Chapter 12

Case studies of WSN-CPS applications

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<A>Abstract

The most representative form of Cyber-physical systems (CPS) involves wireless sensor networks (WSNs) as the main means to interact with physical entities. This chapter reviews a number of such WSN-CPS applications and reveals how these applications bridge the gap between sensing information in the cyber world and diverse entities in the physical world. We divide these applications into five categories: *smart space systems*, *healthcare systems*, *emergency response systems*, *human activity inference*, and *smart city systems*. Smart space systems monitor energy usage, temperature, and various other attributes of appliances in an indoor space. Healthcare systems assist people to improve physical and emotional well-being through automatic sensing and sense-making technologies. Emergency response systems search and rescue people as soon as possible in emergency situations such as fire outbreaks. Human activity inference systems interpret human intention behind sensing information to facilitate human daily activities related to social events, road safety, mood detection, interactive games, etc. Smart city systems concentrate on city dynamics such as urban environmental monitoring, human mobility, and transport information. Our discussion in this chapter is steered from simple to complex systems in terms of networking technologies, service ranges, system integration, and human engagement. We conclude by discussing important technical components, future trends, and open issues in WSN-CPS applications in order to provide readers with technical pointers of designing next-generation WSN-CPS applications.

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<A>12.1 Introduction

Cyber-physical systems (CPSs) which incorporate wireless communications, micro-electromechanical systems (MEMS), intelligent decision making, ubiquitous computing, and integration control among diverse entities have been boosting many promising applications and open up more opportunities to enrich the interaction between the cyber world and the physical world. This chapter will systematically review wireless sensor network (WSN)-CPS applications from static towards dynamic networks, from small-scale to large-scale service coverage, and from simpler towards more complex system interaction, as shown in Figure 12.1, including smart space systems, healthcare systems, emergency response systems, human activity inference, and smart city systems. Figure 12.2 gives an overview of coarse-grained classification based on the three different criteria: network flexibility, service coverage, and human engagement. Generally, from network flexibility and service coverage, a more dynamic system can operate in a more large-scale area. Moreover, based on the degree of human engagement, the former two categories are much simpler and emphasize how sensors interact with hardware devices as well as humans, while the latter three categories are more complex and focus on how humans interact with a whole wireless sensor network, people, and a whole city. The main goal of this chapter is to bring important factors and comparison from system-level, service-level, and the level of human engagement perspectives to audiences' attention through reviewing some promising WSN-CPS applications. We further discuss some future trends and open challenges in future WSN-CPS applications.

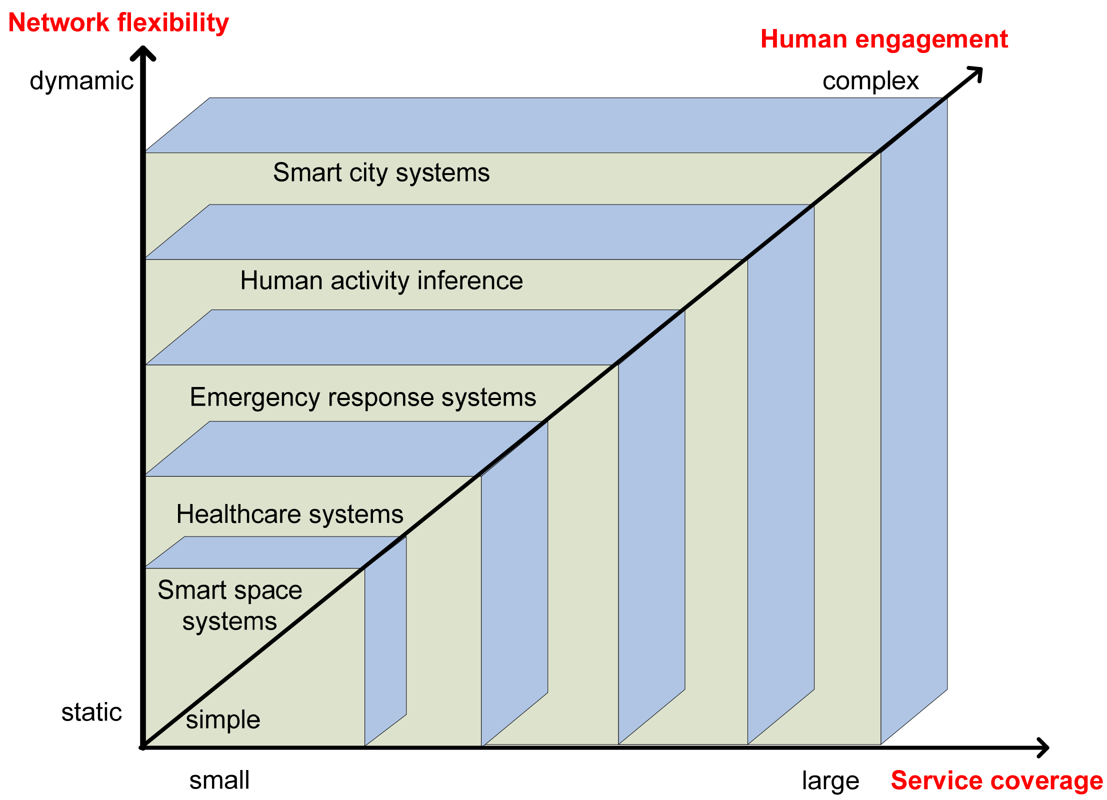


Figure 12.1 General analysis of WSN-CPS applications

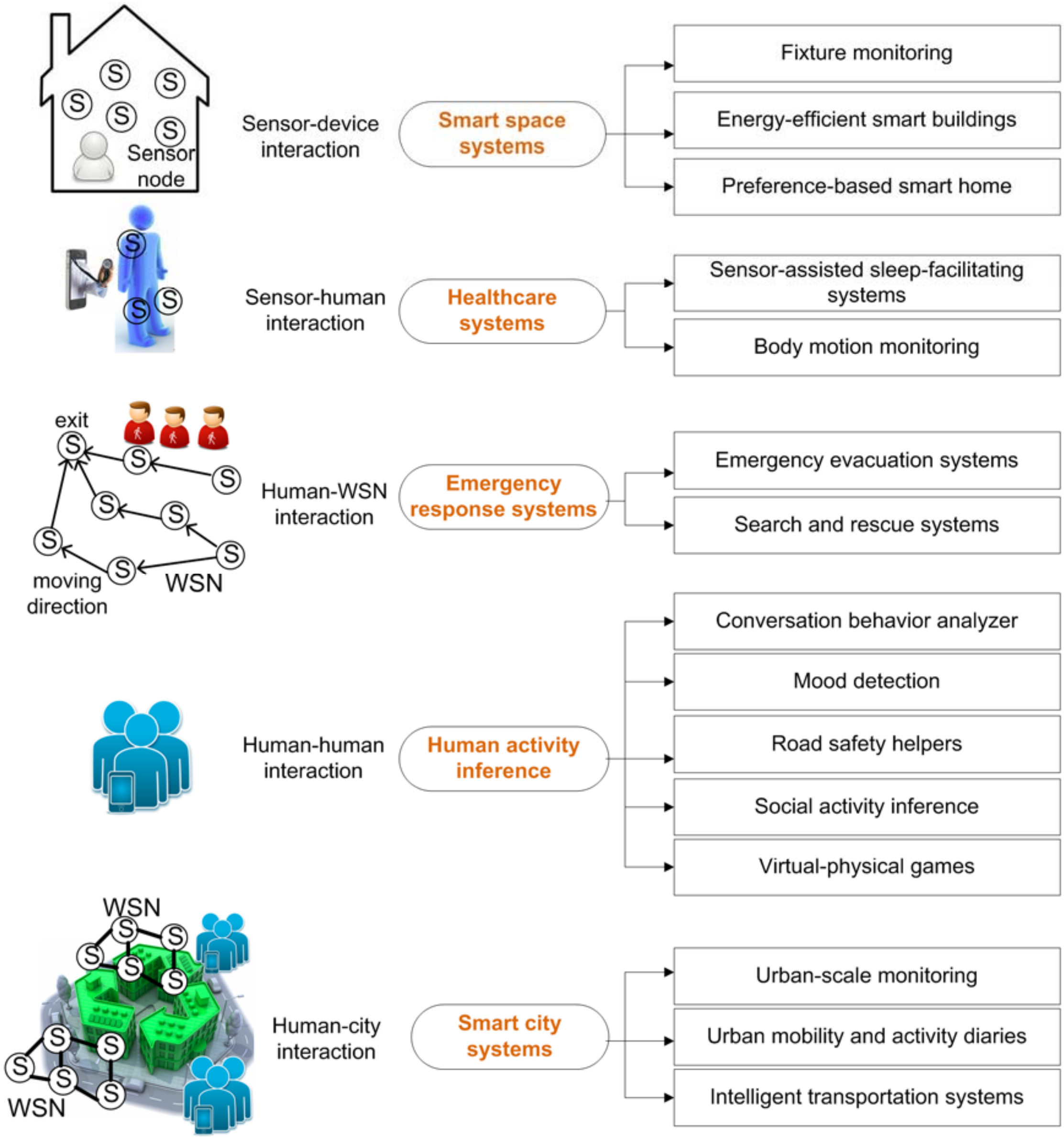


Figure 12.2 An overview of WSN-CPS applications

This chapter is organized as follows. Section 12.2 will review three types of smart space systems, namely fixture monitoring systems, energy-efficient smart buildings, and preference-based smart home. These systems will control the usage of household appliances and utilities in a certain intelligent way. The control principles in the first two types are to avoid waste of resources, while control principles in the last type will depend on personal preference. In Section 12.3, two types of healthcare systems will be discussed, namely sensor-assisted sleep-facilitating systems and body motion monitoring. The goal of the first type is to improve sleep quality of humans, while the second type concentrates on identifying body motion patterns. Section 12.4 studies the integration of real-time monitoring and intelligent decision making in emergency response systems that provide people with adequate instructions when a dangerous event happens (e.g. a fire). Based on the response diversity and actuation capabilities, the existing emergency response systems can be classified into two types, namely emergency evacuation systems and search and rescue systems. The former exploits pre-deployed sensor networks to guide people to exits, while the latter integrates mobile platforms (e.g. robots), opportunistic communications, and parallel computing to support diverse actions. Furthermore, as off-the-shelf smartphones equipped with various sensors are able to bridge data generated in the cyber world and human activities in the physical world, in Section 12.5 we comprehensively study how to infer everyday human activities automatically. We will review five types of applications including conversation behavior analyzer, mood detection, road safety helpers, social activity inference, and virtual–physical games. The first three types aim at human behavior inference, while the last two types focus on inferring social intention to facilitate human-to-human interaction. Section 12.6 reviews interesting applications in a smart city including urban-scale monitoring, urban mobility and activity diaries, and intelligent transportation systems. The former two types are intended to derive deep knowledge behind sensing data for better understanding of city dynamics, while the last type is to provide convenient transportation-related information for improving daily commutes. Finally, Section 12.7 discusses fine-grained classification based on some technical features and requirements of WSN-CPS systems and highlights some important challenges for future systems.

<A>12.2 Smart space systems

This section will review three types of smart space systems based on different requirements in a smart environment. The first type is to monitor the statuses of appliances, the second type adaptively adjusts the temperature for the energy-saving purpose, and the third type is more flexible to fit preferences of multiple users.

<B>12.2.1 Fixture monitoring systems

Monitoring of electrical and water fixtures in smart space is necessary for conserving energy or water cost. Such systems typically comprise three technical stages: (1) fixture discovery, (2) fixture recognition, and (3) fixture disaggregation. The fixture discovery is to infer the existence of electrical and water fixtures in a house automatically. For example, [58] deploys multi-modal sensors including motion sensors, light sensors, water meters and power meters in a house so that each fixture will have a distinctive usage profile (called 'fixture profile') that is a combination of multi-modal sensing data instead of single-modal data from a single smart meter or an ambient sensor. Since a fixture usually creates a pair of 'ON' and 'OFF' events, these multi-modal sensors and smart meters will collaborate to discover the number of fixtures in a house and their fixture profiles through data fusion and matching algorithms.

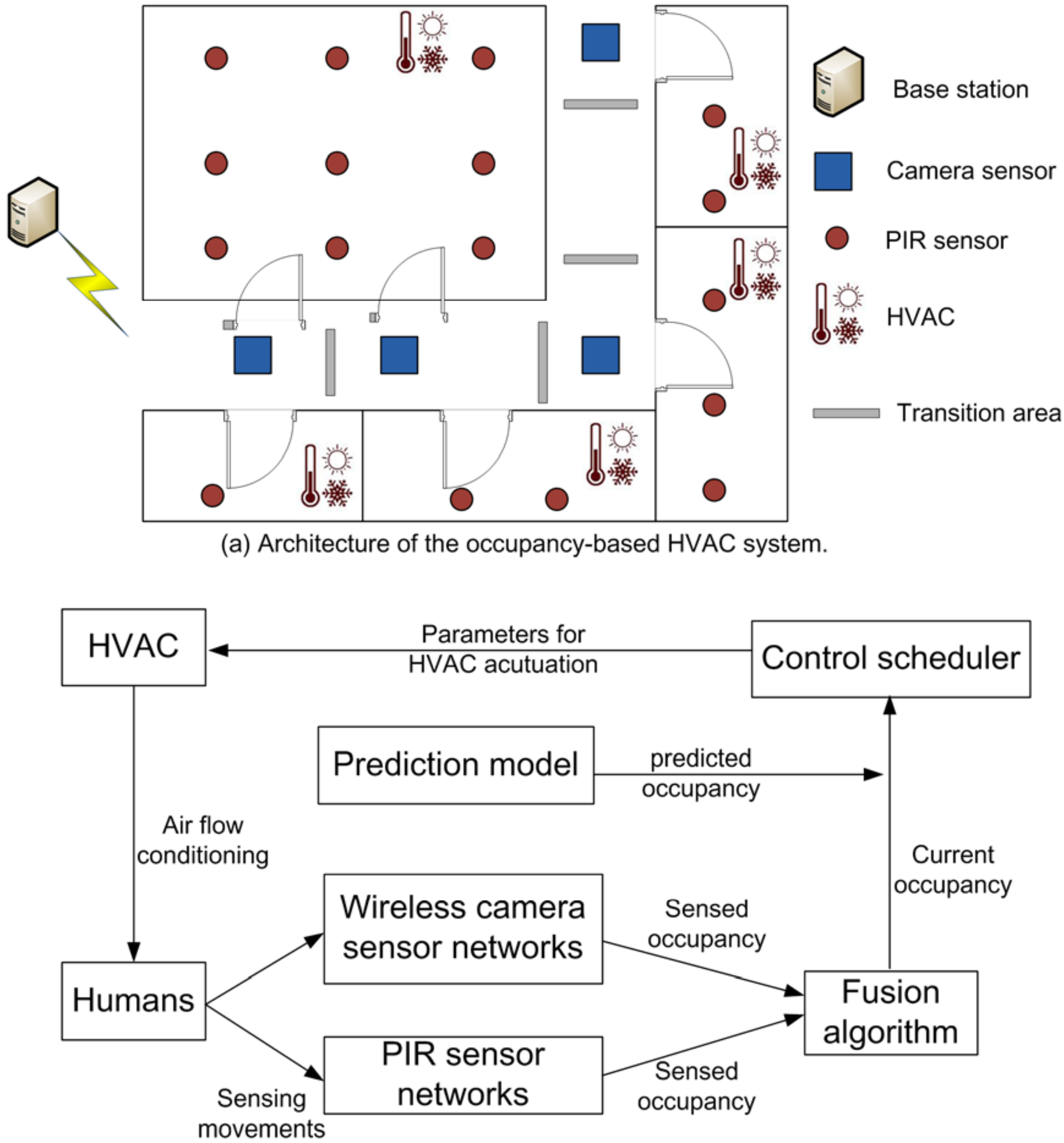
The fixture recognition is to identify when a particular fixture is turned on or off. For example, in [16] and [14] a sensor is attached to a wall socket and a hose to monitor high-frequency signals in the voltage and water pressure, respectively. In the training phase, a user will manually turn on/off each fixture so that the system can learn the fixture profiles based on the usage of fixtures. Afterwards, the system will be able to recognize those fixtures automatically when they are used. Finally, fixture disaggregation is to identify how much energy or water is used by each individual fixture. For example, in [29] and [30] a sensor is attached to each electrical (or water) fixture to recognize when they are used and also a smart meter is used on the electrical (or water) mains to monitor aggregated energy (or water) usage in the entire house. Since the total energy (or water) usage in a house is equal to the sum of energy (or water) usage of each individual fixture, the system can compute the quantity of energy (or water) used by each individual fixture.

<B>12.2.2 Energy-efficient smart buildings

In the USA, 40–50% of the energy consumption in buildings is used for heating, ventilation, and air-conditioning (HVAC) systems. Therefore, optimizing the energy usage of HVAC systems in buildings is critical from both cost saving and sustainability perspectives. Two types of intelligent HVAC systems are designed from two different perspectives, namely occupancy-based HVAC systems and comfort-based HVAC systems. The former utilizes WSNs and ambient Wi-Fi infrastructure to facilitate HVAC control and actuation based on the occupancy estimation, while the latter takes the feedback from occupants (i.e. the comfort level) into consideration for HVAC actuation.

<C>12.2.2.1 Occupancy-based HVAC systems

Since current HVAC systems operate based on a static schedule regardless of whether the room is occupied or empty, the 'occupancy level' (i.e. the number of people inside a building) is considered by some intelligent HVAC systems to facilitate HVAC control in a building [9, 3]. Technically, occupancy estimation can be accomplished by either passive infrared (PIR) sensor networks, camera sensor networks, or existing Wi-Fi infrastructure. However, some challenges arise in a WSN-based occupancy estimation system. The PIR sensors can only provide binary occupancy detection in the sense that an occupied room is assumed to be fully occupied and it is hard to know how many people inside the room, while the camera sensors can only be deployed along public hallways due to privacy issues. Thus, in [9], wireless camera sensors and PIR sensors are combined to estimate the number of people in a building so as to control the HVAC system optimally. Figure 12.3(a) shows the architecture of the occupancy-based HVAC system, where the PIR sensors are deployed on the ceiling to detect if a room is occupied and the camera sensors serve as optical turnstiles to measure the number of people transiting from an area to another area. Figure 15.3(b) shows the workflow of the system, where a fusion algorithm will estimate the current occupancy level based on the sensed occupancy from the combined PIR camera sensor network. To avoid the control delay due to the thermal ramp-up or -down in a room, a prediction model is designed to predict the occupancy level in the near future that will be combined with the current occupancy estimated by the fusion algorithm. The final estimated occupancy level will be the input to the control scheduler to adjust the parameters for HVAC actuation. However, WSN-based solutions rely on costly sensor deployment and maintenance. In [3], a system utilizes the existing Wi-Fi networks in a building and the smartphones carried by occupants to infer the occupancy level for HVAC actuation. In that system, an offline phase will carefully mark the boundaries of each Wi-Fi access point while a smartphone may move and handover between different Wi-Fi access points. Each room is associated with a Wi-Fi access point that can detect user appearance in the room. A user is assumed to be in his/her room whenever he/she is detected by the Wi-Fi access point of this room. Then, the HVAC actuation server controls the ventilation of a room only when its occupancy changes.



(a) Architecture of the occupancy-based HVAC system.

(b) The workflow of the occupancy-based HVAC system.

Figure 12.3 An overview of the occupancy-based HVAC system

<C>12.2.2.2 Comfort-based HVAC systems

Some HVAC systems follow a comfort-based industry standard, American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 55 [2], to evaluate the comfort index, where multiple parameters such as humidity, temperature, and air flow are considered to estimate how warm or cold occupants feel on a discrete scale from –3 to 3. Positive values indicate that occupants are warm, while negative values indicate that occupants are cold. A zero value indicates that occupants are comfortable. However, instead of interaction with sensors or devices, such a system considers the concept of human-as-sensors to adjust temperatures adaptively for improving occupant comfort [27, 10]. To collect feedback from occupants, a mobile application runs on a user's smartphone that allows the user to give a vote at each feedback period, where votes are valued from –3 to +3 representing seven different levels of comfort from 'hot', 'warm', 'slightly warm', 'neutral', 'slightly cool', 'cool', and 'cold', respectively. With the collected user feedback, the system will learn the correction offsets of temperatures for different moments of the day to adjust the HVAC system in a building adaptively. For example, a room will need to adjust temperature if the user feedback indicates the room is hot. Therefore, the system can adjust temperature adaptively throughout the day according to these correction offsets.

<B>12.2.3 Preference-based smart home

Since a one-size-fits-all control system in a smart home environment is inflexible, [15, 48] bring the concept of 'user preference' into a smart home environment. In [15], based on the historical hot water usage of each individual household, a just-in-time hot water supply system is designed to determine when the hot water recirculation pump should operate. Generally, there is a short period of waiting time before hot water comes in a water recirculation system when people want to use hot water in their houses. The waiting time may cause a waste of water and can be an annoyance to people. The system thus leverages the fact that every household has unique patterns of hot water usage at predictable times (e.g. mornings and evenings) to design the hot water supply system. In this system, the hot water recirculation pump is connected to an electric motor that will generate current when the hot water is used. A sensor is responsible for monitoring the current generated by the electric motor. A micro-controller is responsible for learning and predicting the timing of hot water usage. A naive Bayes learning algorithm is used to construct the prediction model of the hot water usage for each household, where the following five features are considered to predict whether hot water will be used in the near future: (a) time of day; (b) day of the week; and the total amount of time in which hot water was used in the past: (c) 15 minutes, (d) 60 minutes, and (e) 120 minutes.

Alternatively, some systems consider an intelligent lighting system. Since the illumination requirements for family members are different according to their activities, a personalized light control system in a house is designed to meet different user preferences [48]. Figure 12.4 shows an example, where user A is reading in G_1 and user B is watching television in G_2. In this scenario, both of them require sufficient background illumination from the whole lighting device, and user *A* requires concentrated illumination from the local lighting device for reading. In this system, a home is modeled as multiple grids, and each grid deploys a light sensor to monitor the light intensity which is provided by the background and concentrated lighting. The user requirement of illumination is modeled as a combination of an interval of illumination and a coverage range of illumination. If the provided light intensity is in the specified interval for all of the grids in the specified coverage range, the system considers that the user is satisfied. However, it may not be possible to satisfy all users simultaneously. In this case, the proposed algorithms will gradually relax illumination intervals of users until all users are satisfied.

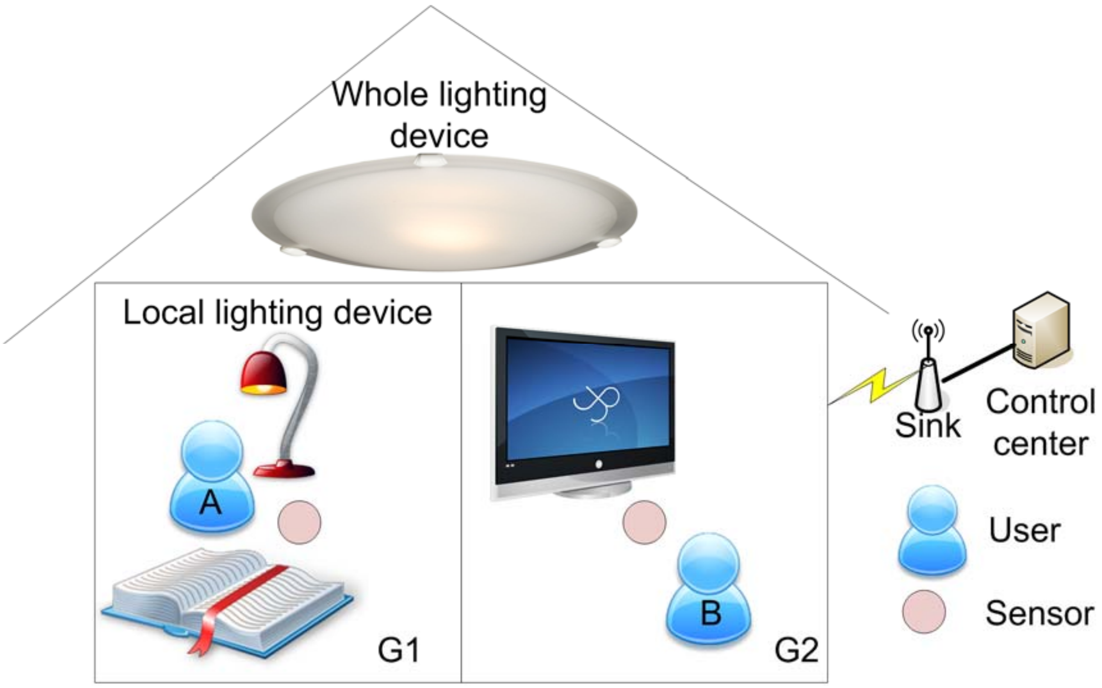


Figure 12.4 An example of preference-based light control systems

<A>12.3 Healthcare systems

Next, we will review how healthcare systems assist static human sleep and track dynamic body motions.

<B>12.3.1 Sensor-assisted sleep-facilitating systems

People with sleep disorders usually suffer from various symptoms, ranging from impaired concentration, memory lapses, loss of energy, fatigue, lethargy, to emotional instability. These can lead to even more serious consequences such as social problems and traffic accidents. Recently, many research efforts have been invested to improve sleep quality, which is one of the important issues in our daily life. Two types of sensor-assisted systems are considered to improve sleep quality of individuals, namely sleep environment monitoring [28] and sleep disorder detection and treatment [72]. The former exploits sensors to better understand the sleep environment, while the latter detects sleep disorder events using electrocardiograph (ECG) sensors or pulse oximeters and adjusts the sleep posture of the user in an non-invasive way. A traditional diagnosis of sleep disorders, polysomnography, is a multi-parametric sleep study that is usually conducted in a sleep center to evaluate the sleep quality of individuals. However, such an evaluation cannot determine actual environmental factors at individuals' homes. Thus, in [28] a system is designed to help people identify when and why their sleep was interrupted at home. To track environmental factors associated with sleep quality, including light, sound, temperate, air quality, and disruptions by others in the household over time, a sensor suite is deployed on the user's night stand to collect sleep environmental factors. The sensor suite consists of several types of sensors including an infrared (IR) camera, two passive infrared (PIR) motion detectors, two upward-facing light sensors, a microphone, and a temperature sensor.

The system provides expert doctors with patients' sleep habits and detailed environmental factors for further treatment. Patients can also track their data through a sleep-monitoring user interface. However, rather than external environmental factors, disordered sleep may result from physiological factors such as 'sleep apnea' (a disturbance in breathing during sleep). Thus, in [72] an auto-adjustable smart pillow system is designed which changes the height and shape of a user's pillow to relieve sleep apnea, where a pulse oximeter is used to detect blood oxygen saturation (also called SpO_2) level for sleep apnea detection in real time. Figure 12.5 shows the system architecture of the smart pillow system which is composed of a pulse oximeter, a smartphone, and an adjustable pillow. The pulse oximeter is attached to the user's fingertip to monitor the user's SpO_2 continuously while the user is sleeping. The SpO_2

and heart rate are collected at a sampling rate of 60 Hz. The data will be transmitted to the user's smartphone through Bluetooth communications. The sleep apnea detection algorithm will detect sleep apnea events based on predefined thresholds of SpO_2. If continuous sleep apnea events are detected for a long period of time, a pillow adjustment decision will be made. The smartphone will send out pillow adjustment commands to the adjustable pillow through Bluetooth communications. Otherwise, the system will not adjust the pillow since the patient can recover from the sporadic events automatically. The adjustable pillow consists of five bladders. Through extensive experiments on the adjustable pillow, bladder 2 and bladder 5 contribute most to the apnea alleviation. Thus the system will adjust the shapes of bladder 2 and bladder 5 according to a sequence of combinations of their shapes.

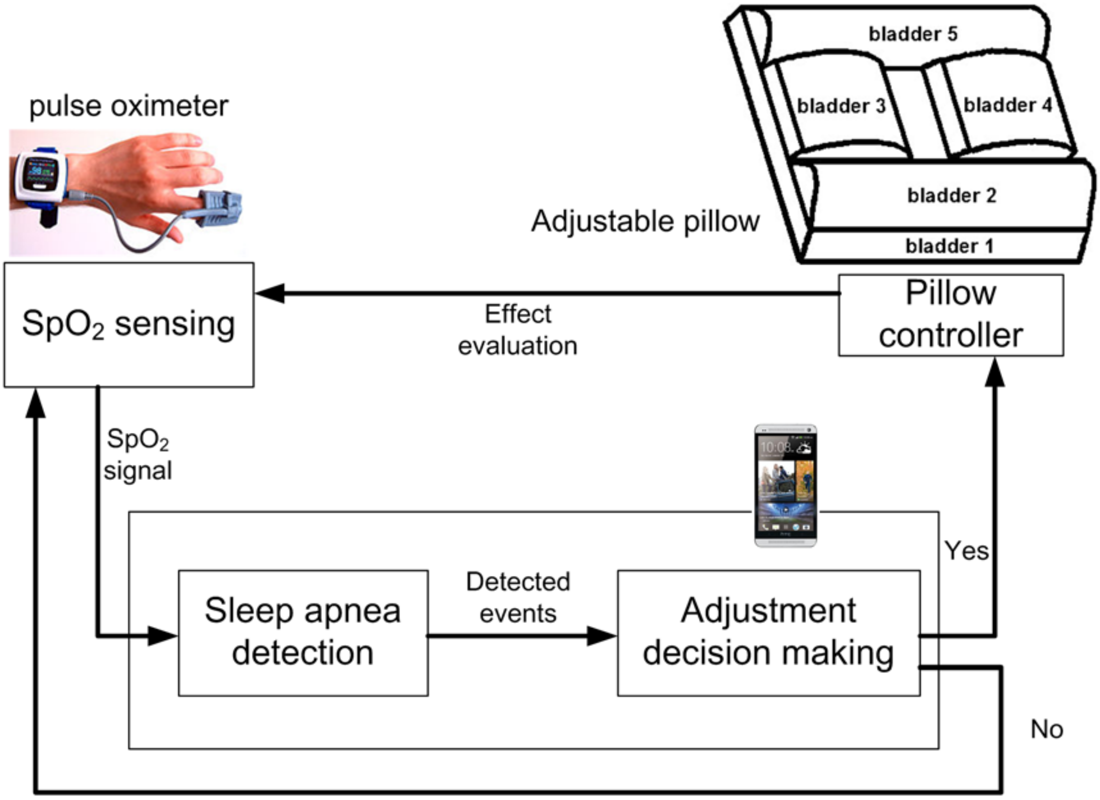


Figure 12.5 Architecture of the smart pillow system

2.3.2 Body motion monitoring

Some healthcare systems focus on identifying injury patterns caused by body motions and muscle usage through body sensor networks. The potential applications may help athletes reduce their risk of injury and facilitate home rehabilitation remotely [44, 61]. In [44], wearable sensors and a sink are attached on a user's muscles for muscular activity recognition and motion tracking, as shown in Figure 12.6. Each sensor node consists of a three-axis accelerometer, gyroscope, and magnetometer. The sensing data is sent to the sink and then to the back-end server. The sink is responsible for performing a time division multiple access (TDMA) protocol to schedule the communications between sensors and the sink. The back-end server will conduct muscle activity recognition and motion tracking. The accelerometer data alone is used to perform muscle activity recognition as it provides significant features; accelerometer, gyroscope, and magnetometer data are all considered together for motion tracking. To recognize muscle activities, the system extracts time-domain and frequency-domain features to build a decision tree which will classify the type of muscle activities for newly arrived sensing data. The selected time-domain features contain root mean square of the accelerometer data and cosine correlation between the accelerometer axes, while the selected frequency-domain features are frequency domain entropy and power spectral density. To visualize and render the body motions, the accelerometer, gyroscope, and magnetometer collaborate to compute accurate orientations of these sensors through sensor data fusion algorithms. A similar system is designed in [61] which helps a patient conduct his/her rehabilitation program at home. Through an interactive program, the system will estimate how well a patient can achieve a certain level of body rehabilitation. This way, patients will no longer need to stay in a hospital as traditional rehabilitation requires.

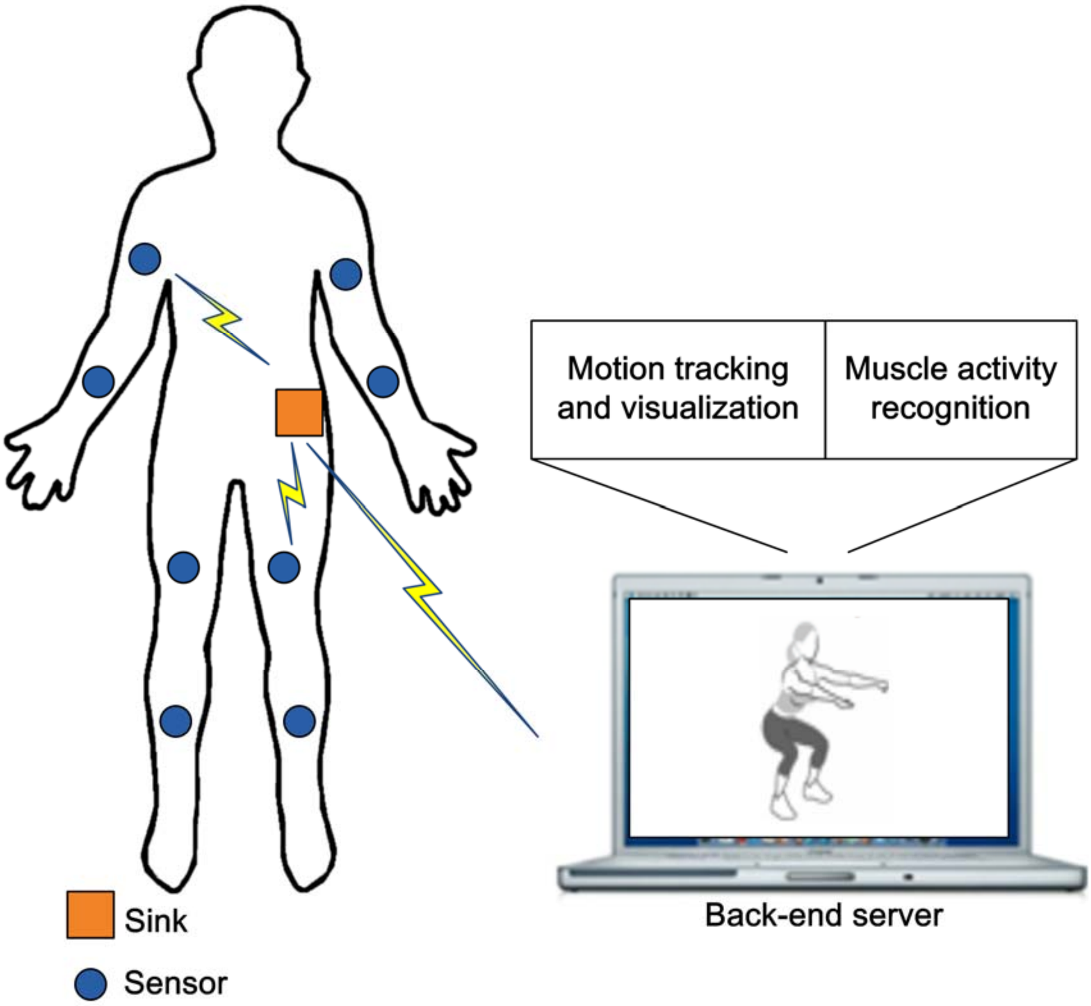


Figure 12.6 The overview of the musculoskeletal monitoring system

<A>12.4 Emergency response systems

In emergencies, the interactions among people and the environment become much more diverse and the complexity of the emergency responses also becomes much greater. Thus, we review two types of emergency response systems: WSN-aided evacuation systems and mobility-supported search and rescue systems. The former type relies on a static WSN to guide people to exits, while the latter type introduces mobile entities to conduct search and rescue tasks.

<B>12.4.1 Emergency evacuation systems

This type of system exploits WSNs to find a safe path to exits in emergencies. Considering a fire, in [60] a distributed protocol is designed to coordinate sensors for computing the evacuation paths. The evacuation principle in [60] is to provide a user with the safest path bypassing hazardous regions instead of the shortest path which may be very close to the sources of hazards. To achieve this goal, each sensor node will maintain a potential value, which is a level of danger, to guide people to the neighboring sensor node with the lowest potential value. Initially, each sensor is assigned a potential value according to its distance to the nearest exit. In case of emergencies, sensors within a certain distance from the emergency locations will form hazardous regions by raising their potential values so that sensors near the exits will have smaller potential values and sensors near the emergency locations will have higher potential values. The distributed protocol will identify the evacuation paths to exits along sensors with higher potential values to those with lower potential values. Moreover, [47] extends [60] to a 3D environment, where sensors are categorized into three classes: normal sensors, exit sensors and stair sensors. A sensor is considered to be in a hazardous region if either (1) it is within D hops away from hazards or (2) it is a stair sensor and its downstairs sensors are in a hazardous region. The evacuation principle is to guide people to the rooftops if there are no safe paths to the downstairs. However, such an emergency evacuation may suffer from a congestion problem and an oscillation problem. To solve the two problems, the objective of the former is to evacuate people as soon as possible in a load-balancing way, while the objective of the latter is to avoid guiding people to move back and forth. To solve the congestion problem, [6] proposes a distributed protocol to balance the number of evacuees between multiple paths to different exits. Each sensor knows its location and is able to detect the number of people within its sensing coverage using image-processing technologies. Similarly, each sensor maintains a potential value to find an evacuation direction towards its neighbors based on the number of people around itself. A sensor with a larger potential value implies that there are more people within its neighborhood. Therefore, each sensor will select the neighboring sensor with the lowest potential value to be its evacuation direction. Here, the potential value of each sensor is computed based on its current potential value, the number of people detected by the sensor, and the total number of people detected by its neighboring sensors. Since the evacuee density may affect the walking speed during evacuation, [5] extends [6] to reduce the congestion level by incorporating walking velocity into the potential value of a sensor, where the walking velocity is determined by a mapping function from the evacuee density to human walking speeds. Moreover, [7] and [4] focus on estimating evacuation time accurately. The system in [7] proposes a distributed protocol to estimate the evacuation time based on pre-stored corridor lengths and the moving velocity derived from the current evacuee density, while [4] analyzes the evacuation time based on a guiding tree of sensors rooted at the exit sensor, the corridor capacity and lengths, exit capacity, and evacuation distribution. On the other hand, a user may move back and find an alternate route since the hazard is spreading. To solve this oscillation problem, the system in [62] predicts the dangerous spreading to compute a path to the exit with the minimal number of oscillations.

<B>12.4.2 Search and rescue systems

By integrating mobility entities and parallel computing, emergency response systems will be able to support more dynamic search and rescue tasks during an emergency. Since the dynamics of hazard spreading may force people to move, and the injured may need to communicate with the external world when the communication infrastructure fails, identifying the number of people and where they are in an emergency is usually the first step before rescue. In [54] a robot-sensor network system is designed to track people autonomously without a prior localization infrastructure. In this system, people generate detectable signals such as heat, CO_2, or sounds; the sensors are responsible for detecting if some people are around them, and the robots will move around to find these people through sensor navigation. Some prototyping platforms provide firefighters with safety navigation while they are expediting rescue missions [50]. Two major components, namely ultrasonic beacons and ultrasonic trackers, are adopted to guarantee safe movements of firefighters. Each firefighter wears an ultrasonic tracker to receive signals from ultrasonic beacons. Three types of ultrasonic beacons are designed in the system for different purposes: firefighter beacons, exit beacons and auxiliary beacons. Each firefighter has a firefighter beacon so that injured firefighters can be found by other firefighters. Exit beacons are used to mark exits, while auxiliary beacons are used to mark way-points inside a building or injured/trapped people along a return path. However, since the pre-deployed sensor infrastructure provides limited information and reduced reliability in case of structural collapse, [52] designs a controllable flying sensing platform in support of search and rescue missions in an indoor emergency. On the other hand, while most existing systems consider an indoor fire emergency, the system in [21] implements a system, termed CenWits (Connection-less Sensor-Based Tracking System Using Witnesses), to search for lost or injured hikers in a large wilderness area. Instead of a well-connected network, all hikers form an opportunistic network to exchange their witnesses which indicate the encounter information with each other so as to locate missing hikers. This system consists of a number of sensors, access points (APs), location points (LPs), and an external processing center. Each hiker carries a sensor with a GPS receiver and an RF transmitter for communicating with other sensors, APs and LPs. A set of APs are deployed at predefined locations (e.g. intersections of footpaths or resting areas), and each AP is connected to the external processing center. A few LPs are deployed at particular locations to update sensors' locations in case GPS cannot work. The external processing center is responsible for collecting the witnesses from all APs. When two sensors are within communication range, they will record the each other's presence and also exchange their earlier witnesses, where each record in the witnesses including the encountered node ID, the current time, the encountered location, and the number of transferred hops. Once a sensor meets an AP, all of its witnesses will be uploaded to the AP. Based on the witnesses, the system can estimate the possible locations of a missing hiker to perform rescue missions. Moreover, search and rescue systems may need to provide real-time and in-situ information for remote rescuers and commanders. However, processing and providing global detailed information is a computation-intensive task. Thus, [17] considers grid computing technology to support parallel computing in an emergency response system. This system is composed of four major components: data acquisition and storage, simulation component, agent-based command-control component, and grid middleware. The data acquisition and storage component collects raw sensing data from multiple types of sensors (e.g. smoke, temperature, and gas sensors), transforms the raw sensing data into an appropriate form (e.g. transforming thermocouple voltage readings into temperatures), and ensures database accuracy and reliability. The simulation component supports the prediction of fire spreading in a parallel and distributed manner. The agent-based command-control component provides remote rescuers and commanders with a user interface in support of query-and-response operations between them and the system. The grid middleware component provides a unified interface for communications between the simulation component and other components.

<A>12.5 Human activity inference

Signals behind human activities provide emerging hints for modern CPS that will incorporate richer human input to design-promising applications. This section will review five different types of systems, each of which considers different signals of human activities to design CPS. The first type aims at conversation patterns, the second considers voice signals, the third pays attention to travel experience, the fourth targets social behavior, and the fifth looks at interactive gaming activities.

<B>12.5.1 Conversation behavior analyzer

As conversation is an important part of daily human activities, many application systems focus on monitoring human conversation for social purposes or verbal behavior therapy that helps children to speak better. Conversation behavior is studied from three perspectives: conversation group identification [38], speaker identification [36], and conversation pattern analysis and consultation [33, 23]. The first one is to figure out how many conversation groups are nearby, the second one is to recognize who is talking, and the third one extracts conversation features of users and reminds users to slow down conversation or listen to conversation more than speaking.

Conversation group identification: In [38], multiple smartphones collaborate to find out the conversation groups nearby. Figure 12.7 shows the workflow of the system. Initially, all smartphones collaborate to discover neighboring smartphones based on a threshold of Bluetooth signal strength. When a smartphone perceives sounds, it will conduct a local classification algorithm to determine if the sounds are voices from the phone owner based on historical information, e.g. average level of loudness. Here, for the decision-making of local classification, this system assumes that the voices of the phone owner are usually louder than the voices recorded from other users. Once a smartphone detects a voice segment from the phone owner, it will request other smartphones to verify its voice detection through a collaborative voting mechanism. If the smartphone receives positive votes from all other smartphones, it will generate a voice vector with a start time T_i and an end time T_j and share the voice vector with all smartphones for conversation clustering. Finally, the system will cluster these users who do not speak at the same time and are not mostly silent at the same time into a single conversation group, since voice segments in the same conversation group are well synchronized and happen one after the other. One of the potential applications for such a system is to provide a communication topology analysis in the real world since conversations imply real-world social connections and are more reliable than online social networks in the cyber world. For example, the system can further find out social centers who have the most connections to other people.

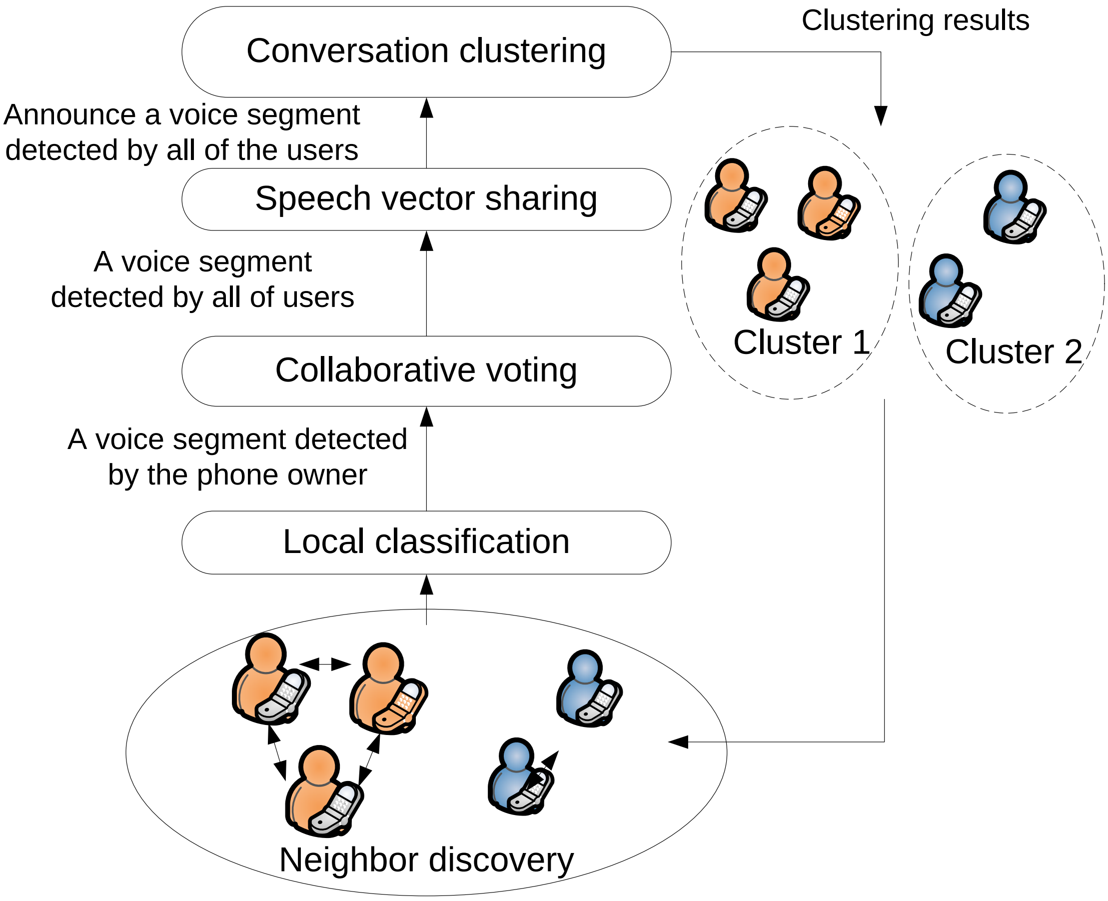


Figure 12.7 The workflow of conversation group identification

Speaker identification: The system in [36] exploits continuous audio sensing to identify the person you are talking with in order to avoid the awkward situation of forgetting his/her name. However, continuous sensing and data processing will quickly drain the smartphone battery since both are computation-intensive tasks conducted by the main processor of a smartphone. Thus, multiprocessor hardware architecture is considered to reduce the energy consumption of continuous sensing in the background, where lightweight sensing and data pre-processing is offloaded to a low-power processor. This system operates on a sequence of two stages from lower power requirements to higher power requirements. The low-power processor is attached with an external microphone and is responsible for sound and speech detection. Once human speech is detected, the low-power processor will wake up the main processor to conduct computation-intensive tasks including identification of high-quality speech frames, feature extraction from the speech frames, and speaker classification, where the speaker classification models are learned from daily phone calls and face-to-face conversations.

Conversation pattern analysis and consultation: In a single conversation group, [33] exploits multiple smartphones to monitor conversational turns for better understanding personal social conversation behavior, so as to remind a user to listen to conversation from a particular group member. Here, a 'conversational turn' is a continuous segment of human speech with a start time and an end time. When a conversation happens among a group, group members' smartphones will perceive different patterns of voice strength from each other depending on their positions. Based on the observation, the system can learn the signatures of each group member's conversation to recognize the speaker and the duration of the conversation. This system analyzes personal conversation patterns including the number of people you are talking with, the number of conversational turns in a group, and the number of conversational turns between each pair of participants. This kind of technology is considered to treat children's language delay through meta-linguistic analysis of parent–child conversation in a real-time manner [23]. Figure 12.8 shows the system architecture of the speech-language-therapy system. The parent has a smartphone paired with a Bluetooth headset, while the child has a smartphone associated with a Bluetooth microphone. Each smartphone collects sounds continuously and extracts the human voice using a bandpass filter. The smartphone on the child will send the filtered voice to the parent's phone in real time for further data analysis. Meanwhile, the speech-turn monitor will transform the collected voice data into conversational turn information including speaker, start time, duration and speech rate based on predefined thresholds and then send the information to the meta-linguistic monitor. Based on the previous turn histories, the meta-linguistic monitor will trigger the reminders based on some reaction rules.

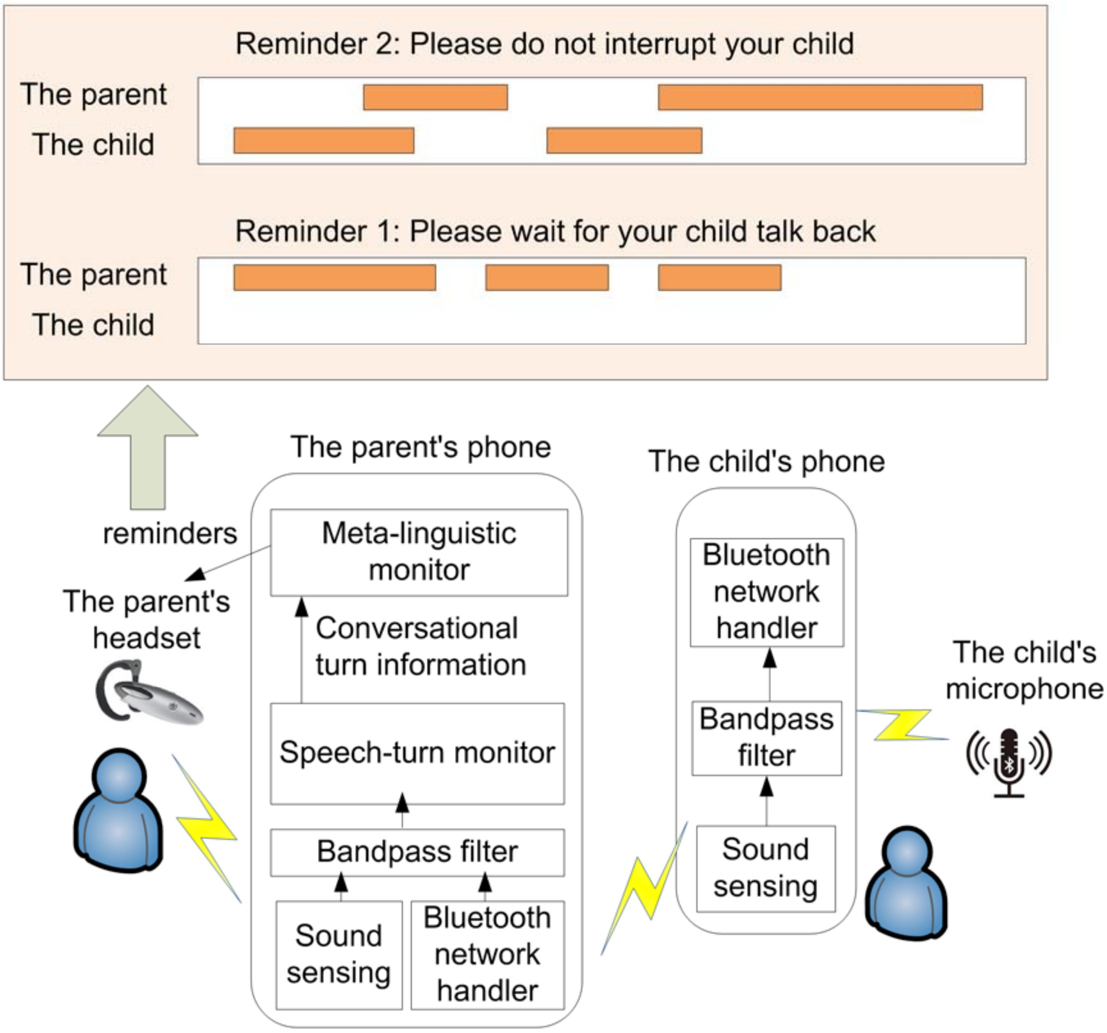


Figure 12.8 The workflow of the speech-language-therapy system

<B>12.5.2 Mood detection

This type of system exploits the physiological signals (e.g. voices) collected by smartphones to infer human psychological states (i.e. human mood).

As psychological and affective states (such as stress and mood) are a significant element in driving social behavior and influencing physical and emotional well-being, [37] and [34] focus on sensing the psychological states of humans. Conventionally, the detection of symptoms of stress relies on biological sensors in an intrusive way, such as chemical analysis, skin conductance readings, and electrocardiograms. However, the use of such intrusive technologies may incur additional stress. Generally, when people feel stressed, their voice changes, which provides significant patterns for detecting symptoms of stress. Based on these observations, [37] exploits smartphones to recognize stress from human voice unobtrusively. A two-phase approach, including an offline training phase and an online estimation phase, is designed to achieve this goal. In the offline training phase, a voice-based stress classifier is built based on eight voice features including standard deviation of pitch, difference between the maximal and the minimal pitch, perturbation in pitch, centroid frequency of the voice spectrum, ratio of frequency above 500 Hz, rate of speech, the power spectrum of a short-term voice, and the level of regularity. In the online estimation phase, the voice-based stress classifier determines if a person feels stressed according to the real-time sensed voices. However, since a smartphone is able to capture richer information in daily life, such as when and where we have been, whom we have been talking with, what applications we have been using, and even more, [34] infers moods of a user by analyzing communication history and usage patterns of applications in addition to assistance of built-in sensors. To build a mood estimation model, comprehensive data collection is launched to gather a participant’s feature patterns including everyday mood scores and usage patterns of smartphone. In the course of data collection, a user can input his/her current mood state with two five-level scores representing the two mood dimensions in [57], namely the pleasure dimension and the activeness dimension. For the pleasure dimension, scores of 1–5 indicate ‘very displeased’, ‘displeased’, ‘neutral’, ‘pleased’, and ‘very pleased’, respectively. For the activeness dimension, scores of 1–5 indicate ‘very inactive’, ‘inactive’, ‘neutral’, ‘active’, and ‘very active’, respectively. A user’s smartphone also captures records of social interaction including SMS information, email information, call information, application usage, web browsing, and user locations to build a multilinear regression model based on the statistical usage for estimating the mood of a user.

<B>12.5.3 Road safety helpers

Many research projects paid attention to improving personal travel experience through crowdsourced data and enhancing the safety of pedestrians and drivers using smartphones. In [18], users can share their journeys with people who have mobility patterns and everyday activities similar to their own. To enrich the information behind collected data and enhance data usage, the system provides users with an interactive interface for getting feedback along their journeys (e.g. traffic accidents or congestion) and exchanging instant messages between users. A publish/subscribe framework is designed to allow a user to access trips contributed to by a community. While travel safety is a critical issue, [63] and [69] focus on detecting unsafe conditions for pedestrians and drivers. A person engaged in a phone call while crossing the road is generally more at risk than others because the phone blocks the view of the user. To improve the safety of people who walk and talk, [63] uses the back camera of the user smartphone to detect vehicles approaching the user. The vehicle detection is based on image recognition technologies with two separate phases, namely an offline training phase and an online detection phase. In the offline training phase, positive image samples and negative image samples are collected. A positive image sample contains the rear or frontal view of a car, while a negative image sample shows side views of cars or random urban environments. Both positive and negative image samples are considered to build a classification model through a machine learning algorithm. Then, the online car detection algorithm running on the smartphone is composed of four steps: (1) image capture, (2) image preprocessing, (3) car detection, and (4) user alert. The system triggers image capture only during an active phone call for energy-saving purposes. The image preprocessing step uses the accelerometer data to estimate the orientation of the smartphone and performs the image alignment according to the direction of gravity. The car detection determines whether an image represents a vehicle based on the classification model built by the offline training phase. If the smartphone detects a vehicle, an alert will be issued from the smartphone to remind the user of the car approaching. On the other hand, an approach using dual-camera smartphones to track dangerous driving behavior is an efficient way to reduce risk of traffic injury. In [69], the front and back cameras on a smartphone are properly scheduled to monitor dangerous driving conditions inside and outside a car. The front camera estimates the head direction and blinking rate of the driver by tracking the head poses and eyes to infer whether the driver is tired and distracted. The back camera monitors the distance between cars to detect whether the car is too close to the car ahead. When either situation is detected by the smartphone, it will change the color bar of driving status on the screen and announce an alert to remind the driver.

<B>12.5.4 Social activity inference

Some systems exploit smartphones to detect social activities and infer social intention. Two types of system are designed for this purpose. The first one is to find out social intention behind group activities, while the second one focuses on how to infer intention for device pairing for automatic data exchanges between two users.

<C>12.5.4.1 Group social intention

In [20], a group-based navigation system is designed to help users find a particular person in a social venue. Generally, since most people stand and walk around together in a social event (e.g. a conference or a party), this system assumes that the moving traces of users in the same group have high similarity. Based on the similarity of moving traces, the system can show the relative positions of users in a social event for finding a person. Figure 12.9 shows the system overview of the group-based navigation system. Each user carries a smartphone which will continuously collect samples of accelerometer, digital compass, and Bluetooth received signal strength (RSS) from the neighboring clients. The accelerometer and digital compass data are considered together to estimate step vectors of a user based on step counts, personal stride length, and direction information. Then, the estimated step vectors and Bluetooth RSSs will be reported to the back-end server for further activity inference. The back-end server will analyze the collected sensing data to create a grouping graph based on proximity and trace similarity. There is proximity property between two smartphones if both of them receive Bluetooth RSSs from each other greater than a predefined threshold. To evaluate the similarity between two user traces, a distance function is defined based on the number of insert, delete, and replace operations needed to convert traces of a user into the traces of another user. For a given pair of proximity and trace similarity, the back-end server will compute the group likelihood between a pair of user clients. If the group likelihood between them is greater than a predefined threshold, there is an edge between them in the grouping graph. Meanwhile, the trace similarity is adopted to correct the estimated initial traces because of the property of group moving together. Once the grouping graph is created, the back-end server will estimate the relative positions of these user clients in the social event and show the group information on each user's smartphone.

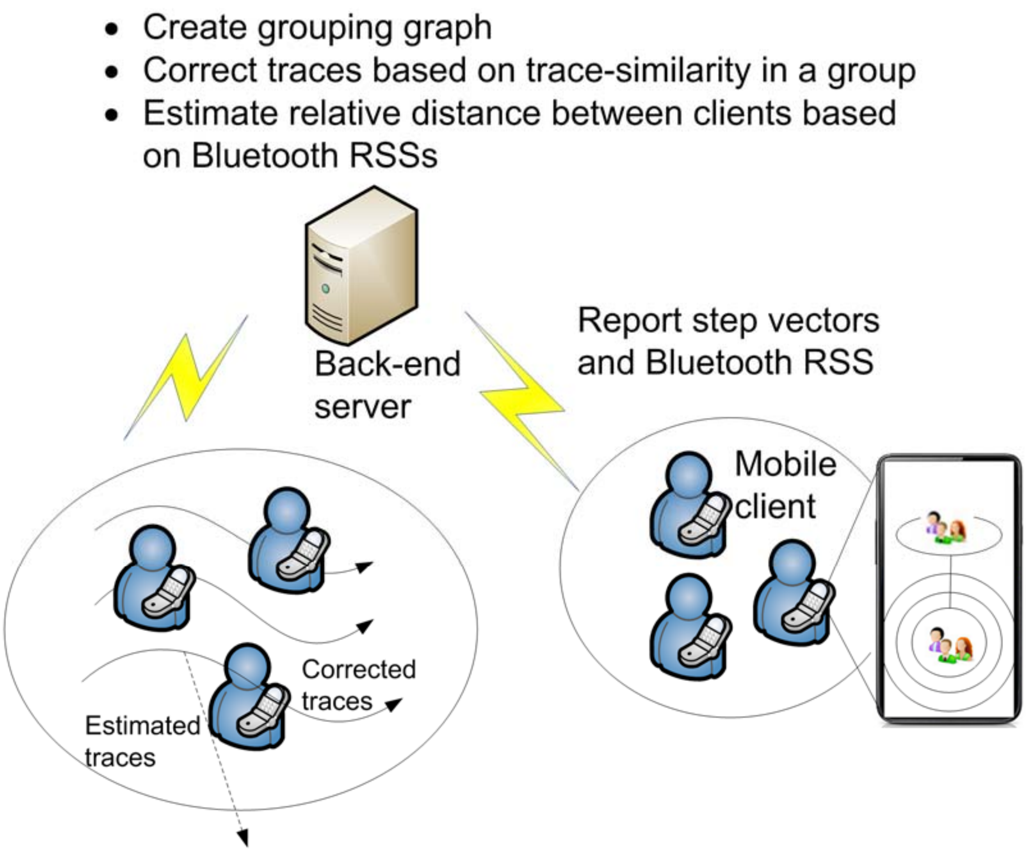


Figure 12.9 An overview of the group-based navigation system

In addition to walking together, a group of people may take photos together in a social activity. The system in [53] identifies people who appear in the same photo and tags more detailed activity information in the photo automatically. A promising application of this system is to automatically share and tag human activities in online social networks (e.g. Facebook) through the analysis of sensing data. The main difference between this system and other automatic knowledge extraction systems (e.g video surveillance systems) is richer human social interaction and human input, while other automatic knowledge extraction systems are focusing more on specific even detection. Thus, the system will tag a photo with a format of'photo-taking time, photo-taking place, photo-taking participants, and activities in the photo' to enrich the information behind the photo. Figure 12.10 shows a scenario of the automatic image tagging system, where user D is ready to take a photo for user A and user B, and user C is in the proximity. When user D activates the smartphone's camera to take a photo, user D's smartphone will broadcast to request all of the users' smartphones in the proximity to collect sensing data from the microphone, GPS, compass, light sensor and accelerometer. When user D clicks the camera, these smartphones will record all sensing data for a short period of time for further image tagging. The image tags will be generated by the four modules: location detection, time detection, participant recognition, and activity recognition. The former two modules tag the location and time of the photo based on existing localization technologies and the system timestamp of smartphones, where the light intensity is considered to determine if the photo is taken indoors. The participant recognition infers people in the photo based on the motion signatures of users captured by the accelerometer, user facing extracted from the compass data, and motion vectors of moving objects extracted from consecutive snapshots. For example, the motion signatures of users A and B will be very different from the motion signatures of user C at the photo-taking moment because user C may move around at that moment, the photo-taking participants' facing angles are usually opposite to the photographer's, and the motion vectors of moving objects from these consecutive snapshots will have high correlation between these participants' accelerometer data when they are playing a sport (e.g. table tennis). The activity recognition conducts activity classification to classify the user activity based on the accelerometer data and acoustic data, where limited types of activities including standing, sitting, walking, jumping, biking, playing, talking, music, and silence are considered.

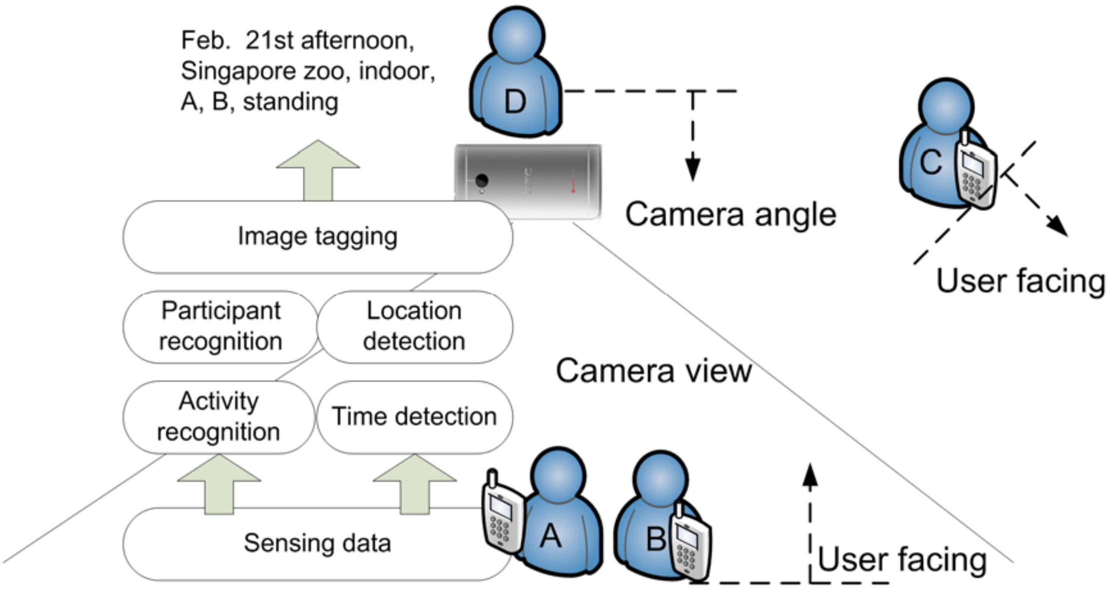


Figure 12.10 Architecture of the image-tagging system

<C>12.5.4.2 Device pairing intention

Some systems infer social intention behind body motions and gestures to facilitate information sharing automatically. In [51], a user can pair his/her mobile device with another nearby user's mobile device by pointing his/her smartphone towards the intended person. Figure 12.11 shows how to detect user intention of device pairing before data exchanges, where user A points the smartphone towards user B with two consecutive beep signals emitted at P and P′ positions. Each nearby smartphone will compute the elapsed time of arrival (ETOA) between the two beep signals. Finally, user A's smartphone will select the one with the maximal ETOA difference between the two beep signals for device pairing based on the triangular inequality $d_{PP}(= d_{PB} - d_{P'B}) > d_{PC} - d_{P'C}$.

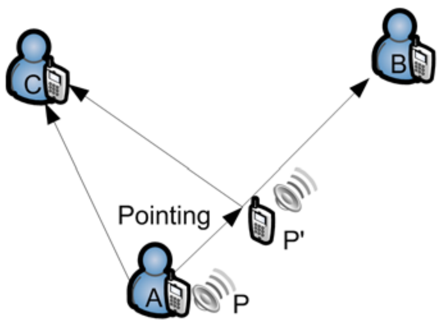


Figure 12.11 Principle of device pairing

Another system in [66] automatically infers human handshake behavior in a social event to enable natural information exchange after detecting handshaking behavior between two persons. As shown in Figure 12.12, in the physical world, the handshake behavior between two people implies that a social link will be authenticated between them before they exchange personal information (e.g. exchange of business cards). On the other hand, in the cyber world, a handshake procedure is adopted by two nodes to authenticate each other before they exchange data. The system follows the concept of 'handshake' to design an authentication mechanism to facilitate automatic data exchanges between two users following the handshake behavior. In this system, the similarity of the accelerometer data between two user smartphones is considered to determine if they have handshake behavior. Each user carries a smartphone and wears a watch-like sensor node with an accelerometer on his/her wrist. Each sensor node is associated with the user smartphone through Bluetooth, while the communications between sensors are through IEEE 802.15.4. Each sensor node is responsible for detecting handshaking events and reporting accelerometer data to its smartphone. Upon receiving accelerometer data from sensors, each smartphone will compute the similarity between the two users' accelerometer data. If the similarity is greater than a predefined threshold, the smartphone will exchange the user's personal contact information with the other user automatically.

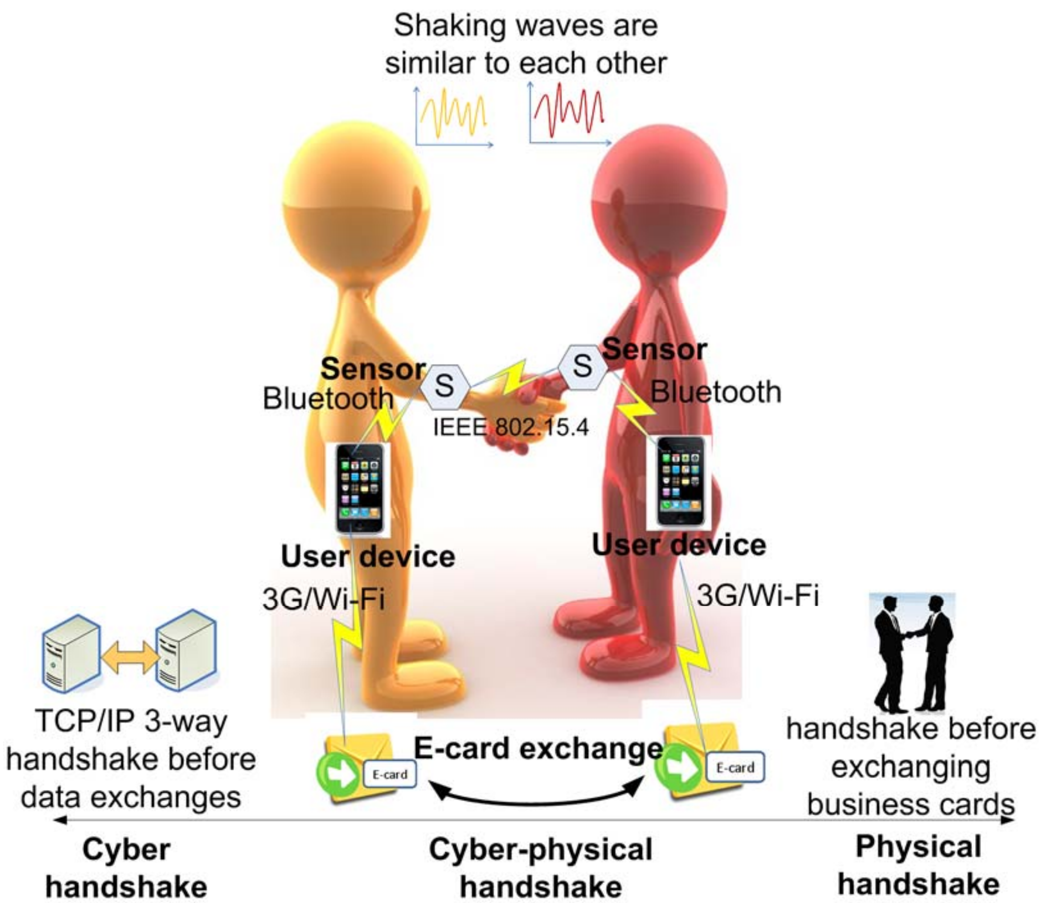


Figure 12.12 System architecture of cyber-physical handshake

<B>12.5.5 Virtual-physical games

Recently, the confluence of sensing capabilities of mobile devices and wireless networking technologies has made social gaming systems more user-friendly, where people carry portable gaming devices with built-in sensors to interact with remote users anytime, anywhere. Exploiting diverse devices to enhance game interfaces opens up many opportunities to interweave body motions in the physical world with the fabric of social games in the virtual world. Thus, this kind of application focuses on designing virtual-physical gaming systems to achieve such sophisticated interactions.

In [49], a social exergame supporting multiple exercise devices is designed for playing repetitive exercises among several users, where each user can choose a preferred device to play the game such as treadmill running, stationary cycling, hula hooping, and rope jumping. Figure 12.13 shows the system architecture of the gaming system, where a user's exercise intensity can be measured using standard metrics, e.g. rotations per minute for hula hoops, rope jumps, and stationary bikes, or speed (km/h) for treadmills. There are four key components in this system, the game input converter, the voice channel manager, the network manager, and the exercise information manager. The game input converter will map the intensity of body exercises from devices to input values of the game. The voice channel manager provides voice communications among users to facilitate social interaction during game play. The network manager supports communication fairness among users due to network delay variation. The exercise information manager summarizes exercise statistics, e.g. duration and total calories burned.

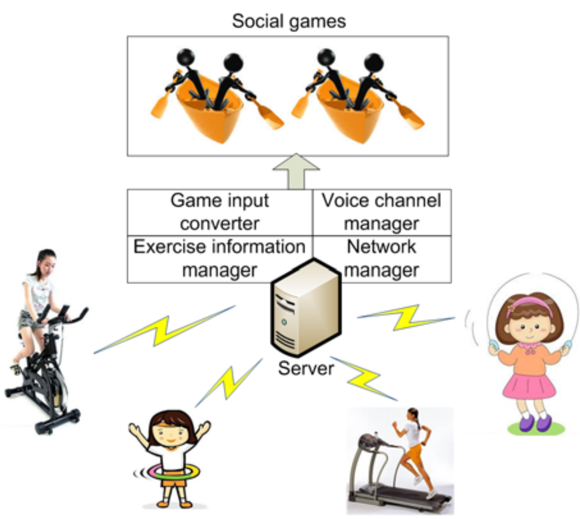


Figure 12.13 System architecture of a social game with multiple heterogeneous

controllers

Instead of repetitive exercises, [67] exploits body sensor networks (BSNs) to build a virtual-physical social network platform which can facilitate group Tai-Chi exercises, a popular sport in Chinese communities with continuous and diverse body motions. As shown in Figure 15.14, through this system, users can share with each other remotely their Tai-Chi motions on conventional social networks (e.g. Facebook). In this system, there are three major components: (1) the BSNs, (2) the social network, and (3) clients. In a BSN, each user wears nine sensors and a sink node. Each sensor has a three-axis accelerometer and a digital compass, and the sink node runs a polling protocol to collect sensory data from these sensors to the social network. The social network contains two components, the Tai-Chi engine and the community engine. The Tai-Chi engine is responsible for computing and rendering users' motions, and the community engine provides a web service embedded in the conventional social network to facilitate social interaction among users (i.e. sharing users' Tai-Chi motions). To enhance user experiences of gaming systems, [65] exploits BSNs incorporated with multiple game screens to broaden players' views and provide more realistic interaction with the fabric of games. As shown in Figure 12.15, the player wears four inertial sensor nodes, one on the broomstick, one on the forearm, one on the upper arm, and one on the club to play the Quidditch sport from the *Harry Potter* movie. In addition to the BSN, the game engine is responsible for computing the orientations of sensors to represent angles of four cameras (east, west, north and south) for providing a 360-degree panorama of the game.

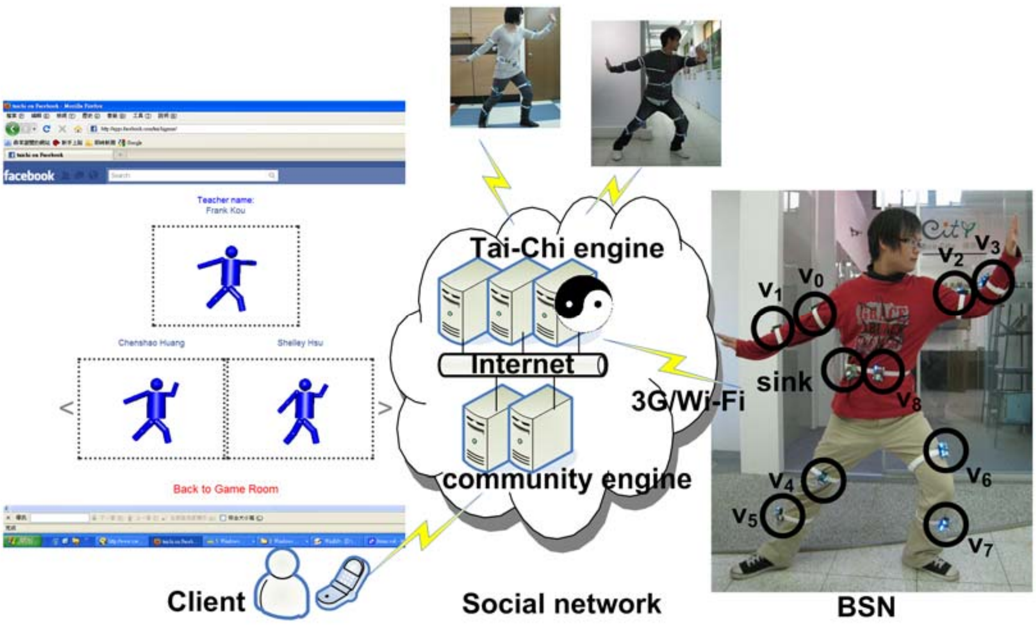


Figure 12.14 System architecture of virtual-physical Tai-Chi exercise

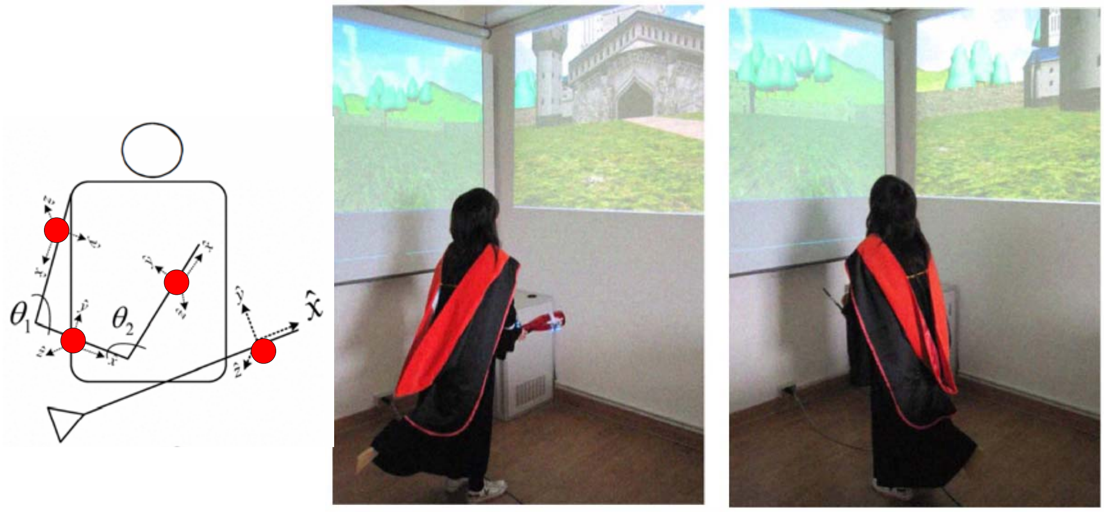


Figure 12.15 A multi-screen video game

<A>12.6 Smart city systems

Finally, we review three types of urban-scale systems that will involve large-scale environmental data, long-term human activities, and urban transportation behavior.

<B>12.6.1 Urban-scale monitoring

Many research efforts exploit crowdsourcing and participatory sensing (e.g. using sensor-equipped mobile devices) to collect urban-scale sensing data such as noise levels, air quality, and network connectivity. In general, smartphones can collect dynamic sensing data at an incredible rate to generate a huge amount of data, contributing to the so-called Big Data. While data quality is a significant concern, which is addressed in [59], sensing capability has spurred the development of promising applications that can extract knowledge from Big Data to reflect city dynamics.

<C>12.6.1.1 Noise monitoring

Noise pollution is one of the important problems in urban environments which will affect human mobility, well-being and health. Conventionally, a noise-monitoring system deploys a few sound level meters at certain locations to measure noise level and creates a noise map by extrapolating city-wide noise levels from local measurements. However, the typical approach is error-prone, costly, and only available for outdoor places. Emerging sensing methodologies consider the better support of participation and engagement of citizens to collect fine-grained and city-wide sound data using smartphones. The system described in [42] uses smartphones as noise sensors and involves citizens who carry them to measure, locate and collect qualitative sound data intermittently. Data collection is conducted by a mobile application running on a smartphone to collect sound data from a microphone, location data from the GPS sensor, timestamp, and user inputs at given intervals. The collected data is then sent to the back-end server for further data analysis. The collected sound data will be visualized using three colors which indicate the health risk of the current exposure level based on predefined thresholds, where green is for ‘no risk’, yellow means ‘be careful’, and red is for ‘risky’. In addition to the measured sound data, a user is allowed to input free text (e.g. car, home, or offices) to provide richer information in the collected data.

<C>12.6.1.2 Air quality monitoring

The monitoring of air quality in an urban area has also attracted many researchers’ attention recently. The system in [73] concerns the real-time and fine-grained information of air quality in a city area based on spatial and temporal features extracted from existing monitoring stations and diverse data sources observed in the city which have a strong correlation with air qualities such as meteorology, traffic flow, human mobility, structure of road networks, and point of interests (POIs). Figure 12.16 shows the framework of the air quality inference system that consists of two major stages, namely offline learning and online inference. This system models the city area as grids, where some of the grids contain air quality stations to collect air quality index (AQI) records. A mapping algorithm is incorporated to represent the meteorological data, POIs, and vehicle trajectories on the road network for further feature extraction. The temporally related and spatially related features will be extracted from the collected data. The temporally related features (i.e. features that vary with time) are extracted from meteorological data and the spatial trajectories including temperature, humidity, and average speed of vehicles, while the spatially related features (i.e. features that vary with location) are extracted from POIs and road network databases including the density of POIs and the length of roads in a region. After the inference model is created in the offline stage, the online stage will infer the air quality for those grids without air quality stations and visualize the city-wide air quality information for further use cases.

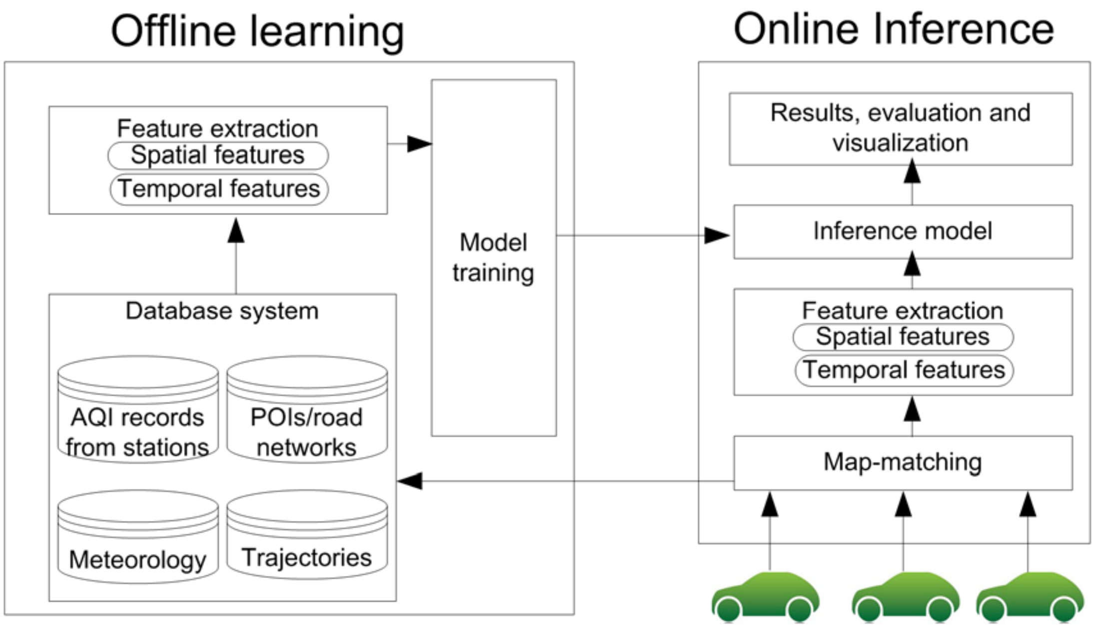


Figure 12.16 The framework of the urban air quality inference system

<C>12.6.1.3 Network quality assessment

Network quality (in terms of connectivity, etc.) is an important aspect of smart cities. As operators tend to over-claim network qualities such as connection speed, and actual measurements on devices are error-prone, assessing network quality in terms of real *user experience* may yield a more "useful" reference. Therefore, some systems exploit sensing capabilities of smartphones to *crowdsource* for such user experience for Wi-Fi [74] and cellular networks [75]. In [74], a Wi-Fi advisory system called *WiFi-Scount* has been developed on Android to fulfil this purpose. It crowdsources from smartphone users their ratings ("fast", "medium", "slow") on WiFi hotspots, as well as (implicitly) obtains various other useful data including locations, SSIDs, signal strengths, link speeds, uploading and downloading speeds of Wi-Fi access points. WiFi-Scout provides three advisory modes: (1) offline search, (2) online review, and (3) gamification-based Wi-Fi map. The first mode allows users to search for available WiFi access points in the proximity of specified queried regions even when users do not have Internet connection. The second node allows users who already connect to WiFi access points to report their experience on using these Wi-Fi access points through their smartphones. The last mode displays the crowdsourced locations of WiFi access points on a city map, but unlike other similar applications, each access point is represented by a user who has contributed the most useful information to it. The contributions of users are quantified using a social-economic scheme [76], which provides incentives for users to report and improves the trust level of user reports. Another system [75] assesses quality for cellular networks, also using crowdsourcing techniques. Other than the locations of cellular towers, it also provides assessments of signal quality and coverage for nearby cellular towers.

<B>12.6.2 Urban mobility and activity diaries

Many research efforts pay attention to human mobility data collected by smartphone which is represented as an activity diary for better understanding city dynamics and facilitating urban planning. We study two types of activity diaries, namely transportation activity diaries and everyday life diaries. The former type focuses on everyday commute patterns, while the latter finds out more about various patterns in our daily lives.

<C>12.6.2.1 Transportation diaries

This type of system exploits smartphones to figure out the transportation behavior of individuals. In [8], a mobile sensing system is designed to collect personal cycling experience and share cycling-related data among cycling communities through the developed web service. This system consists of three tiers: the mobile sensor tier, the sensor access point tier, and the back-end server tier. For the mobile sensor tier, each bicycle is equipped with several types of sensor including a GPS, a CO_2 meter, an accelerometer, a microphone, a magnetic sensor, a pedal speed meter, and a Bluetooth/802.15.4 gateway, while the cyclist carries a mobile phone. These sensors form a bicycle-area network (BAN). The intra-BAN communications between sensors are through IEEE 802.15.4, while the sensor data is sent from the BAN to the mobile phone via a Bluetooth/IEEE 802.15.4 gateway. The sensor access point tier consists of a number of mobile phones with global system for mobile communications/general packet radio service (GSM/GPRS) data network service and static IEEE 802.11 access points. This tier provides reliable network access to convey sensing data from the mobile sensor tier to the back-end server tier. The back-end server tier implements data-mining and data-visualization algorithms incorporated with a query-response handler to display detailed information about cyclist experience, such as cyclist routes on the map, current speed, average speed, distance traveled, calories burned, and CO_2 levels along the cycling routes.

In addition to cycling experience, [68], [19] and [56] figure out everyday commute behavior. The system in [68] uses smartphones to automatically carry out transportation activity survey which investigates when, where and how people travel in an urban area. This system is composed of two major components, namely a front-end sensing system and a back-end data analysis system. To optimize energy usage of a smartphone, the front-end sensing avoids using the GPS sensor in the user's long-stay places. To achieve the objective, a place-learning algorithm is implemented on each smartphone to collect the Wi-Fi signatures of a place if the user stays in the place for a long period of time. When the user enters a place, the user smartphone will conduct place matching based on the learned Wi-Fi signatures and avoid using GPS if the current place has the same Wi-Fi signatures as one of the learned places. In the back-end data analysis system, clustering algorithms are implemented to detect if a user stops at certain locations. In addition, a decision-tree-based classification algorithm is considered to detect the transportation modes of users, where the maximal speed, between-stop average speed, accelerometer force variance, and distance to the closest bus and mass rapid transport (MRT) stops are extracted to construct the decision tree. However, GPS-based detection of transportation mode has some essential limitations on energy consumption, availability in indoor/underground environments, and detection accuracy. Thus, [19] considers accelerometer-only approaches to detect transportation modes, where the gravity is estimated based on the accelerometer measurements. This system designs a hierarchical classification algorithm incorporating three classifiers from coarse-grained towards fine-grained to detect the transportation mode of a user. The first classifier detects if a user is walking. If not, the second classifier will detect if the user is stationary. If not, the last classifier will perform fine-grained detection to classify the current transportation behavior into one of five transportation modes: bus, train, metro, tram or car. In [56], a route-sharing and recommendation system is constructed, where users can contribute and search fine-grained elevation and distance information along their routes to know if a route is suitable for a certain mode of transportation (e.g. hiking or cycling).

<C>12.6.2.2 Everyday life diaries

In addition to transportation activities, this type of system considers more diverse mobility and activity patterns [13, 43]. The system in [13] constructs a text-searchable diary which transforms collected GPS data points into textual descriptions of semantic locations and activity categories so that users can search their historical activities using text inputs (e.g. ‘where did I have dinner?’). There are four phases to extract meaningful information from continuous and massive GPS raw data: (1) segmentation of moving patterns, (2) trajectory clustering, (3) creation of semantic places, and (4) activity matching. Since the collected continuous GPS signals contain a lot of redundant information, the first phase represents these continuous GPS signals as a sequence of linear routes with non-uniform representative GPS points. The second phase links these segments into a small number of trajectories based on the spatial correlation between these segments, where each trajectory is represented by a pair of ‘begin point’ and ‘end point’ segments. In the third phase, to transform these GPS locations into semantic places, the system conducts reverse geo-coding which maps the GPS coordinates into textual descriptions (e.g. Starbucks). Finally, the last phase infers possible user activities in a certain location by matching the location categories provided by Yelp which collects user reviews and recommendations of restaurants, shopping, nightlife and entertainment. On the other hand, [43] focuses on identifying live points of interest (LPOIs) which are real-time activity hotspots in a city. This system uses smartphones to collect audio clips and location information through GPS, Wi-Fi, and cellular networks in those places where people spend a significant amount of their time. The audio data is used to infer the gender of a participant. Once the location data is sent to the back-end servers, a density-based clustering algorithm is adopted to find out the activity hotspots and the detailed information of participants (e.g. 20% males and 80% females).

<B>12.6.3 Intelligent transportation systems

As intelligent transportation systems are important elements in a smart city, we will review some systems from four perspectives of services including finding a taxi or passengers, carpooling services, traffic monitoring, and finding parking lots.

<C>12.6.3.1 Taxi/passenger finder

There are two essential requirements of taxi services in a city area: (1) finding the best locations where a taxi driver can find passengers easily and (2) finding the best locations or road segments where people get a taxi easily. To meet the two requirements, [70] proposes a recommendation system for finding passengers and vacant taxis based on historical GPS trajectories of taxis. This system consists of an offline data-mining component and an online recommendation component. The offline data-mining component is responsible for collecting and detecting parking places of taxis to learn statistical results of taxis' pick-up/drop-off behavior (e.g. parking places, time interval between two consecutive vacant taxis, and queue length of passengers) and passenger mobility patterns (e.g. when and where passengers get on/off a taxi). The online recommendation component incorporates a taxi recommender and a passenger recommender to provide recommendation of taxi services. The taxi recommender provides taxi drivers with the better locations and routes to these locations so that taxi drivers can maximize the profit of the next trip, while the passenger recommender provides a user with the nearby parking places of taxis with the minimal waiting time.

<C>12.6.3.2 Carpooling services

Finding the best route schedule for taxi carpooling is an efficient means to reduce transportation cost and air pollution. To achieve the goal, an urban-scale taxi carpooling service is considered in [41]. Figure 12.17 shows the framework of the taxi carpooling service which considers a dynamic scheduling problem of carpooling in a city. Each taxi will update its status including its ID, the current time, the geographical location, the number of on-board passengers, and its current schedule if the taxi driver is willing to join the carpooling service. Each mobile user can submit a user query anytime, anywhere, where the user query will be associated with the submission time, the pick-up point, the drop-off point, and the early and late bounds of pick-up and drop-off times. When a user query is submitted by a mobile user, the carpooling search and scheduling components will search the candidate taxi that satisfies the user query and has the minimum additional incurred travel distance. This system incorporates a spatiotemporal index of axis which will speed up the searching process based on a grid-based road model. If the user query is satisfied, the system will update the spatiotemporal index of taxis and inform the corresponding taxi of the new schedule. However, as many systems have focused on how to exploit the mobility patterns of taxis/passengers to schedule carpooling routes, [71] integrates software and hardware design as well as a win-win fare model which is an incentive mechanism[40, 39] to encourage both taxi drivers and passengers to join the carpooling service. In this system, there are three components: passenger clients, Cloud server, and onboard TaxiBox. The passenger client will provide delivery requests to the Cloud server for taxi dispatch. Based on the delivery requests provided by passengers, the Cloud server will return a carpooling option with a reduced fare for passengers' approval, along with a non-carpooling option with a regular fare for comparison. When a passenger approves taxi carpooling, the Cloud server will find a suitable taxi for carpooling and send out the route schedule to the taxi's onboard TaxiBox. The onboard TaxiBox is equipped with several types of sensors including alcohol/smoke sensors, a three-axis accelerometer, a camera, a microphone, a GPS sensor and a communication module. The onboard TaxiBox is responsible for reporting the taxi's physical status (e.g. locations and speeds) and the delivery status (e.g. delivery distance, the number of passengers, fare, working duration, start time, end time, pick-up locations and drop-off locations) to the Cloud server. A unique feature of this system is the win-win fare model which shares the benefit of taxi carpooling among the taxi driver and all of the passengers proportionally. For example, three passengers request a taxi with 17, 3, and 45 non-carpooling fare, respectively. If they join carpooling, the total carpooling fare is 52. Thus, the total benefit of carpooling is $(17 + 32 + 45) - 52 = 42$. If α denotes the sharing percentage of all passengers, then $1 - \alpha$ is the sharing percentage of the driver. Accordingly, each passenger will get the benefit proportionally based on his/her travel distance.

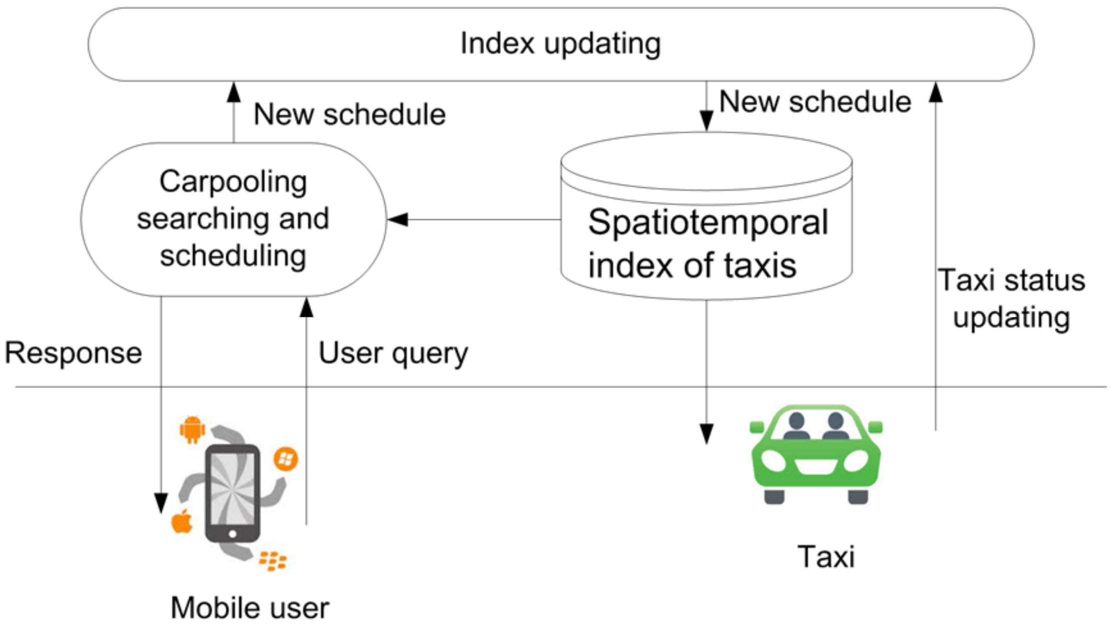


Figure 12.17 The framework of the dynamic taxi carpooling service

<C>12.6.3.3 Traffic monitoring and navigation

Providing real-time and in-situ traffic information for remote users is an essential requirement in a smart city. A participatory CPS prototype system called ContriSense:Bus is presented in [31] for public transportation. It provides bus commuters with information such as estimated time to arrival and bus speed in order to ease travel planning and improve travel experience for bus commuters. It employs RESTful API and designs algorithms for near real-time sensing and mapping of GPS readings to correct sequences of bus stops. One key feature of the system is that the traffic information is crowdsourced from the public mass, i.e. bus commuters. This makes incentives critical to such crowdsourcing or participatory sensing systems, which are addressed by [40] using a game-theoretical approach and by [39] using an auction-based approach, respectively.

The system in [22] considers a vehicle sensor network for traffic monitoring. Each vehicle is equipped with a set of sensors including a GPS sensor, a Wi-Fi communication module, and a camera. These vehicles collect traffic-related sensing data and report to the back-end server through opportunistic communications in the sense that the sensing data is allowed to be exchanged among vehicles and between a vehicle and a wireless access point if they are within communication range of each other. A remote user can acquire traffic information through a visualization interface. Since the bandwidth and connection are not always available, this system allows users to specify how to prioritize data (e.g. preferring to deliver a summary before detailed values). In [35], GPS data of vehicles are exploited to estimate real-time speed information of roads, where the data uploaded by parked cars and cars waiting for traffic lights are given lower weights in determining the road speed. The Waze system [64] is a community-based traffic navigation system, where crowdsourced traffic information is shared among users to improve driving experience in their daily lives.

<C>12.6.3.4 Parking finder

Finding available parking lots sometimes wastes time and fuel consumption in daily life. To find an available parking lot efficiently, [32] considers WSNs to monitor availability of parking lots and provide drivers with real-time parking information. Figure 12.18 illustrates the system architecture. Each car park is deployed with a WSN with a sink, where each sensor node is composed of a heat sensor, a light sensor, a variation sensor, and an RF communication module. Each sensor is powered by a solar system. These sensors will cooperate to detect if a parking lot is occupied and send the collected information to the sink in a multi-hop way. Then, the information of parking lots will be collected to the back-end system for further analysis. A driver can view the number of available parking lots and their locations through a mobile application.

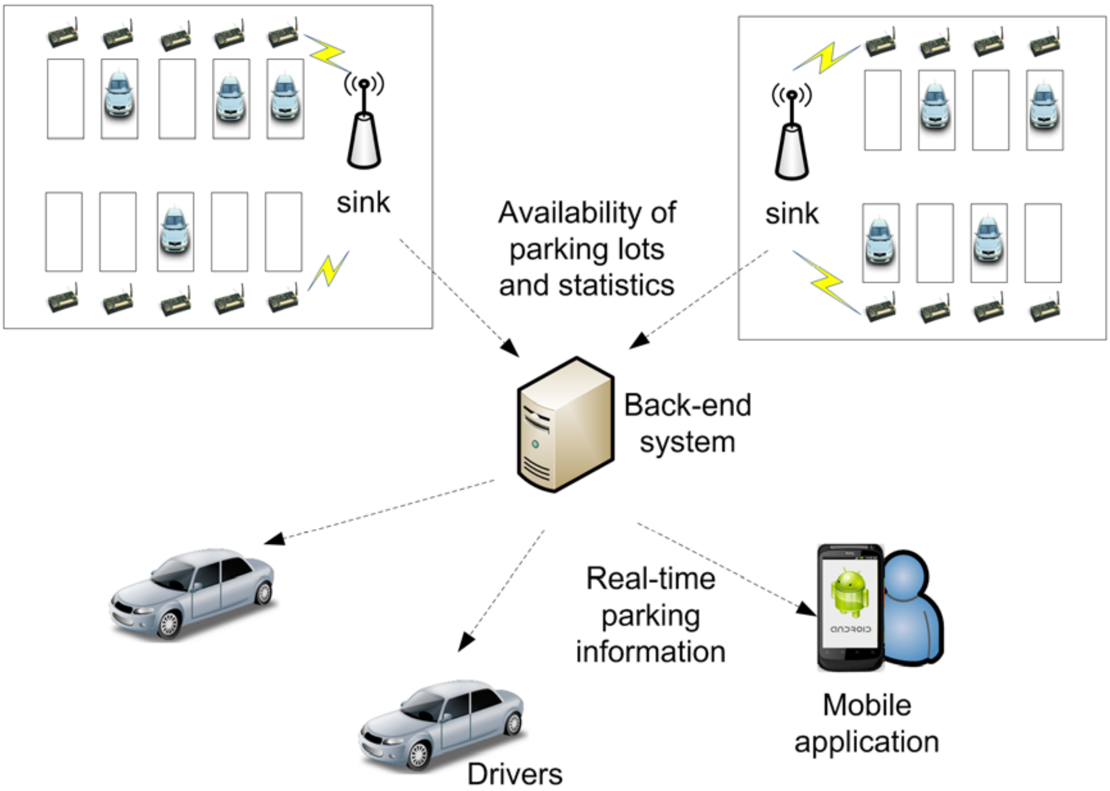


Figure 12.18 System architecture of a parking finder application

<A>12.7 Conclusion: discussion, comparison, and future challenges

Finally, we discuss fine-grained classification based on some technical features and requirements of these systems and point out opportunities and challenges in future systems.

<B>12.7.1 Discussion and comparison

Technically, we classify these systems from the following six perspectives: network configuration, communication patterns, sensing techniques, information diversity, decision-making techniques, and service ranges, as shown in Table 12.1. For network configuration, smart space systems, healthcare systems, and emergency response systems are usually deployed in a particular place with fixed network deployment; emergency response systems, human activity inference, and smart city systems contain some mobile entities in the network (e.g. robots or mobile phones); nodes and mobile entities in human activity inference and smart city systems can join/depart the network dynamically. For communication patterns, the traffic patterns in the former three types of systems are collecting sensing data periodically; the communications in emergency response systems and human activity inference sometimes are on-demand only when some specific events are detected (e.g. hazards and human conversations); emergency response systems and smart city systems may have cross-network information flows among heterogeneous networks. For sensing techniques, the former three types of systems rely on WSN-based sensing techniques, human activity inference exploit built-in sensors on smartphones, and smart city systems incorporate WSN-based and mobile sensing techniques together. For information diversity, the former four types of systems usually perceive data in a small-scale area; the latter three have multi-modal data sources; and dynamic human data input (e.g. conversation voices and human mobility) is an important factor in the last two types of systems. For decision-making techniques, the former three can be solved using some deterministic algorithms or in-network decision-making; the latter three sometimes need non-deterministic algorithms, data mining, and machine learning in support of decision-making in an uncertain environment and situation; the last one even relies on Big Data analytics to extract knowledge behind sensing information. For service ranges, the former two are usually in a home area; the emergency response systems and human activity inference serve people in multi-stair buildings or small-scale road segments; the last one works in a city-scale area.

Table 12.1 Features of WSN-CPS applications

Aspects for system classification	Features	Smart space systems	Health-care systems	Emergency response systems	Human activity inference	Smart city systems
Network configuration	Place-centric deployment	✓	✓	✓		
	Network with mobile entities			✓	✓	✓
	Dynamic network formation				✓	✓
Communication patterns	Periodic communications	✓	✓	✓		
	On-demand communications			✓	✓	
	Cross-network data flows			✓		✓
Sensing techniques	WSN-based sensing	✓	✓	✓		
	Mobile sensing				✓	
	WSN + mobile sensing					✓
Information diversity	Small-scale data monitoring	✓	✓	✓	✓	
	Multi-modal data sources			✓	✓	✓
	Human data input				✓	✓
Decision-making techniques	Deterministic algorithms and in-network decision-making	✓	✓	✓		✓
	Non-deterministic algorithms, data mining, and machine learning			✓	✓	✓
	Big Data analytics					✓
Service ranges	Home areas	✓	✓			
	Multi-stair buildings or small-scale road segments			✓	✓	
	City-scale areas					✓

<B>12.7.2 Opportunities and challenges beyond

Finally, we look ahead to some potential research challenges and open issues for next-generation WSN-CPS applications and emerging Internet of Things (IoT) applications.

<C> 12.7.2.1 Cross-domain intelligence for urban Internet of Things (IoT)

As the European Smart Cities Project [12] has been considering different service sectors such as Smart Governance, Smart Mobility, Smart Utilities, Smart Buildings and Smart Environment to assess the level of smartness of European cities, cross-domain technique integration will be an essential requirement in the future of WSN-CPS applications, where data sensing, knowledge extraction, and data visualization techniques are important technical elements in future system. The data sensing techniques will aim at how to collect multidimensional and high-quality data effectively, how to collect data without compromising personal privacy, and how to design incentive sensing models which may incorporate participatory sensing, crowdsourcing, cooperative and opportunistic sensing technologies for novel applications. The knowledge extraction will focus on how to figure out deep information behind data through data mining, machine learning, and knowledge discovery methods, how to infer human intentions and activities, and how to design distributed, parallel, and scalable algorithms to handle large, multi-modal, heterogeneous and distributed streams of data. The data visualization will emphasize how to visualize heterogeneous streaming data in a real-time way, how to represent data in a more intuitive way, and how to abstract the relationship between data.

<C>12.7.2.2 Software-defined networking (SDN) for future internet

With the Internet Engineering Task Force (IETF) and the Telecommunication Standardization Sector of the International Telecommunication Union (ITU-T) standardization efforts for SDN [24, 26], SDN architecture provides more flexible networking operation for the future internet, where the control plane is decoupled from the data plane. To accomplish such an SDN architecture, OpenFlow [46] is one mechanism to facilitate the communications between the control plane and the data plane. The SDN represents potential trends to support future IoT applications for conveying information between different entities.

<C>12.7.2.3 Machine-to-machine (M2M) communication issues

As some M2M standard groups are making efforts on a common M2M service layer [25], a lightweight publish/subscribe messaging transport protocol [45], and M2M architecture and interworking technologies [11], automated M2M communications and intelligence enables a wide variety of applications incorporating wired or wireless communications, sensors, devices, computers, robots, mobile equipment, and the Cloud to communicate and exchange information efficiently. Future trends are to enable WSN-CPS with standard-compliant M2M technologies to develop more scalable, flexible, secure, and cost-efficient WSN-CPS applications.

Coupling cyber security and physical privacy: Cross-architecture data flow is a basic concept of future IoT systems that will considerably increase the difficulty of protecting system security and personal privacy. Since all of the physical entities are interconnected in the cyber world, an abstraction layer in-between will be an essential requirement to convey information between physical entities and cyber systems so that information flow security in the cyber world and personal privacy in the physical world are guaranteed simultaneously. For example, when an entity A commits an actuation to an entity B in a condensed and privacy-preservation way, the abstraction layer will be able to authenticate the interdependence of behavior; meanwhile, entities can keep pre-fetched content (e.g. an aggregated map with location-enhanced information) [1] via a pull-based information flow instead of pushing the content of itself.

Flexible human–computer interaction: As the promising M2M applications attract a lot of research and ad industry attention, human input becomes a critical commodity. Therefore, cross-platform human–computer interfaces will be important elements in next-generation systems to bridge human intention in the physical world and actuation in the cyber world. Moreover, with portable, wearable, and mobile human–computer interfaces becoming popular, innovative human–computer interfaces will be able to facilitate the interaction between humans and systems naturally. For example, a magnet could be a kind of human–computer interface to cooperate with a magnetic sensor grid that can recognize distribution of the applied magnetic field and further infer human intention [55].

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