologies

As mmWave technologies are integrated into WiFi standards, they also emerge as a promising solution to enhance the resolution accuracy in wireless-based smart healthcare systems. mmWave signals have higher frequencies than traditional WiFi signals (i.e., 2.4 and 5 GHz). They typically operate in the tens to hundreds of GHz range and thus can utilize a broader bandwidth [45]. Although mmWave signals have limitations in penetrating materials and long-range transmissions due to shorter wavelengths, their sensitivity to environmental changes can be highly advantageous in fine-grained sensing. Such features allow mmWave signals to detect subtle movements caused by heartbeat and breathing, making them an excellent choice for advanced smart health applications. Futhermore, the smaller antenna array used in mmWave transmission allows these systems to remain portable and easy to integrate into mobile healthcare sensing systems.

1.1.1.3 Inertial Sensor-based Technologies

Motion sensors, including accelerometers, gyroscopes, and magnetometers, can detect linear accelerations, rotational rate, and force along 2–6 degrees of freedom, depending on levels of sophistication. Furthermore, motion sensors find frequent utilization in commercial items like smartphones and wearable devices. These sensors are often integrated into Inertial Measurement Units (IMUs) to adhere to compact size prerequisites. To maintain high accuracy, accelerometers, gyroscopes, and magnetometers can be utilized jointly, with each performing a different function. Accelerometers function by generating electrical charges, which are proportional to the force of vibration or contraction, based on the piezoelectric effect [19]. Since the mass of the device remains constant, the generated charge is proportional to the acceleration and can be utilized to derive linear indications of position, such as velocity or distance. Gyroscopes, on the other hand, provide additional information on the axis of rotation by measuring low-current electrical signals produced by an internal rotor [35]. These sensors are susceptible to accumulating errors over time, which can result in a drifting effect when further calculations are made using flawed measurements.

Data from motion sensors is one of the most straightforward and comprehensible metrics, and as a result, many basic mobile health monitoring systems utilize this data to provide a quantifiable trace of an individual's physical activity [32, 34]. Studies have demonstrated that patterns in motion data can indicate periodic motions and gestures associated with walking, running, stretching, breathing, and other activities [10]. This data can be gathered using standalone sensors or by utilizing existing devices such as smartphones, smartwatches, and fitness trackers [14, 26].

1.1.1.4 PPG-based Technologies

Photoplethysmography (PPG) is an optical technique that measures blood volume changes through light reflection or absorption from the skin and underlying tissues. A typical PPG setup involves shining single-frequency light from an LED onto the skin and measuring the absorbed or reflected light with a photodiode [33]. Traditionally, PPG data is instrumental in determining heart rates, pulse oximetry, and heart rhythm irregularities. In existing health monitoring systems, PPG measurements are known to be susceptible to body motion artifacts, which generate interference in blood volumes and reduce system performance. However, recent studies showed that such motion artifacts can be leveraged to analyze muscle movements, expanding the use of PPG to more smart healthcare-related applications, including sign language interpretation and user authentication.

1.1.2 Mobile Healthcare Systems

1.1.2.1 Daily Activity Recognition

Activity recognition plays a crucial role in long-term mobile healthcare systems, particularly in monitoring Activities of Daily Living (ADLs). It allows for non-intrusive tracking of a patient's routine activities and physical state, providing valuable insights into their health and well-being. Furthermore, the significance of activity recognition extends to being a foundational element upon which other functionalities such as fitness monitoring, eating tracking, and more are constructed. By identifying pre-defined patterns in sensory data, activity recognition can monitor a user's daily tasks, such as eating, dressing, and moving around [4, 20], as well as their postures [2, 31]. It can also detect potential health risks, such as falls [5]. This information not only offers a comprehensive view of the patient's daily functioning and independence but can also aid in early detection and prevention of health issues.

Smartwatches [37], sensor networks [44], and mobile phones [37] are all devices that can be used for device-based activity recognition. These devices can be worn or carried by the patient, allowing for easy tracking of their body motions. Additionally, hardware such as mobile phones and WiFi access points can be repurposed for device-free activity recognition [43, 47], enabling the monitoring of patients at a distance.

Integrating activity recognition into mobile healthcare systems, particularly for monitoring Activities of Daily Living (ADLs), can significantly enhance mobile healthcare. This technology allows healthcare providers to understand a patient's daily routines and physical habits, enabling them to offer personalized care based on the patient's unique lifestyle and needs. By tracking these daily activities, early signs of potential health issues can be detected, allowing for timely intervention before they escalate into serious problems. This proactive approach not only improves patient outcomes but also enhances the quality of life for patients by promoting independence and maintaining their daily functionalities.

1.1.2.2 Fitness Assistance

Different from regular activity recognition, smart fitness assistance systems place emphasis on providing personalized guidance and support to users during their fitness activities. These systems often integrate wearable devices or smartphone applications that collect data related to heart rate, calorie expenditure, distance covered, and other relevant metrics. By processing this information, smart fitness assistance systems can offer real-time feedback, exercise recommendations, and progress tracking to enhance the effectiveness of workouts and improve overall fitness levels.

Sustaining fitness is a vital aspect for individuals engaged in activities such as regular gym visits and the general public. The dynamic nature of exercise calls for portable sensing solutions to accurately monitor and adapt to their active routines. As users may be moving quickly in larger public spaces such as gyms or outdoors, fitness assistance systems tend to prefer small, device-based solutions [28, 48]. However, device-free methods can still function well in indoor scenarios [46, 50]. With the increasing demand for personalized healthcare, smart fitness assistance systems have the potential to become an essential component in the overall mobile healthcare ecosystem.

1.1.2.3 Daily Dietary Tracking

One of the primary concerns for nutritionists is to develop and verify adherence to a daily dietary plan for their clients [17]. With the increasing stress at work and fastpaced lifestyles, people are more prone to forming unhealthy habits, particularly unhealthy eating habits, which can lead to various illnesses. According to a survey by the World Health Organization, more than 1.9 billion adults worldwide are overweight, and 650 million are obese. These people are at risk for dietary health problems [23]. Therefore, finding solutions to diet-related issues is an urgent matter, and efficient daily dietary tracking is a necessity.

Monitoring eating behaviors, such as food types, quantities, and eating speed, can provide valuable insights into an individual's diet and health status. Traditional methods for tracking daily dietary intake require self-reporting from the users [7, 12, 13, 16, 40]. However, self-reporting can be inconvenient and inaccurate due to the user's lack of experience in recording nutritional content or forgetfulness in making timely log updates.

To address these limitations, there have been a recent surge of research on automatic dietary monitoring. Vision-based approaches that use cameras to capture food information, such as photos or videos of meals, have been proposed [38]. Kong et al. [22] suggest using the user's mobile device to take photo strings or short videos to perform automatic dietary assessment. Zhu et al. [49] provide an image analysis method to recognize eating and evaluate food amount and type. O'Liughlin et al. [29] explore the feasibility of using the Microsoft SenseCam [15] to estimate dietary energy intake in various sports populations.

Beyond just relying on vision-based techniques, the prevalence of wearable devices integrated with diverse sensors has surged, serving as effective tools for tracking daily dietary intake. This book will delve into the utilization of mmWave technology for the purpose of monitoring daily dietary intake, as dietary tracking involves capturing gestures on a smaller scale. The application of mmWave technology is well-suited for this task due to its capacity to offer high-resolution insights.

1.1.2.4 Fine-grained Sign Language Recognition

The demand for wrist-worn wearable devices has witnessed a remarkable surge since 2015, with an estimated global shipment of 101.4 million units in 2019 [21]. This increasing popularity of wrist-worn wearables opens up exciting opportunities to harness diverse sensing modalities for pervasive hand or finger gesture recognition. Hand and finger gestures encompass a wide spectrum of combinations, providing rich information that can power numerous intricate human-computer interaction (HCI) applications. These applications include wearable controls, virtual reality (VR)/augmented reality (AR) systems, and automatic sign language translation. To illustrate the potential of automatic sign language translation, consider a wrist-worn wearable device like a smartwatch or a wristband. Equipped with sensors, it can convert sign language into audio and text, and vice versa. This technology holds immense promise in facilitating communication between individuals who are deaf or have hearing difficulties and those who are unfamiliar with sign language. A recent review conducted by Er-Rady et al. [6] sheds light on the existing methods of automatic sign language translation, which are still in their early stages. This review serves as a driving force for us to develop a robust finger-level gesture recognition system that can effectively address this challenge.

1.1.2.5 User Identification and User Authentication

User Identification and User Authentication are crucial components of ensuring secure access to systems and protecting sensitive information. User identification refers to the process of uniquely identifying individual users within a system or application. This is typically achieved through recognizing unique identifiers. User authentication, on the other hand, involves verifying the identity of a user to ensure that they are who they claim to be. This verification process is essential for granting access to resources or restricted areas that are exclusively designated for authorized users. Common authentication methods include passwords, biometric authentication (such as fingerprint or facial recognition), and two-factor authentication. The combination of robust user identification and authentication mechanisms play a vital role in preventing unauthorized access, protecting user privacy, and safeguarding sensitive data from malicious actors.

Recently, there is a growing body of research and development focusing on utilizing mobile devices for user identification and authentication. For instance, gesture recognition is emerging as a promising approach in this field. To establish user identity, gesture recognition algorithms analyze the unique patterns and characteristics of individual gestures [9, 36]. These algorithms can distinguish between authorized users and impostors by assessing factors like gesture speed, duration, direction, and shape. Furthermore, behavioral biometrics, such as keystroke dynamics [1, 3, 8] and gait analysis [11, 27, 39], concentrate on the distinctive behavioral patterns exhibited by individuals. These methods monitor factors such as typing rhythms, touchscreen gestures, or walking patterns to establish and authenticate user identity.

1.2 Challenges

In this section, we will further discuss the challenging issues in designing long-term mobile healthcare systems.

1.2.1 Issues in Raw Data Collection for Mobile Healthcare

Utilizing mobile technologies and mobile sensing for applications like activity recognition, fitness monitoring, eating monitoring, user identification, and user authentications introduce numerous data collection challenges. The complexity and diversity of human activities demand highly accurate and reliable sensors, yet sensor limitations, including signal variability, noise, and drift, often impact data integrity. Moreover, activities such as eating or exercising may result in drastic changes in body motion and physiological signals, which can further complicate data interpretation. When it comes to fitness tracking, the data collected from different individuals can vary significantly due to personal factors such as age, gender, fitness level, and health status, making it challenging to design universally applicable algorithms. For user identification and authentication applications, issues like false positives and negatives, and spoofing attacks are major concerns. Besides, privacy and security are of great importance, given the sensitivity of the data collected, yet ensuring these while providing seamless user experiences can be challenging. In addition, dealing with the large volume of data generated by continuous monitoring, along with battery life considerations for mobile devices, adds another layer of complexity to these applications.

1.2.2 Extracting Effective Features for Designing Mobile Heathcare System

Another challenges of employing mobile technologies for mobile healthcare related applications in feature extraction. Feature extraction is crucial for transforming raw sensor data into meaningful information, but achieving this reliably and accurately is a complex task. For applications like activity recognition and fitness monitoring, the dynamic nature of human activities demands robust features that can capture unique patterns amid a wide range of movements and physiological responses. Selecting the right features is equally challenging, particularly when it comes to recognizing diverse eating behaviors or authenticating users based on biometric data. The variability between individuals' behaviors or biometric patterns requires the extraction of highly discriminative features to ensure accurate identification and authentication. Furthermore, extracted features should be resistant to noise and sensor errors, which is challenging given the inherent variability in mobile environments. Another obstacle is computational efficiency. Mobile devices have limited processing capabilities, so feature extraction methods need to be optimized to function effectively under these constraints. Finally, ensuring privacy while extracting meaningful features from sensitive data is a delicate balance that requires sophisticated strategies and protocols.

1.2.3 Enhancing System Robustness in Practical Environments

When designing long-term mobile healthcare system, environmental changes also pose significant challenges. Mobile devices are often used in diverse and dynamically changing environments, which can significantly affect the quality and accuracy of the system. For example, activity recognition and fitness monitoring may be influenced by changes in lighting, weather, terrain, and user context, such as indoor versus outdoor activities. These changes can introduce variations in sensor data that may not necessarily correspond to changes in the user's activity, leading to misinterpretations. Similarly, for eating monitoring, different environments like restaurants, homes, or offices could impact user behavior, and hence the sensor data. User identification and authentication systems also have to contend with environmental variations, such as changes in ambient noise that could affect voice recognition, or lighting changes impacting facial recognition. Furthermore, environmental factors can also affect the device's performance itself, for instance, temperature fluctuations influencing battery life, or signal strength variation due to changes in location. Therefore, designing robust systems that can adapt and respond to these environmental changes remains a major challenge for mobile sensing applications.

1.3 Book Organization

The book commences with an introduction in Chap. 1 that gives an overview of the content, followed by a detailed discussion on the background of the topic. It specifically covers advanced mobile sensing technologies and mobile healthcare system design. This section sets the context and highlights the importance of the subject matter. Subsequently, the challenges and contributions to the field are presented, with the organization of the book succinctly outlined. The book then delves into detailed chapters on specific topics including contactless activity identification using commercial WiFi in Chap. 2, personalized fitness assistance using commodity WiFi in Chap. 3, multi-person fitness assistance via millimeter wave in Chap. 4, non-intrusive eating habits derivation using millimeter wave in Chap. 4, Fitness Assistance Using Motion Sensor in Chap. 6, Fine-grained gesture recognition and sign language interpretation via PPG on smartwatches in Chap. 7 and continuous user authentication via PPG in Chap. 8. Each of these chapters starts with a background study, related works, and detailed system design with its implementation and evaluation. In conclusion, the book integrates cutting-edge technologies and novel methodologies to provide a comprehensive understanding of mobile sensing technologies and long-term mobile healthcare systems.

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