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ORIGINAL ARTICLE

Information and communications technologies for elderly ubiquitous healthcare in a smart home

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Abstract Over the past century, in most countries, there has been a continual increase in life expectancy primarily due to improvements in public health, nutrition, personal hygiene and medicine. However, these improvements are now coupled with aging population demographics and falling birth rates, which, when combined, are expected to significantly burden the socioeconomic well-being of many of these countries. In fact, never before in human history have we been confronted with such a large aging population, nor have we developed solid, cost-effective solutions for the well-being, healthcare and social needs of the elderly. One efficient and cost-effective solution to the problem of elderly/patient care is remote healthcare monitoring so they can continue to live at home rather than in nursing homes or hospitals that are very expensive and with limited spaces. These remote monitoring systems will allow medical personnel to keep track of important physiological signs with reduced human resources, at less cost and in real time. This paper introduces several low-cost, noninvasive, user-friendly sensing and actuating systems using information and communication technologies. Such systems can be used to create engineering solutions to some of the pressing healthcare problems in our society, especially as it pertains to the elderly. One example is the integration of sensors, wireless communications, low-power electronics and *intelligent* computing to determine health-related information using signals from walking patterns. Such a sensing system will be suitable for prolonged use in a home environment. It will be wearable, noninvasive and non-intrusive, similar to *smart socks*, *smart wrist-bands* or *smart belts*. Other examples such as a *smart joint monitor* and a *smart sleeping environment* will be discussed, and future perspectives and research challenges in smart home technologies will be described.

Keywords Smart home · Smart medical home · Smart home technology · Elderly healthcare · Ubiquitous healthcare · Walking age analyzer · Smart joint monitor · Smart knee monitor · Smart sleep environment · Sensor fusion · Information modeling · Data security

1 Background and motivation

Worldwide, there is a tremendous interest in aging, because collectively, we are now growing older at an astonishing rate [1–3]. This situation is due to the continual increase in life expectancy because of improvements in public health, nutrition, medicine and personal hygiene on the one side and falling birth rates on the other. However, these improvements are now coupled with aging population demographics, which are expected to significantly burden the socioeconomic well-being of most countries around the globe. For example, by 2017, for the first time in human history, there will be more elderly persons (defined here as individuals 65 years or older) than children less than 5 years old, and by 2050, the elderly are expected to outnumber children under 14 years of age [4]. This aging population demographics is particularly acute in eastern Asia and parts of Europe—see, for example, *Global AgeWatch Index* [3] that includes data from 96 homogeneous and heterogeneous countries.

This is an invited paper.

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In homogeneous societies such as Japan, South Korea and China, the economic costs associated with this rapidly aging population are enormous and unsustainable under present economic and social systems. Even in heterogeneous societies such as Canada with a large, highly educated, immigrant influx each year, the elderly population will grow from 14 % in 2011 to approximately 25 % by 2036 [5]. This aging population demographics is compounded with the dilemma healthcare professionals face of delivering improved care to a better educated, elderly population under increasingly constrained budget conditions. One efficient and cost-effective solution to elderly well-being is remote healthcare monitoring so people can continue to live at home rather than in expensive and limited nursing homes or hospitals. Such remote, noninvasive and non-intrusive monitoring systems can allow physicians to keep track of important physiological/vital signs with reduced human resources, at less cost and in real time, if needed. Therefore, in societies facing this elderly healthcare tsunami, sound economically viable solutions for the following key questions must be developed.

- What strategies and technologies can governments adopt so that the elderly remain independent in a home environment?
- How can the physical environment of the home be improved/modified to better suit the needs of the elderly in their later years?
- How can community-based healthcare providers benefit from the latest in aging research, and in wearable and in-home monitoring technologies to take better care of the elderly?
- How can accurate methods to forecast future needs be developed and implemented so that the elderly can start preparing for a healthy, happy and independent old age in a home setting?

Home: for ages, this has been the place where individuals seek security, comfort and provide or receive care, when necessary [3, 9, 10]. Now, adolescents live comfortably and without the need for assistance in their homes. But, as they age, their health usually deteriorates, limiting their mobility and independent lifestyle. For many elderly persons, the needed care comes primarily from younger family members, friends or healthcare professionals. However, with changing job markets and families being dispersed over wider geographic areas, or focusing more on their own children, there is less time or opportunities to take care of their elderly family members. Consequently, there are stronger and stronger political and societal demands for the development of sustainable, cost-effective healthcare and home environment solutions so that the elderly can remain in their own homes. These solutions must consume fewer human and economic resources, provide care for more people and concurrently preserve and improve their well-being and dignity in our society [1–8].

The needs of the elderly are made more difficult because most healthcare systems are challenged by three interlocking crises related to **rising costs, aging demographics** and the **demands of higher quality medical services**. For most healthcare systems around the globe, the existing and near-term projections of healthcare costs are unsustainable. Furthermore, these scenarios illustrate the conflicting trends of demands for: improved healthcare, independent living, increasing elderly population, constraining rapidly rising healthcare costs and decreasing the burden and stress to family members.

To address the sustainability of current healthcare systems, one very promising and viable solution is to improve the home environment using the same low-cost, pervasive technologies that have driven the information and communication age over the past half a century, that is, ubiquitous healthcare solutions using information and communication technologies (ICT). In this regard, the home can be made *intelligent* to provide remote, noninvasive and non-intrusive healthcare monitoring. In addition, for the elderly, homes can be customized to be a more comfortable and less resource-consuming environment. In some sense, it can be argued that the future home, especially for the elderly, will have *eyes, ears and hands to see, listen and provide what is necessary and needed* at the appropriate times. A schematic diagram of a future autonomic smart home architecture is shown in Fig. 1 on the next page, illustrating the important roles of technology, healthcare and service providers, and computation for a smart medical home for the elderly.

In the discussions above, we described the acknowledged importance of elderly care in their own homes and the looming economic and social crises if this is not addressed soon. For example, in Canada, The National Post (August 19, 2013) article [11] titled ***Most Canadians doubt health care system prepared to handle 'tsunami' of*** aging boomers, new poll shows ***Six in ten Canadians*** *surveyed said they lack confidence in the health system's ability to care for Canada's rapidly greying population.*, The article quoted the President of the Canadian Medical Association (CMA) who stated that *All levels of government, including the federal government, need to act to address the demographic tsunami that is heading toward the health care system* … and that a *vast majority of Canadians*—93 %—*support a national, seniors' health strategy for home care and long-term care*. Further, it was stated that *It costs nearly* $1000 *a day to keep a senior in a hospital bed, and* $126 *a day for a bed in a long-term care facility. To keep them in home with supportive home care and assisted living costs about* $35–$50 *a day*. Therefore, there could be enormous savings to the healthcare system if more support

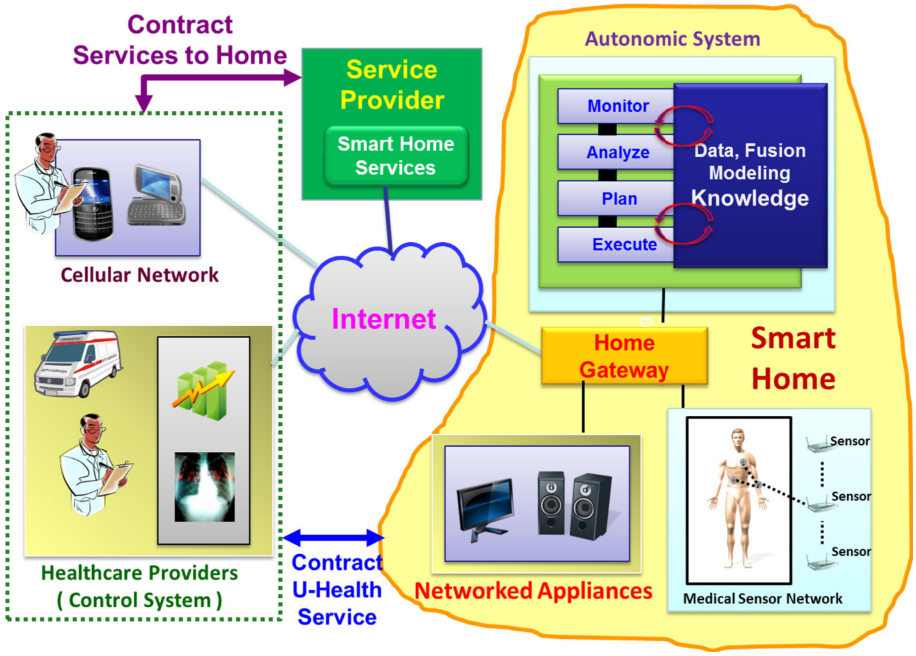


Fig. 1 Schematic diagram of a future smart home showing the different stakeholders—healthcare providers, medical services providers (insurance companies and government health departments), internet, communications and security service providers, data and information service providers (for autonomic systems), smart home with physiological and environmental sensors and actuators, and home builders

was provided to the elderly in their own home environment.

An article in the Globe and Mail, a major Canadian national newspaper (October 1, 2013) [12] stated that *The world is aging so fast that most countries are not prepared to support their swelling numbers of elderly people according to a global study … by the United Nations and an elder rights group*. That report further stated that *In* 2011, *an estimated five million Canadians were* 65 *years of age or older, a number that is expected to double in the next* 25 *years*. The report from the global study *reflects what advocates for the old have been warning, with increasing urgency, for years*: *Countries are simply not working quickly enough to cope with a population greying faster than ever before*. This is corroborated by the Canadian Institute for Health Information *National Health Expenditure Trends,* 1975–2014 report [13] that stated that while *Canadians older than age 65 account for less than 15 % of the population, they consume 45 % of provincial and territorial government health care dollars* (p. 77 of report). The situation is similar in many countries. For example, *The Economist* (July 26, 2013) [14] reported that the European Union (EU) working age population, defined as aged 20–64 years, will start falling in 2013 and the dependency ratio defined as persons aged 65 and over to those of working age will rise from 28 % in 2010 to 58 % in 2050.

These and other similar articles in the popular news media (newspapers and magazines) highlight the impending elderly healthcare problems. However, as with most problems, there are also tremendous opportunities for high-impact, rewarding research and technology development, commercialization opportunities with new products and services, as well as for entrepreneurial initiatives. Fortunately, the continued development of materials and manufacturing for existing cost-competitive, pervasive information and communication systems can be leveraged directly and also used in the creation of new products to make the home ***smart***, thereby providing **u**biquitous healthcare (**U**-Healthcare). A key goal in these initiatives will be to cleverly combine technology with computing which are then deployed in homes so that they *care* for the home occupants and communicate in emergencies. In this

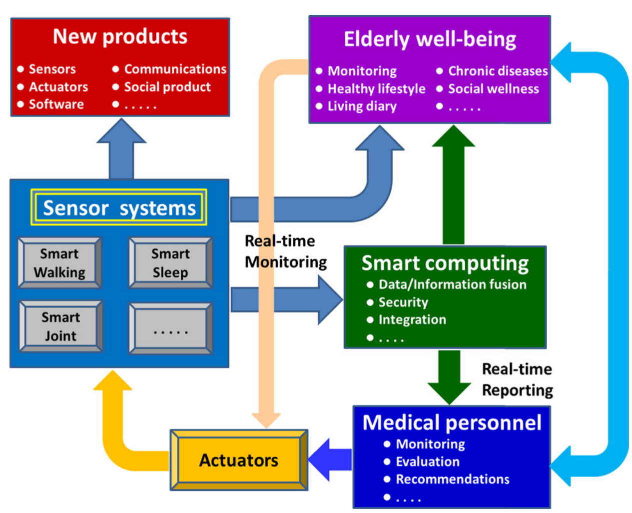


Fig. 2 Schematic diagram illustrating how smart sensors and actuators systems can be integrated with smart computing and medical personnel for elderly healthcare, well-being and improved living

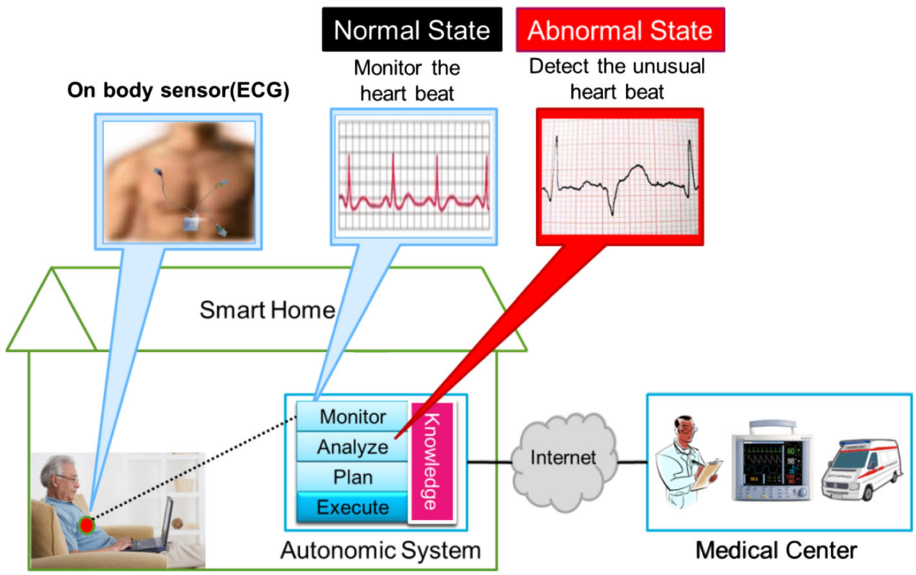


Fig. 3 Schematic diagram of an example of a vital signs technology for elderly healthcare. Here, an on-body sensor used to monitor the electrical activity of the heart using electrocardiography (ECG)

way, ubiquitous, non-intrusive, continuous and long-term care will be feasible with fewer personnel, at significantly reduced costs, and without affecting the comfortable living style of our elderly.

The block diagram in Fig. 2 schematically illustrates how sensors, actuators and smart computing can be integrated with the activities of the medical personnel to meet the social and well-being needs of the elderly. In this way, the elderly can continue to live in their homes in comfort, making the twenty-first century one with *smarter* homes for *smarter* healthcare [15, 16]. It also includes great opportunities for the creation of new products in a variety of areas related to smart home technologies for elderly healthcare. As one example, Fig. 3 is a schematic diagram of a wearable, minimally invasive, on-body sensor used to monitor the electrical activity of the heart using electrocardiography (ECG) [17], so cardiac issues can be identified and remedies developed in a timely manner.

2 Introduction

Around the globe today, the governments in many countries are trying to figure out how to address the major problem related to their rapidly increasing aging population demographics. It is recognized that as the average age of the population increases, the demand for better and more efficient healthcare is becoming a primary concern in the budgets of public and private health service providers. Existing approaches of clinical health services usually translate into high costs that most countries would be unable to afford in coming years [3, 11–14, 18]. This is compounded by the lack of sufficient resources to provide daily care. Also, hospitalization is usually a last resort of health service providers, and it is not the desire of persons that require health aid or personal healthcare. Furthermore, according to a US national survey, nearly two-thirds of the non-institutionalized individuals with functional limitation relied on informal care from family, friends and volunteers, and fewer than 10 % could afford formal paid care [19]. With the increasing aging population, this informal service is an increasing challenge.

In absence of family or healthcare personnel regular checkup visits, the elderly may seek frequent, unplanned emergency or in-patient care, which may be preventable through the use of smart medical home technologies [9, 10, 15, 16]. Also, in-patient care is the most expensive in the healthcare delivery system, and within in-patient services, emergency room expenses are one of the highest. Therefore, it can be argued that one viable and sustainable option for healthcare would be when individuals are rarely patients in doctors' offices or hospitals. In this case, they must have the possibility to capture and record important physiological signals in their own comfortable living environment. Then, this health-related information should be made available to healthcare professionals so appropriate action can be taken when required. Some of these monitors (such as wearable blood pressure and electrocardiography systems) can identify acute life-threatening conditions. Some others (such as walking analyzers) may be employed to detect/identify early diseases to avoid their further progression that would have resulted in subsequent significant health complications.

To improve the quality of the healthcare while striving to reduce costs, one key ingredient is to develop predictive techniques that can identify symptoms of illness in the early stages of diseases. In this way, guidance can be provided and corrective actions toward healthier living can be taken immediately. As an example, an individual's walking pattern is one general indicator of their health condition. As reported in [20], walking patterns are closely related to the health condition of individuals. Persons with illness(es) tend to walk differently compared to healthy individuals. Many medical professionals are able to make the preliminary diagnosis of arthritis and rheumatism, for example, by observing how someone climbs the stairs. However, while professional observation is useful, it requires time and the presence of a healthcare provider, and it is subjective.

It would be immensely better if the walking patterns can be quantified and classified. If such quantitative information can be obtained continuously, then it can also be provided remotely to healthcare professionals. If a problem is observed, then the clinician can determine whether it is arthritis, rheumatism or musculoskeletal problems, for example. This is the exact function of the *walking analyzer*—to collect, quantify, classify and interpret information from walking patterns so early corrective actions become feasible if a problem is identified. This analyzer will be described in detail later.

At present, the importance of wearable devices for quantifying motion or physical activity [21, 22] is gaining popularity. For example, in Table 1, we list some commercial products with details of the types of sensors used and their principal applications.

One aspect of the rising healthcare cost is related to the huge resources needed during recovery after an illness or injury. Most injuries are accidental, and among the elderly, joint injury is very serious and a major growing problem. Further, recovery from a joint injury, for example a knee injury, requires lengthy rehabilitation care [23]. Knee or other leg injuries affect mobility, thereby compromising the ability of the individual to do essential activities in daily life. Examples of such daily activities include shopping, going for a walk, visiting grandchildren, or even going to the washroom or taking a shower. At present, the rehabilitation process is costly and subjective. Rehabilitation relies significantly on the experience and expertise of the physiotherapist or kinesiologist as no low-cost, easy-to-use, quantitative measures are currently available. However, the rehabilitation process can be shortened and the recovery process optimized, if the injured joint is properly monitored, and the method of rehabilitation is adjusted to the state and rate of the recovery. Unfortunately, the quantitative assessment of the state of the joint is not simple. Therefore, the *smart joint monitor* approach can be used to provide the missing quantitative assessment, and this is discussed later.

Another major problem in our modern societies is that many people do not rest well, since they are exposed to pressures and stresses of work, family (and extended family), and the increasing avalanche of information. This causes problems with their sleep, especially in older persons. Often, the elderly take sleeping pills, but then get tired by the middle of the next day and may become drowsy, in addition to other side effects that sleeping medication have when taken for a long time. A better and healthier alternative is to customize the sleep environment using sensors and actuators in a *smart bedroom*. In this customized/optimized sleeping environment, an individual can be noninvasively, non-intrusively and seamlessly monitored with remedial responses/measures for their improved sleep. With better sleep and the associated health/well-being benefits described later in Sect. 3.3, individuals can more effectively and calmly deal with daily problems/issues (work pressures, stress, etc.) that could affect their subsequent sleep. Finally, it should be stressed that in this paper, we only discuss the merits and benefits of using information and communications technologies for

Table 1 Listing of some commercial products for quantifying motion or physical activity

Product details	Comments
Product 1: Accelerometer, gyroscope, magnetometer, bluetooth. Watch system	Physical activity measurements, heart rate monitoring, proximity detection, basic sleep scoring
Product 2: MEMS (Microelectromechanical systems) microsensors, miniaturized digital recording technology. Worn on thigh	Classifies free-living activity—time sitting, standing and walking; estimates daily energy expenditure; changes in activity profile—medication/treatment
Product 3: Accelerometer, rechargeable battery, USB connection, MicroSD card. Attached to waist	Body sway analysis, gait analysis, physical activity monitoring, energy expenditure, sleep movement
Product 4: MEMS accelerometer, temperature, light, event logger, USB connection. Watch system	Physical activity, sports/performance research, sleep/wake
Product 5: Accelerometer, rechargeable battery, bluetooth. Worn on waist, lower back, pockets, thigh, bra, etc.	Daily activity monitoring—research, rehabilitation, therapy, fall detection, gait analysis, posture

elderly ubiquitous healthcare in a smart home. This is not to imply that there are not challenges. In a future document, we will discuss some of the challenges.

3 Smart medical home technologies

In our work, we are using advances in *information technology, wireless communication, sensors, actuators, information fusion, computers and autonomic computing to develop new, smart and cost-effective solutions for **U**-healthcare* applications [9, 10, 24]. Our proposed solutions would enable many of the elderly to lead independent and socially rewarding lives in their modern homes or apartments while being seamlessly, noninvasively and non-intrusively monitored. Such monitoring would allow for the early detection of health-related symptoms and the provision of recommendations for their improved health and well-being.

The proposed U-healthcare solutions will also allow for diseases or health problems to be detected and treated earlier rather than in later stages as is currently done, to promote improved health and wellness, as well as to treat chronic illnesses. In particular, we are interested in *developing and using low-cost, compact and sensitive engineering systems to tackle some pressing problems related to elderly healthcare* which are currently at epidemic levels [25]. Examples of three of these problems are the following.

- Walking/falling signals.
- Maintenance/improvement of motility by quantitative joint monitoring, especially during rehabilitation.
- Evaluation and improvement of the sleeping environment and monitoring sleep vital signals for better health and well-being.

The major components of a smart medical home are illustrated in Fig. 4. These components are related to healthcare, autonomic computing, networking and sensors/actuators for both the occupant(s) and the home environment. The smart medical home developed at POSTECH (Pohang University of Science and Technology), Pohang, South Korea, as part of the World Class University (WCU) research program is shown in Fig. 5. Here, environmental and vital signs sensors, appliances and floor light-emitting diodes to indicate the path from bedroom to bathroom or kitchen are shown. The apartment's layout is shown at the top left, and some of the furniture, sensors and user conveniences are indicated in the other five pictures.

Below, we concisely describe our ongoing research and technology development work in these three areas (walking, joints and sleeping) listed above, as well as some of the challenges. We will also focus on the critical role of technology and data handling in developing innovative, low-cost and high-impacting solutions to the impending elderly demographic crisis. The proposed solutions, with appropriate modifications, are applicable to other individuals and will find applications to infants or in sporting activities, for example.

3.1 Smart walking analyzer

Walking patterns have been investigated and analyzed in the context of fall prediction. In [20] and [26], for example, the elderly walking patterns have been continuously monitored in order to predict falls, to identify weak joint conditions or to detect early, the symptoms of related diseases such as with the lungs or heart. However, few studies have been performed on analyzing the general walking patterns of individuals. Recently, the investigations in [27] and [28] have linked walking patterns to the age of the individuals. Since the shape of human bodies, muscular strength and musculoskeletal support change with age, then persons in different age groups would have distinct differences in their walking patterns. Therefore, it is possible to classify, with a high degree of confidence, individuals by their walking patterns, and then relate these patterns to their age or health.

Healthy individuals tend to have walking patterns [29, 30] that correspond to their actual (biological) age, or a lower age. If a discrepancy between their age and walking patterns for this age or age group is observed, that is, their walking patterns belong to an older age group, for example, then such a discrepancy often indicates some health issues. These health problems could be due to an imbalance between the two legs, e.g., due to a weakness or pain in a joint, or asymmetric leg acceleration due to problems in muscles. Hence, the walking pattern is a good indicator of the general state of health. It can also be used to provide necessary guidance for healthier living and a more active lifestyle.

Human walking varies much among individuals. Stability and balance are decreased significantly in elderly persons. Reduced walking stability in elderly people can lead to falls with serious consequences, such as hip fractures, and in many instances, eventually death. In fact, recent studies [31–35] have shown that hip fractures are a strong predictive factor of death in the elderly. These studies reported that there is a significant increase in risk of death after an elderly person suffers a hip fracture. In [31], it was reported that for hip fracture patients, the risk of death was three times higher than the comparable general population of elderly. Also, it was found that around 20 % of the elderly with hip fractures die within a year [35]. These statistics indicate that there is urgent need to develop inexpensive, user-friendly systems that can be used analyze walking and stability.

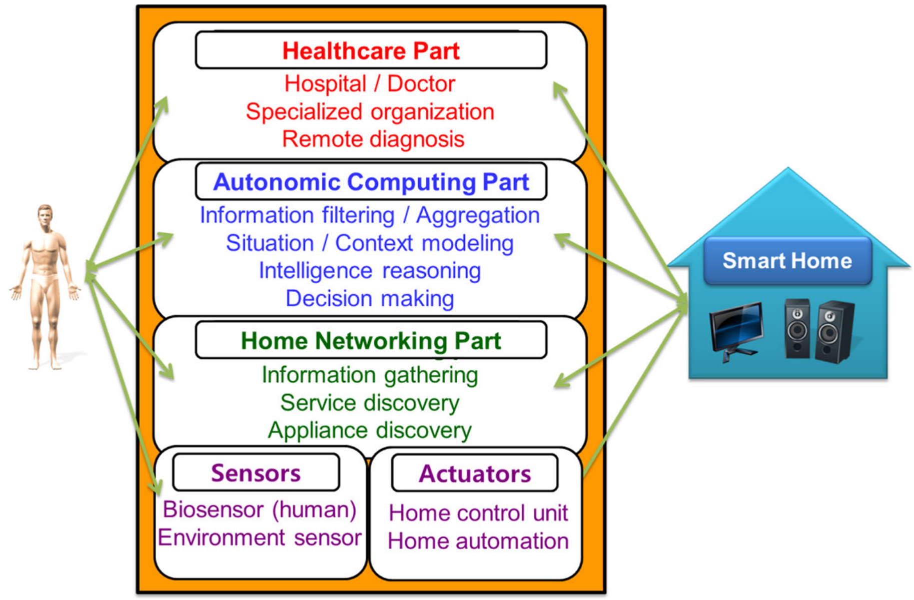


Fig. 4 Schematic diagram some major components in a smart medical home

Fig. 5 POSTECH's smart medical home with some of the sensors and living accessories shown

Our project on the *walking analyzer* classifies the walking patterns [36] based on walking anomaly and walking stability, which may be an indicator of susceptibility to falling. Using cheap, compact and sensitive accelerometers and gyroscopes, we have developed a proof-of-concept *walking age* pattern analysis, classification and identification system. Our goal was to classify walking into distinct groups of walking patterns based on collected signals during walking and to relate the information from these processed signals to age, health condition and body type. The walking patterns suggest that a walking age can be determined quantitatively and the associated walking features can be used as an indicator of potential health and walking/motility problems, such as weak joints, poor musculoskeletal system, early onset of Alzheimer's, Parkinson's disease, and sensory or cerebellar ataxia. In future, we plan to develop *sensing systems for walking* in the form of *smart socks*, *smart wristbands* and *smart belts* that can be easily worn on the body. In this way, we will be able to collect all walking-related signals.

To understand the walking pattern of a person, there are a number of important walking parameters such as speed, acceleration and tilting/rotation of the legs to be measured through continuous monitoring [27, 28]. These parameters are *mechanical* and can be measured by accelerometers and gyroscopes. From the implementation perspective [37–39], these sensors are inexpensive, with small form factors, low-power consumption, and can provide immediate and concise data for the mechanical parameters of interest. This is in contrast to existing methods that utilize video imaging systems and require sophisticated analyses of the data-intensive video streams that eventually produce little mechanical information, when investigating the walking stability of young and old people [40], and also different gaits by age and gender [27]. It is also necessary to control the scene by video capturing, which is quite difficult outside a specialized laboratory or in a home environment. In contrast, our proposed sensing system is virtually applicable in any environment and can be used without affecting the individuals' daily routines.

Previous investigations [41–44] have analyzed and showed different walking gaits that depend on the walking environments, such as a sloping up/down, flat floor, grass, carpet, tile, concrete or asphalt. The walking patterns differ significantly on these surfaces, even for the same person. Therefore, video recording of the walking patterns is difficult in varying scenes of such diverse environments. However, in our sensing system, the sensors can be used equally well in any of these walking environments. Also, one can wear the sensors with normal clothing, e.g., in socks. On the other hand, techniques using video capture require spatial arrangement of several cameras (for example, four or more) with particular distances between the cameras (for example, four to five meters).

The *walking analyzer* that we have developed is easily wearable and applicable for varying real-world walking environments. Since the level of activity varies with the environment, then a normalization of the signals from mechanical sensors is needed. For example, the gait attributes are three accelerations in x-, y- and z-axes, and the tilt value r. These signals have to be normalized, and different parameters such as the height of the person [27, 45, 46] can be used in the normalization. Then, after normalization, the parameters quantifying a person's walking pattern can be extracted.

A schematic diagram illustrating the design details of a *walking age analyzer* system is shown in Fig. 6. In this example, two sensors, an accelerometer and a gyroscope, were used to measure walking-related signals. These signals are transmitted to a computer nearby using *Bluetooth* wireless communications, or stored in a compact, on-body data logger. The sensors are used to measure acceleration and tilting. Since the sensors and wireless system are placed on the leg near the ankle of the individual, then the walking signals would be person-specific. The walking signals can be analyzed to determine the walking pattern.

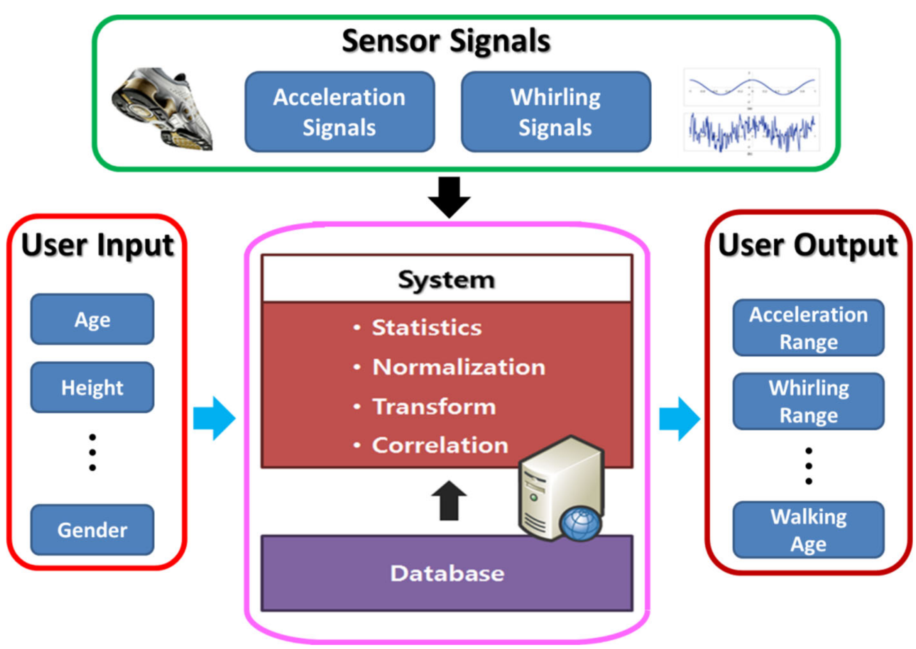


Fig. 6 Schematic diagram illustrating the design details of a "*walking age*" analyzer system

For example, baseline information for the individual can be determined. Then, the *walking information* and deviations from norms may indicate potential health problems or can be correlated with health problems of the individual. In this way, not only can the walking signals be correlated to existing health problems, but they could also be used to provide recommendations to help people walk at their own age, or even better, at a younger walking age to improve their fitness/well-being.

In the illustration shown in Fig. 6, the user inputs are age, height and gender. Other inputs such as weight, leg length or ethnicity can also be used to provide a more complete set of inputs for finer classification and more extensive correlations among walking features and user inputs. Here, acceleration and whirling signals were measured. Future systems with five sets of sensors on two legs, two hands and the torso could be used to provide more complete sets of information for correlations between walking and fitness/health, and as indicators for some disease diagnosis. Examples of correlations include coordination between feet, hands and/or body during walking, waking speed, synchronization between feet and hands (similar to the situation of soldiers marching), how much the feet are lifted above the ground and how walking signals vary with types of surfaces.

The walking age analyzer may seem simple, but walking signals are very rich in medical-related information. This is because walking requires energy, movement, control and support. When an individual walks, this place demands on multiple organs and other body systems including cardiovascular, respiratory, central nervous, autonomic nervous and musculoskeletal. Irregular walking or a slowing gait may indicate health problems in which one or more walking-related organ system or the musculoskeletal system is damaged, resulting in a higher energy cost when walking. For example, individuals suffering from neuromuscular diseases usually have difficulties walking or moving, so gait analysis could be used as a diagnostic technique to identify the severity of this disease and recommend suitable rehabilitation pathways. Also, this walking age analyzer can be configured to behave like a citograph in cytology. More details on the "walking age analyzer" can be found in [29].

In Fig. 7, a block diagram of the *walking age analyzer* for data collection, storage and classification system is shown. Here, the collected signals are filtered to remove noise and then decomposed to extract feature vectors corresponding to the walking signals. After the walking features are extracted, they are analyzed and classified using a clustering algorithm such as K-means. Then, the classified features are stored in a database with input parameters such as age group, leg length and sex. Then, when a new data sample for a new individual is inserted into the database, the analyzer would extract its feature vectors. From classification, the individual will be placed into the appropriate group using the K-nearest neighbors algorithm, for example. In the diagram shown, the output is the walking age of the new individual.

We have investigated and published the classification of walking patterns among a population of South Koreans in several age groups and have develop a proof-of-concept system for determining the person's *walking age* [29]. Using accelerometers and gyroscopes, walking signals were analyzed. Then, normalized mathematical metrics or features that collectively capture the characteristics of a signal were extracted using the feature extraction method for gait described in [40] and reported in [29]. After filtering and decomposition into intrinsic mode functions (IMFs), the first three that were sufficient to describe the walking signals were retained. The remaining IMFs were

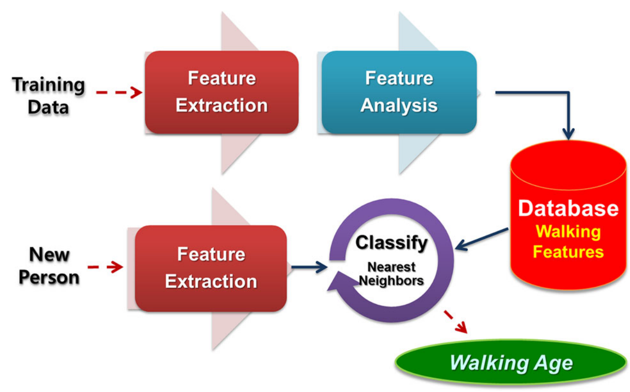


Fig. 7 Schematic illustration of the "*walking age analyzer*" data collection, storage and classification system

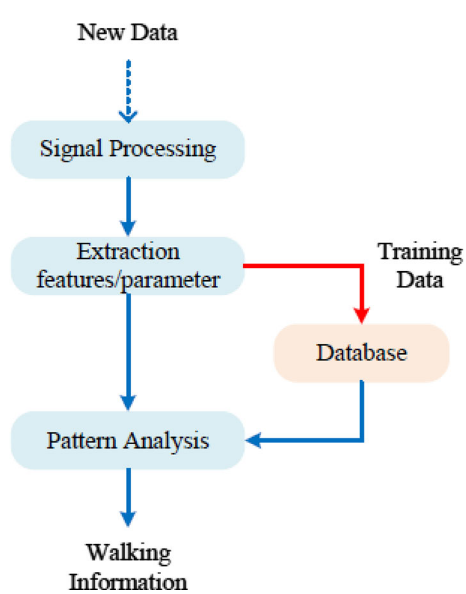


Fig. 8 Flow chart illustrating the walking information system

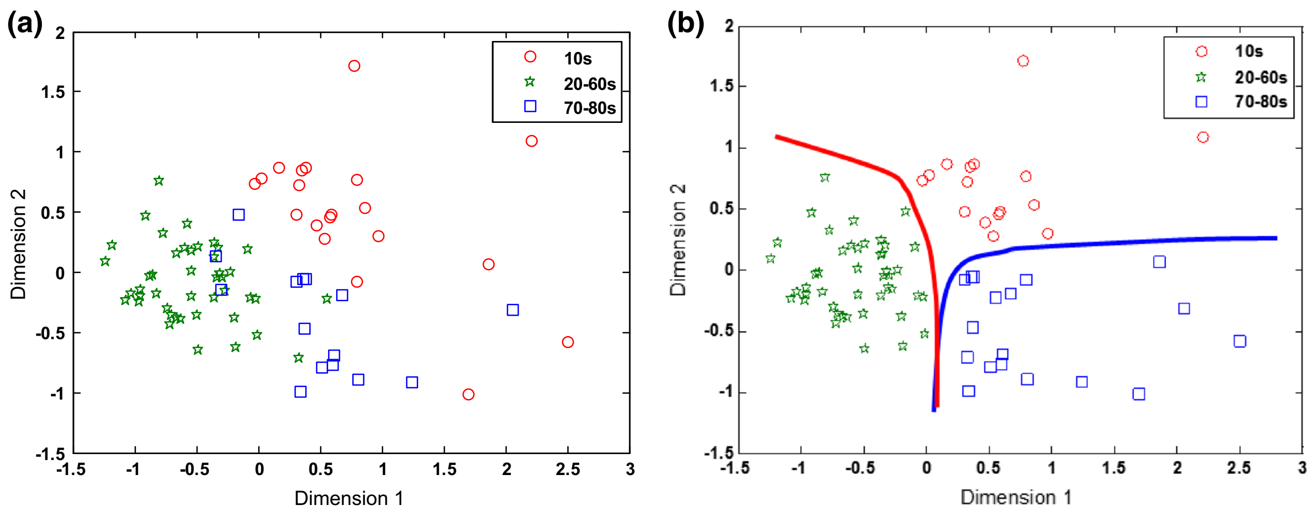


Fig. 9 Plot of data distribution (**a**) before and (**b**) after clustering. Three distinct walking age groups are identified

included in a 16-length vector, and the energy of each IMF was computed to produce a feature vector containing the 16-length energy elements. This was reduced using principal component analysis into 2-length principal components. The K-means clustering algorithm was then applied to the 2-length component vector. A flow chart illustrating the functioning walking information system is shown in Fig. 8.

A user-friendly computer interface was used for the experiments (the interface could also be easily implemented in a smart phone) and the user only needed to click on "Get Walking Data" to start the measurements. For our sample of test subjects, the simplest classification was with three groups after clustering—children in the "10 s" (20 individuals), adults in the "20–60 s" (44 individuals) and older people in the "70–80 s" (15 individuals). The results from our 79 test subjects before (a) and after clustering (b) are shown in Fig. 9.

The results from this investigation on *walking age analyzer* indicate that walking signals can be used for monitoring general health conditions and to provide some recommendations to help people walk at their own age. A summary of the main objectives of this analyzer is shown in Fig. 10. The walking analyzer system described here can also be used during rehabilitation after injury, or for the early stage detection of the symptoms of some diseases such as Alzheimer's. Further, it can be used for gait recognition, recording physiological indices and activity patterns, detecting sway, unstable movement and eventually the risk of falling. Other existing and our proposed monitoring methods for walking signals are non-intrusive, and the devices do not interfere with the normal activities of the individual. The walking analyzer system can also be used to observe the effects of medications on gait and daily activities. Thus, they are potentially very acceptable to the public. Further, the proposed walking age analyzer method has a high probability for commercialization, since it will provide qualitative and quantitative information both to the person and to his/her immediate family members, and remotely to the healthcare professionals.

Future research is described in more detail in Sect. 4 on ***Future Perspectives and Research Challenges***. One example of such research will use more sensors (five sets on legs, hands and torso, e.g., waist) to provide a more complete set of walking signals and metrics. Using these signals, we can investigate any correlations between walking signals and various diseases, balance and falling. Walking signals can also be used as a predictor for the early onset of Alzheimer. One theory is that the onset of Alzheimer's is associated with the destruction of brain cells. So the signals to nerves may become inconsistent or distorted, similar to periodic static on a radio. So periodically, the signals are fuzzy and people hesitate while walking, creating varying activity patterns that are different from the individual's normal variations.

3.2 Smart joint monitor

Joint injuries are very common and can occur in an individual at any age. Among the various joint injuries, knee injuries are arguably the most common and strongly limit human motility for essential daily activities. The knee is one of the largest and most complex joints in the body. It connects the thigh bone (femur) to the shin bone (tibia) and the kneecap (patella), which serves as an aid to protect the knee joint. The knee joint is divided into three compartments—two tibiofemoral and one patellafemoral. The knee ligaments and meniscus are essential to maintain the

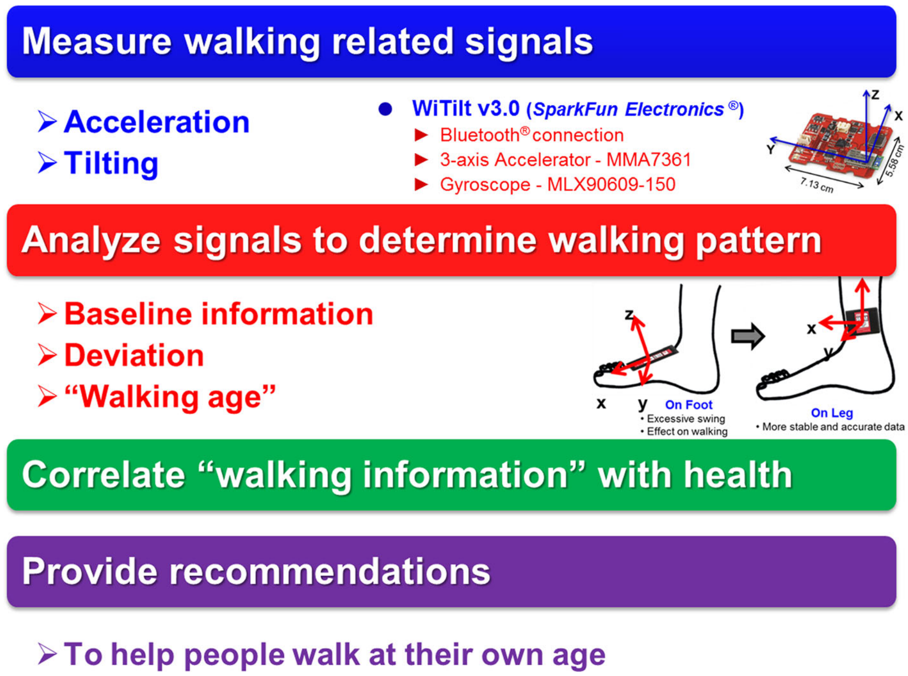


Fig. 10 Summary of the objectives and outcomes of the "*walking age analyzer*" system

stability of the knee joint structure. The knee ligaments join the knee bones and the tendons join the knee bones to the muscles. The knee cartilage functions as shock absorbers between the femur and tibia. And the knee joint acts through gliding and rolling.

When in action, much stress is placed on the knees as they must function at many different angles, undergo flexion/extension, and even slight rotation. Sudden changes in the direction of the knee and motions involving twisting movements are among the major causes of knee injuries. Knee injuries are often the result of a significant amount of force applied on the knee. Monitoring the function of the knee is possible with a *smart joint monitor* or *smart knee monitor* prototype system in the form of a smart knee brace, for example [47, 48, 50]. A smart knee monitor can be used to provide information on physical activity such as walking, climbing or descending stairs and fast locomotion. Together, the walking age analyzer [29] and the knee monitoring system [47] could provide information on physical activities of daily living. Such activities are important for the elderly as they help to prevent or reduce the impact of chronic conditions such as diabetes, obesity and heart diseases on their daily living.

As mentioned above, knee injuries are very common [51]. There are several conventional methods to diagnose injuries of the knee [49–52]. These include looking, feeling, movement and the imaging of the injured area. A goniometer is a simple handheld tool used to manually measure and record the knee angle. It depends on the experience and expertise of the physiotherapist, is inefficient and takes time away from monitoring to record the measurements. It is also mostly qualitative and often it relies on the physiotherapist's sense of touch and memory of the last session to determine progress.

Some common techniques for angle measurements during knee flexion and extension include optical, ultrasonic, magnetic or inertial tracking. Among these techniques, a popular method is to use wearable inertial sensors—accelerometers and gyroscopes because they are of small size, user-friendly and can be used for long-term monitoring. However, such sensing systems must be carefully designed, calibrated and used to minimize the impact of noise, drift, etc., on the measurements.

Recently [53], an electronic system comprising of ultra-wideband (UWB) transceivers and antennas was used to measure the angle of knee flexion/extension. This was not an integrated system as the subjects wore small-sized UWB antennas (12.2 mm × 18.5 mm × 1 mm), and benchtop equipment such as impulse generator and sampling oscilloscope was used. In [54], an ultra-miniature accelerometer taped to the subject's patella was used to measure rotation while they performed flexion–extension rotation of the leg. Significant differences were obtained for patients with knee joint ailments—rheumatoid arthritis and spondyloarthropathy. These results indicated that noninvasive acceleration signals represent a potential tool to easily and quickly distinguish between spondyloarthropathy and rheumatoid arthritis. In [55], the researchers performed force–time measurements to determine the knee muscle functions of patients with multiple sclerosis. For these measurements, an isokinetic dynamometer was used to dynamically measure the torque of the knee extensor and flexor muscles to record the course of the disease and plan the treatment program.

The above methods relied on human expertise, were laborious, were performed in a clinical setting studying differences between healthy and sick persons or were using complex sensors. Therefore, our work focuses on a simple, low-cost solution to automatically and easily measure the important knee parameters such as knee angle, flexing, extension, rotation, force and temperature. The main objective is to design a *smart knee monitor* as a knee brace, onto which various sensors including accelerometers, gyroscope, force sensor, temperature sensor, plus a communication module, microcontroller, memory and signal processor are attached [47] as small, lightweight system(s). A schematic block diagram of such a knee monitoring system is shown in Fig. 11.

The s*mart knee monitor* that is an easy-to-use brace [47] is in consonance with our vision for noninvasive and non-distracting health monitoring devices. It has several user-friendly features. When necessary, for example, when sleeping or taking a shower, the s*mart knee monitor* can be removed and easily used again. Correlating the information from the *knee monitor* and the *walking analyzer* (the latter with wearable sensors in the socks, wristbands and belt), it might be possible for the physiotherapists and kinesiologists to develop better and faster recovery programs and to propose necessary activities for improved lifestyle.

A key goal of the *smart knee monitor* prototype system is that it can be used to quantify the condition of the knee joint (or any other joint) by providing the means for objective assessment of the progress in the rehabilitation and eventually to find a better customized rehabilitation program for a more complete recovery of the injured person's knee. Faster and more complete recovery, in turn, results in other benefits, including personal and family well-being, reduction in economic losses due to temporary

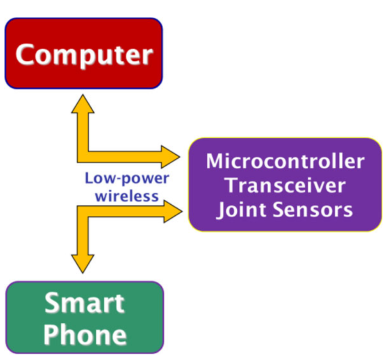


Fig. 11 Schematic illustration of the general system design of a smart joint sensor system

disability, and lowering the costs and burden on our healthcare systems.

When the smart knee monitor is in use, data from the sensors are collected via a communication module and sent to either a personal computer or a smart phone. Then, the physiotherapists or kinesiologists can use the quantitative data to diagnose knee problems and evaluate the rehabilitation progress with minimum uncertainty due to objective judgement. We expect that such a monitoring system will help the physiotherapists to diagnose the state of a knee more accurately and objectively than existing methods using the measured data collected wirelessly. When fully integrated into a single electronic sensing system, the smart knee monitor can be used for other joints in the body.

The *smart joint monitor* can be made by several approaches. One approach is to attach the sensors to a two-piece brace with one degree of freedom of rotation aligned with the rotation axis of the knee [47]. Such brace has superior accuracy for determination of angles, but needs some skills from the person attaching it to the leg to align the rotation axes of the knee and the brace. Our initial prototype of the *smart knee monitor* was mostly suitable for tests by the physiotherapist. The second variant is comprised of two independent braces, connected with flexible cord around the leg. The angles will be estimated from gyroscopes and accelerometers in the braces [47]. The accuracy of the angle measurement might be lower, but additional information for trajectory and accelerations can be gathered, which allows for real-time on-body measurements. The arrangement is also convenient for the person wearing it. And the information from the second brace can be coupled with the *walking analyzer*.

The preliminary prototype of our smart knee monitoring system is shown below in Fig. 12. This prototype has several sensors and electronics—a force sensing resistor, an accelerometer, a gyroscope, a temperature sensor, a potentiometer to measure knee angle or measure range of motion (RoM) and a wireless transceiver. A sensitive temperature sensor was mounted at the top of the knee brace and was used to record the skin temperature above the quadriceps. Measuring the external skin temperature uses the concept that the accumulated strain of a muscle can be measured through the temperature of the muscle. Thus, by measuring the skin temperature above the muscle, it may be possible to determine the cumulative strain on the muscle.

The angle of the knee (range of motion) was measured with the potentiometer sensor that was mounted to the joint of the knee. Two low-power consuming and small-sized accelerometers—one on the lower part and another on the upper part of the knee brace—were used to track the linear acceleration of the lower and upper parts of the leg. A low-power consumption gyroscope was placed on the upper

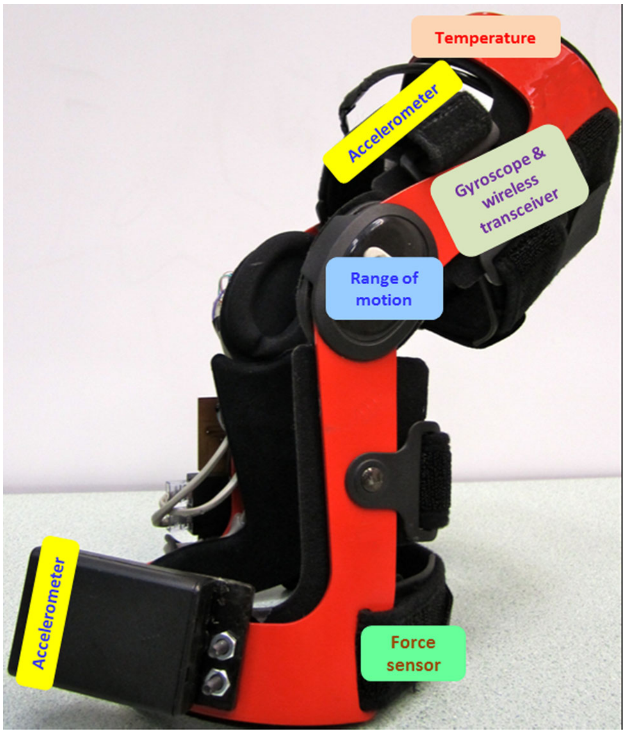


Fig. 12 Photograph of the knee brace with the types of sensors/electronics used and where they were positioned

part of the knee brace, and it measured the angular velocity of the leg and was also used in determining the acceleration. The gyroscope had built-in signal conditioning/low-pass filtering capabilities. Also, a force sensing resistor (FSR) was attached to a twisted pair wire running down the back of the person's leg and placed under the heel to measure foot impact and force. This ultra-thin sensor gives high-resolution outputs at the high force levels that are typical when the heel makes contact with a surface.

A microcontroller was used as the primary data processing unit on the knee brace. The selected microcontroller contained a number of analog-to-digital converters (ADCs) and could provide other types of sensor interfaces. The microcontroller was used to collect and process the data which was then transmitted using the ANT protocol (an open access, ultra-low-power wireless technology used in sensor networks for applications such as performance and health monitoring) at ten data points per second, enough for real-time results. The PIC (peripheral interface controller) microcontroller communicates with the ANT device at 4800 bits per second. The ANT transceiver included an on board transmitter, operating at 2.4 GHz and can communicate at distances up to 30 m. A USB serial interface allows the graphical user interface (GUI) on the personal computer (PC) to receive wireless ANT transmissions. All sensor systems and electronics were mounted on three printed circuit boards (PCB), which were secured to the knee brace at positions shown in Fig. 12. Also, note that in real systems, practical issues such as calibration, sensor drift, thermal fluctuations, and electrical and mechanical noise must be carefully considered when acquiring and analyzing data from the sensors. Some key details of all sensors and electronics used in the smart knee monitor are provided in Table 2.

In the smart knee monitor, a custom program was used to filter, process and display the acquired sensed signals/data in real time. The data were transferred wirelessly to a personal computer for display and storage in a database so that all incoming data are saved. In this way, the physiotherapist has the ability to track progress through multiple sessions. By collecting the sensed data via the communication module on either a personal computer or a smart phone, physiotherapists or kinesiologists can use the quantitative data to diagnose knee problems and evaluate the rehabilitation progress with minimum uncertainty due to subjective judgement. It is believed that such a monitoring system can help the physiotherapists diagnose the state of a knee more accurately and objectively with the measured data wirelessly collected. Furthermore, such a system can be used for other joints in the body; for large segments of the population, including children and younger adults; and for rehabilitation after sport, work and other accidental joint injuries.

A GUI was implemented to initiate the data gathering from the smart knee monitor (Fig. 13) and to display the acquired data. With the GUI, data are collected, stored, analyzed and displayed from each sensor, and some examples are shown in Fig. 14. The system can log data from different sessions. Therefore, a record is available to the kinesiologist or physiotherapist so progress can be tracked and when needed, remedial actions taken. The data record can be used to make statistical calculations that may indicate whether the person is over-exerting themselves with the potential to cause further damage. In addition, the knee monitor can be used to dynamically monitor patient exertion to provide recommendations for optimum and customized exercises through real-time sensor information to the physiotherapist or the user.

Some experiments were also performed to demonstrate the effects of filtering on accurate measurement of the range-of-motion or angle as the knee bends and unbends (Fig. 15). A gyroscope was used in these measurements. The experiment was performed ten times for bending/unbending in which the angle varied from 30°–40° to 120°. Without Kalman filtering, there are significant errors during the quick movement of the knee (Fig. 15b). With filtering, the errors are minimized (Fig. 15a).

The *smart knee monitor* can be used to investigate the relationship between range of motion, flexibility and balance in the elderly. It can also be used to provide

Table 2 Listing of the specific hardware used in the smart knee monitor and some of their key specifications

Hardware	Product information	Sensor/electronics features
Temperature sensor	Analog devices AD22103	0 to 100 °C; onboard signal conditioning; accuracy >2/5 % FS, linear response
Force sensor	Tekscan A201 force sensing resistor	Ultra-thin; gives higher-resolution outputs at higher force levels; linear; low drift
Accelerometer	Analog devices ADXL335	Low-power; small size; signal conditioned output
Gyroscope	ST microelectronics LPY503AL	Build in signal conditioning and low-pass filtering capabilities
Knee angle, ROM	Panosonic, EVW-AE4001B14 potentiometer	Linear (±2 %); measures angles up to 343°; small size; long operating life
Microcontroller	PIC24FJ64GA004	Has 10-bit ADCs with 13 channels; 500k samples/s; both digital and analog peripherals; low power
Transmitter (Tx)	Tx-Dynastream ANTAP281M51B	ANT protocol; 2.4 GHZ; communicate ~30 m; low power; 1 MBps; coin cell battery
Receiver (Rx)	Rx-Dynastream, nRF24AP1	

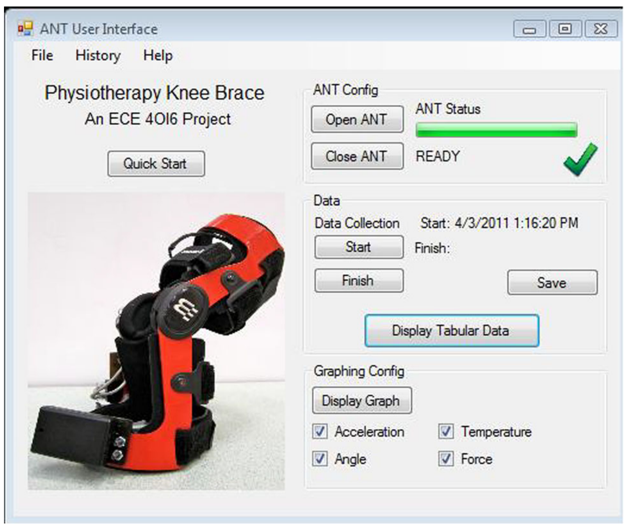


Fig. 13 User interface of program to collect data

quantitative answers to a variety of questions such as the following.

- Is the range of knee movement in the recommended range?
- Is the injured person dong adequate exercise or following the exercise program at the recommended times and frequency?
- Are there any physical problems that should be reported to the medical specialist?

Coupled with the *smart walking analyzer*, the *smart knee monitor* could provide real-time information for predicting susceptibility to falls. It will be possible to define styles and sizes of the *smart knee monitor*, and wear them comfortably, even for prolonged periods of autonomous recording of information for the knee. Further, this monitoring will be done in a non-intrusive and non-distracting manner for the person wearing the "knee monitor."

3.3 Smart sleeping environment

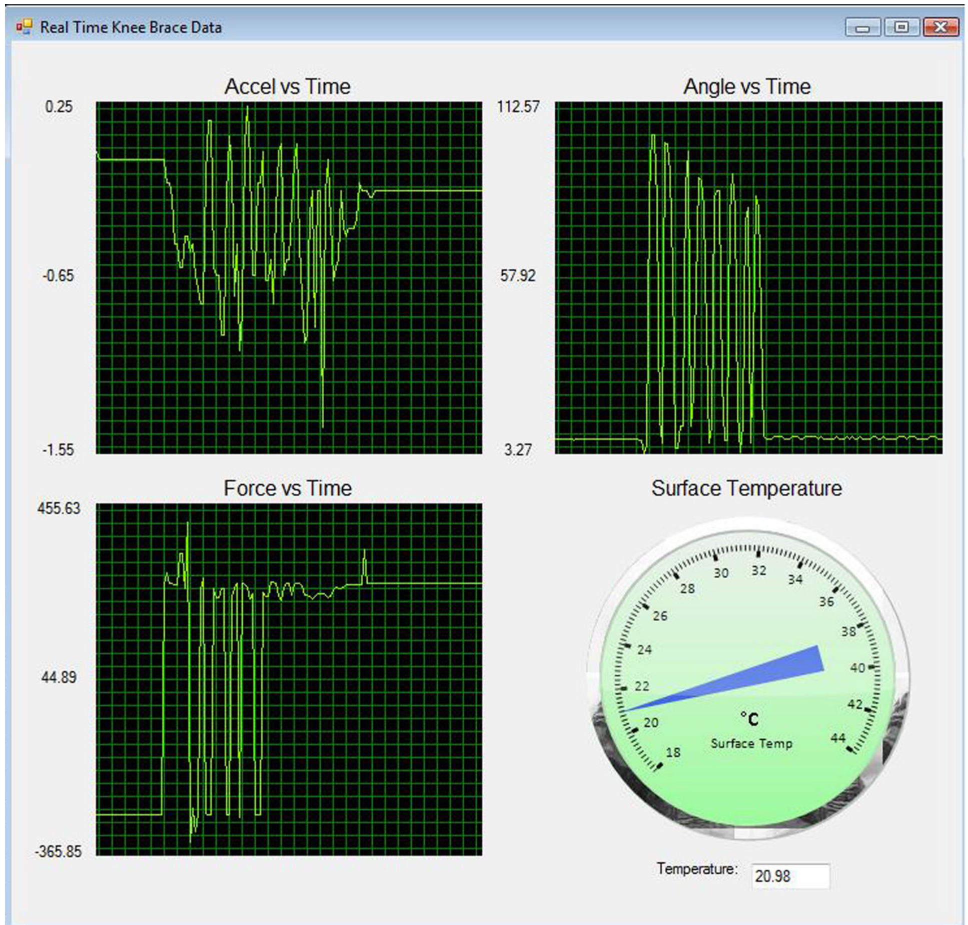
Sleep is essential to our healthy brain function, good physical health and emotional well-being so we can properly function in our daily activities. Normally, our lifestyle is rhythmic with periods of daytime activity alternating with nighttime inactivity or sleep during which time, we rest and conserve energy. Most adults need between 7 and 9 h of sleep each night for good health and optimum performance the following day [56, 57]. When we sleep, our body is working to support our brain function, energy levels are restored, and our good physical and mental well-being is positively affected.

During sleep, our body produces proteins that help cells repair damage, and it is important for the healing and repair of our heart and blood vessels. Sleep is important in maintaining a healthy balance of the hormones responsible for the correct level of our hunger so we do not overeat. While the body rests during sleep, the brain remains active to control functions such as breathing, new information is committed to memory by memory consolidation and new pathways are formed for learning. Sleep helps in improving concentration and memory, and the immune system is refreshed to reduce the risk of some diseases.

Sleep is composed of two distinct states: non-rapid eye movement (NREM) and rapid eye movement (REM) [58]. Typically, each night involves four to six repeated cycles, each lasting ninety to one hundred and ten minutes, of NREM and REM sleep, respectively. NREM sleep is divided into three stages (previously four with the last two combined in recent sleep classification [59–61]). In NREM sleep, the first two stages are when you transition into sleep and are in light sleep when your heart rate slows and temperature drops in preparation for stage 3.

In stage 3 NREM sleep, also known as the deep sleep stage, brain activity is low and body muscles are fully relaxed. In this stage, most of the good benefits such as

Fig. 14 User interface of program to display data. Here, acceleration, angle and force versus time are displayed. At bottom right, knee surface temperature (∼21 °C) is displayed



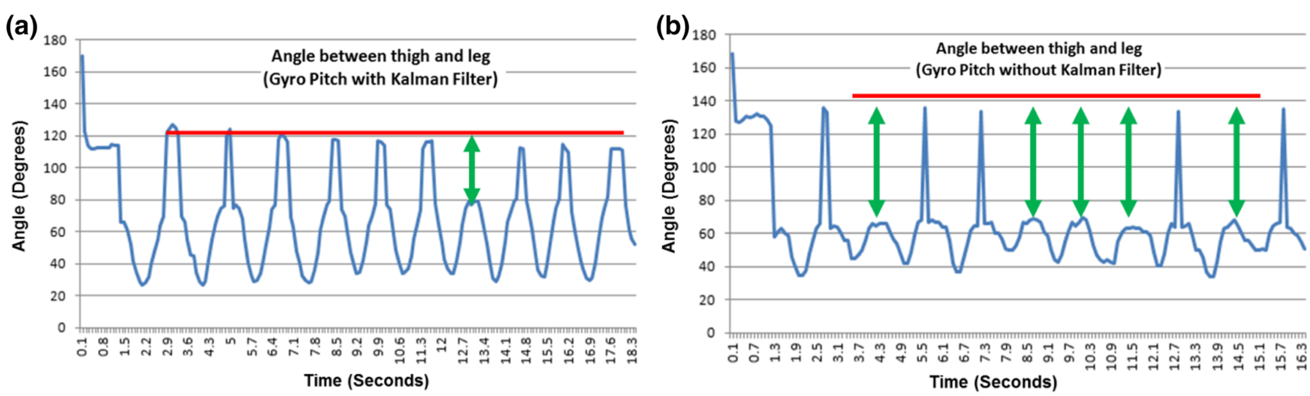


Fig. 15 Results of bending/unbending the knee **a** Kalman filtered and **b** without filtering

healing and regrowth of tissues, memory consolidation and energy restoration occur. In REM sleep, our heart rate and breathing quicken, brain activity is usually high, and we can have dreams. REM sleep is about 20 % of the sleep cycle in adults. For everyone and especially the elderly, sleep is very important.

Despite its importance to our overall cognitive function, good health and emotional well-being, a huge number of persons representing significant fractions of the population in the developed world, do not get enough sleep or suffer from lack of sleep. For example, in [56], it was “estimated that 50–70 million Americans chronically suffer from a disorder of sleep and wakefulness, hindering daily functioning and adversely affecting health and longevity.”

According to the *The National Center on Sleep Disorders Research* (NCSDR) in USA [62], ∼70 million Americans suffer from sleep problems and approximately

60 % have a chronic sleep disorder. NCSDR also reports that "sleep disorders, sleep deprivation and sleepiness add an estimated $15.9B to the national healthcare bill" annually. Further, "additional costs to society for related health problems, lost worker productivity and accidents" would significantly increase the annual costs [62]. Also, *"The Institute of Medicine* recently estimated in its report, *Sleep Disorders and Sleep Deprivation*: *An Unmet Public Health Problem* [63, 64], that hundreds of billions of dollars a year are spent on direct medical costs related to sleep disorders such as doctor visits, hospital services, prescriptions and over-the-counter medications."

Sleep problems typically go undiagnosed, untreated and are often overlooked or ignored. Chronic sleep problems may affect balance, coordination, vigilance and alertness. Lack of sleep or poor sleep may lead to poor functioning of the central nervous system [65]. In many individuals, daytime sleepiness can interfere with their daily activities and work performance [66]. Inadequate sleep or sleep deprivation leaves the brain exhausted, so it functions less efficiently.

Lack of sleep also affects our concentration, ability to learn new things well, stifles creativity, and impedes or degrades decision-making processes. It affects long- and short-term memory. Constant sleep deprivation is a risk factor for impulsive behavior, depression, paranoia or chronic illnesses. Also, in [67], it was reported that substandard or insufficient sleep and disruption of the body's natural circadian cycle are linked to negative health outcomes such as heart disease, diabetes, obesity and cognitive brain impairment.

Some obvious signs of sleep deprivation are excessive sleepiness, yawning, irritability, impatience, anxiety and depression. Chronic sleep deficits contribute greatly to "microsleep", that is, falling asleep for a few seconds to a few minutes without realizing it. Microsleep has been linked to a significant number of traffic accidents, trips and falls. According to [68], from a survey of approximately 150,000 persons, 4.2 % reported that they fell asleep at least once during the previous 30 days, especially among those with 6 h or less sleep. According to the National Sleep Foundation [69], changes in sleep patterns, in addition to outwardly visible physical changes, are part of normal aging. With aging, many older persons take longer to fall asleep (increase in sleep latency); there is an increase in the number of sleep/wake cycles (more sleep fragmentation) and less REM sleep.

The environment plays a major role in sleep problems. For example, a room that is too hot or cold, noisy, bright, or too high or too low humidity may prevent us from getting adequate deep sleep. There is also evidence that certain smells may have an effect on your sleep [70]. For example, lavender has been shown to decrease heart rate and blood pressure, potentially putting you in a more relaxed state. In [71], the brain waves of subjects at night were monitored. It was reported that individuals who sniffed lavender before bed had more deep sleep and felt more vigorous in the morning. It was also found that lavender oil caused significant decreases in blood pressure, heart rate and skin temperature, which indicated a decrease in autonomic arousal. In terms of mood responses, the subjects in the lavender oil group categorized themselves as more active and relaxed and fresher than subjects just inhaling base oil. Compared with base oil, lavender oil increased the power of theta (4–8 Hz) and alpha (8–13 Hz) brain activities, indicating better sleep [71].

During sleep, at a basic level, your brain continues to register and process sounds. While sleeping, noise can cause you to wake, shift between sleep stages, or experience change in heart rate and blood pressure for periods so short that you do not remember when you are fully awake. White noise and nature sounds that rise and fall in intensity such as ocean waves or raindrops gently falling may be relaxing and help you drift off into sleep. Light and darkness are also signs that tell us when to wake and when to rest. So a dark room is preferable for improved quality sleep. To initiate sleep, your body temperature usually decreases, so a cooler room is preferable to a warmer one. Thus, room temperature also impacts sleep quality, and it is believed that a room temperature between ~ 16 and ~ 20 °C is optimal for sleeping.

From the above discussions, a *smart sleeping environment* may help individuals, and especially the elderly enjoy the fruits of a good night's sleep. Therefore, we have developed a specialized hardware–software management system that controls and customizes the room environment to the optimum conditions for an individual's sleep. We used environmental sensors and actuators for light, temperature, humidity, sound and oxygen. When an individual sleeps in the *smart sleeping environment*, some physiological signs such as temperature and heart rate were easily and conveniently monitored using small, wearable sensors. A schematic illustration of the smart sleep environment system architecture is shown in Fig. 16. Also shown is the feedback/check-up questionnaire to help customize the sleep environment for each sleeper.

The check-up sheet used was electronic, and it was implemented as a smartphone application within our smart apartment (see Fig. 17 for an example of a composite question in the smart phone) [72]. The smartphone application has functions to display the history of the sleep environment and the sleep patterns of the individual [73, 74]. Using the data collected from the sensors and answers from the sleep questionnaire, recommendations for improved sleep and adjustment of the sleeping room environment, based on assessment from a medical professional and sleeper needs, can be provided.

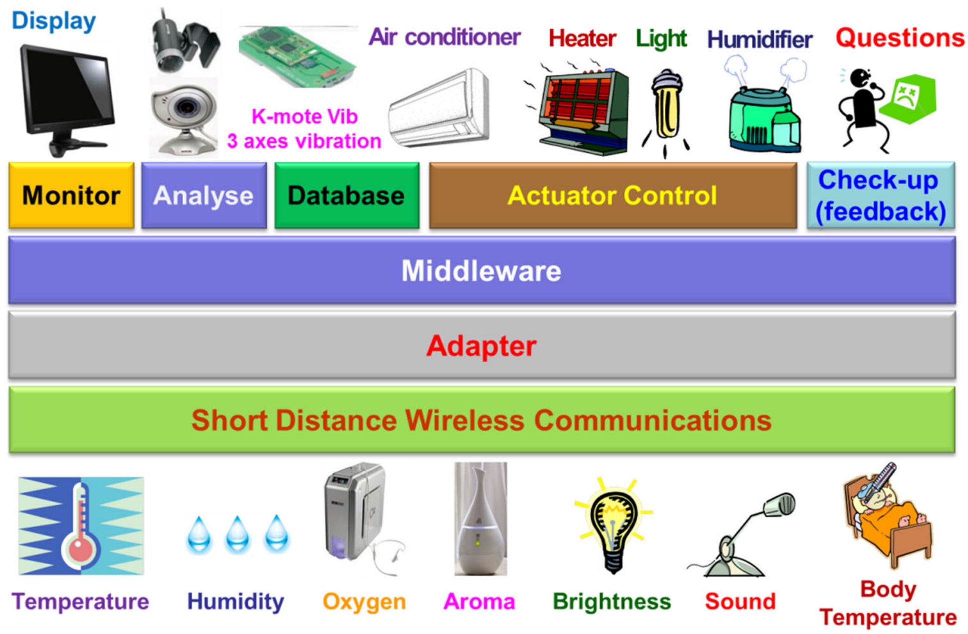


Fig. 16 Schematic of the system architecture for our "smart sleeping environment" system. The sensors used are shown at the *bottom*, and the actuators are shown at the *top*

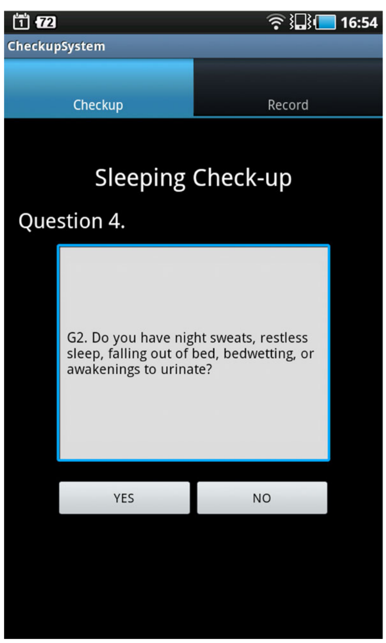


Fig. 17 Sleeping check-up as a smartphone application. A composite question—Question 4—is shown here

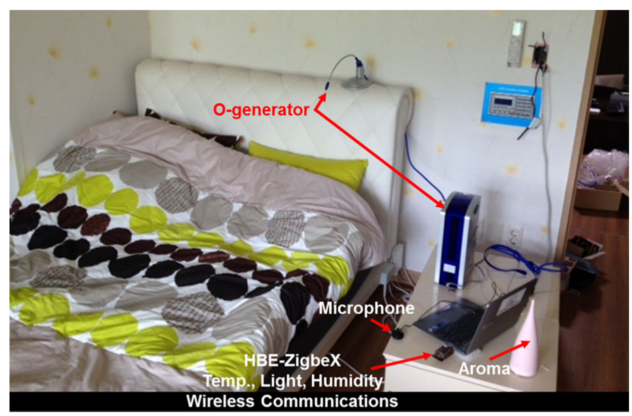


Fig. 18 Photograph of the bedroom with only some of the sensors and actuators used

A more elaborate example of a sleep check-up questionnaire is the Pittsburgh Sleep Quality Index (PSQI) [75] that can also be implemented using various sensors. The PSQI contains nineteen questions, each of which was scored between zero and three. Higher scores indicate more severe sleeping problems. Among the nineteen questions, eight can be automatically tracked and evaluated using audio and visual sensors.

In the smart sleeping environment, vital sign sensors will provide a simple criterion of the sleep stages and a sound sensor will detect breathing patterns. Then, a computer program checks the sleeping duration in the sleep cycle. This system can be used to detect sleep disorders from the check-up sheet's results. An important characteristic of the proposed system is the use of computers to automatically control the environment and to diagnose some sleep disorders by recognizing anomalous breathing patterns, for example.

A photograph of the actual bedroom in our smart medical apartment, with some sensors and actuators, is shown in Fig. 18. In this photograph, environmental sensors for temperature, light, humidity and sound; actuators for aroma (lavender) and enhanced oxygen (to approximately 30 %

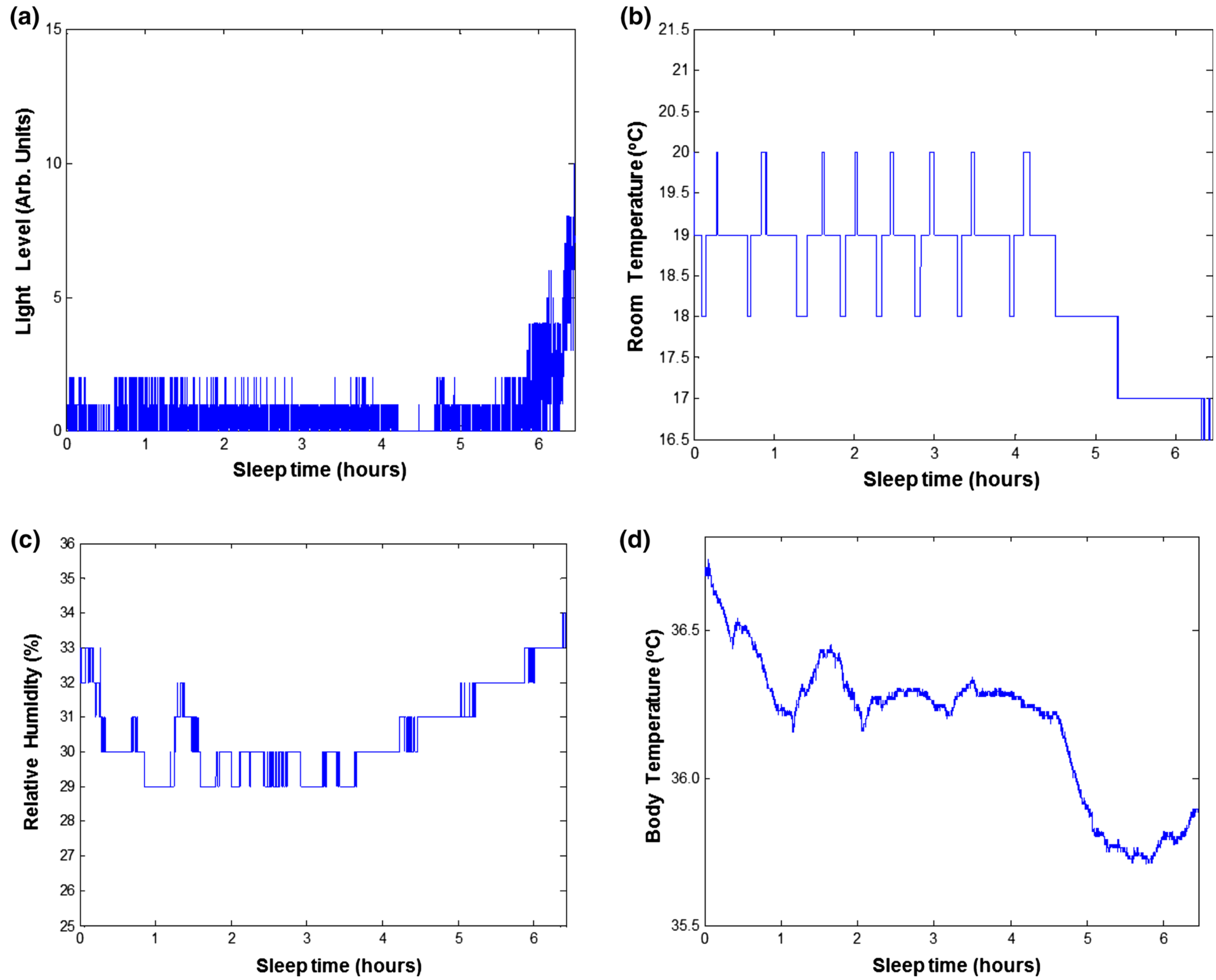


Fig. 19 Sensor data for **a** light level (0—dark), **b** room temperature, **c** relative humidity and **d** body temperature

air composition); and a wireless system for transmitting data to a laptop, are shown. Examples of sensor data recordings for light, room temperature, relative humidity and body temperature throughout the night are shown in Fig. 19.

To illustrate the importance of controlling the environment for a good night's sleep, some experiments on modifying the room atmosphere were conducted. In particular, sleeping experiments with four sets of conditions for the room atmosphere were conducted. The conditions were (a) basic sleeping room atmosphere environment with normal air; (b) environment with enhanced oxygen (to ~30 %); (c) environment with aroma (lavender); and (d) room atmosphere environment with both enhanced oxygen and aroma. Typical results from an adolescent sleeping in the bedroom under these four sets of conditions are shown in Fig. 20.

In Fig. 20a, a comparison of the sleeper's body temperature in normal room atmosphere and enhanced oxygen (flowing above the sleeper's face for the first hour—see oxygen dispenser shown in Fig. 18) is shown. Here, we observe that the sleeper goes into deep sleep (low body temperature indicated by red arrow) much earlier when there is an enhanced oxygen environment—1 h with enhanced oxygen compared to 2–3 h in a normal room environment (see indication at blue arrow in Fig. 20a). With a mixture of enhanced oxygen and aroma, the results are similar to those with only oxygen (Fig. 20c, d). For this sleeper, no effect of aroma on the sleep cycle was observed (Fig. 20b). These results are interesting for they show that enhancing the oxygen to ~30 % for 50 min by blowing the oxygen over the face of the sleeper results in a faster transition to deep sleep and the sleeper remains in deep sleep for a much longer period.

In the smart apartment, our smart sleeping bedroom can be used to help alleviate sleep problems or poor quality sleep. Here, a centralized system collects the sensed data and after sleeping, the sleeper completes a check-up sheet

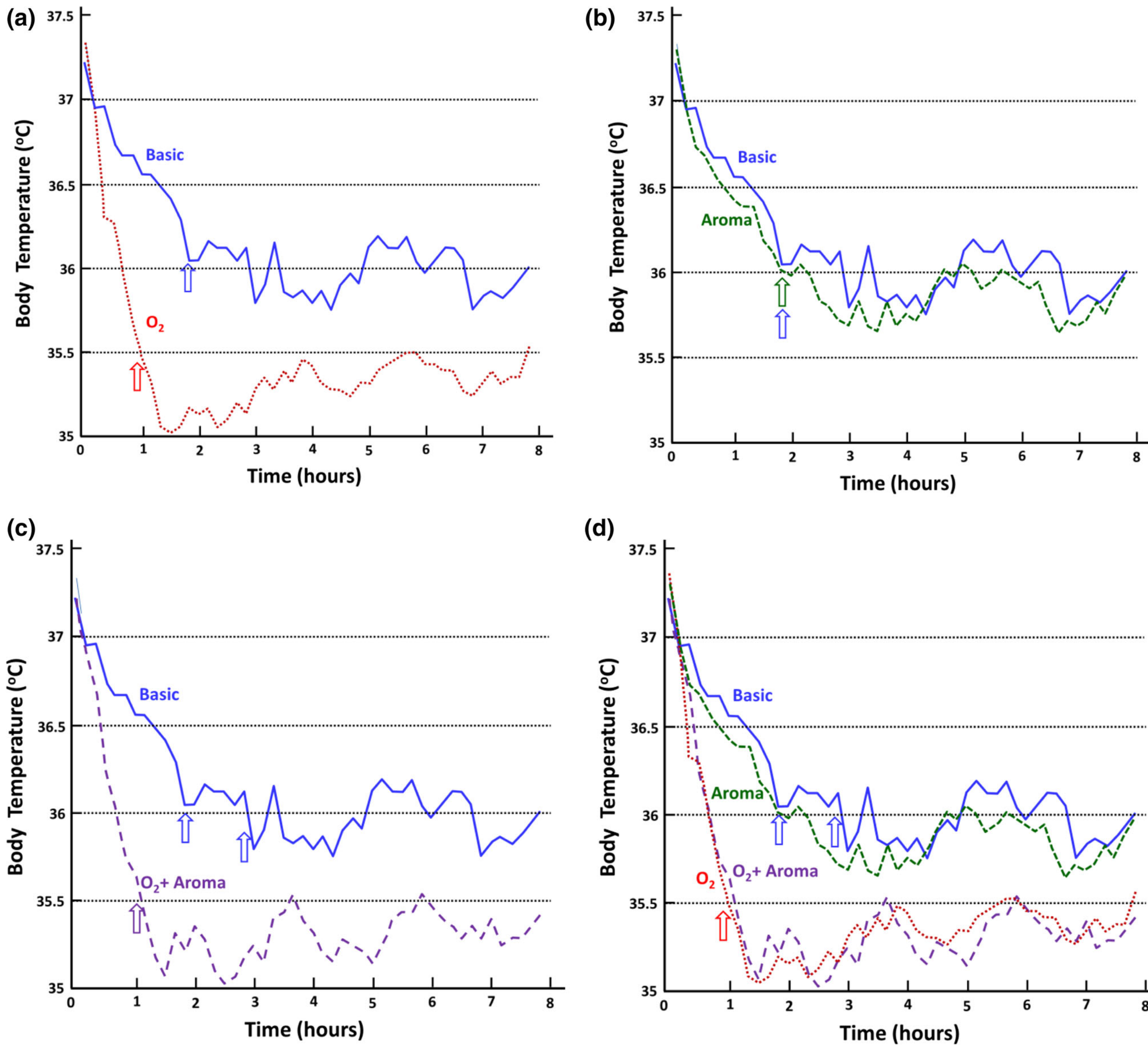


Fig. 20 Body temperature (y-axis in °C) sensor data for **a** basic room environment and enhanced (∼30 %) oxygen flowing above face, **b** basic room environment and lavender aroma in room, **c** basic room environment and lavender aroma plus enhanced (∼30 %) oxygen flowing above face and **d** all four measurements of basic room, enhanced oxygen, lavender aroma and (oxygen plus aroma) together for easy comparisons

questionnaire. The centralized system is used to analyze the collected data and control environmental actuators such as an air conditioner, humidifier, oxygen generator and lighting. The centralized system can also be used for diagnosing some common sleep disorders. A simplified schematic block diagram of the functioning of the sleep environment system is shown in Fig. 21. Here, using sensors, electronic feedback actuators and the sleeper's feedback/input, we can optimize the room environment such as the temperature or humidity, to help the sleeper have a better night's sleep. The software system also keeps a record log of the quality of sleep from the answers to the questionnaire and the environmental parameters.

Our *smart sleeping environment* included sensors, actuators, short-distance wireless and custom programs for adapters and middleware. It also included a preliminary sleep check-up questionnaire that was implemented on a smart phone. We have demonstrated how the sleeping environment (bedroom) can be monitored and the conditions adjusted based on the sleeper's requirements. Our custom solution also included some vital signs monitoring such as body temperature, breathing patterns, snoring and heart rate signals.

The sensing and actuating systems were deployed in our smart apartment with a local wireless network. The entire system was computer controlled, and the local wireless

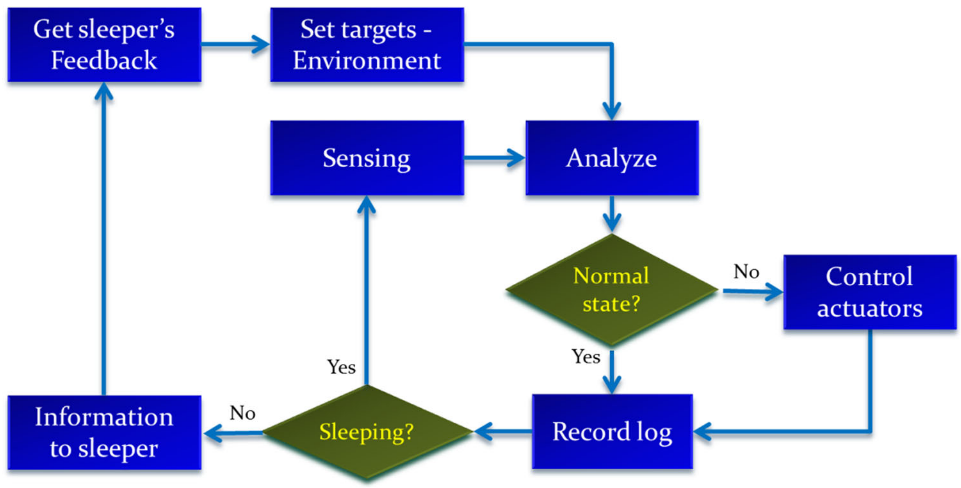


Fig. 21 Schematic of sleep environment system with feedback mechanisms to help improve an individual's sleep and customize the sleeping environment. Sleep relevant information is kept in a record log

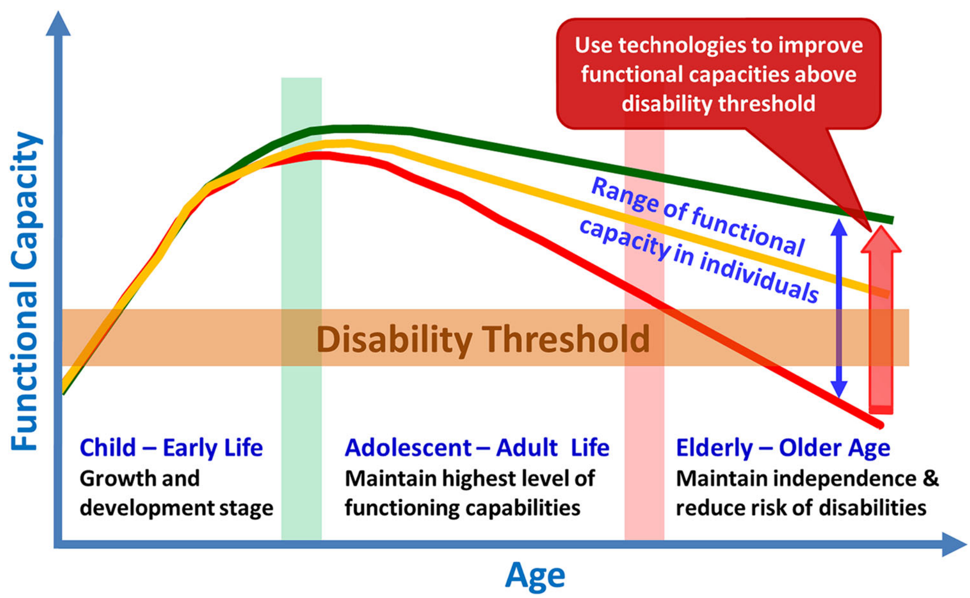


Fig. 22 Functional capacity as a function of our age. The expectation is that appropriate technologies can help the elderly maintain functional capacity above the disability threshold as they age. Adapted from [76]. Here, functional capacity includes respiratory capacity, muscular strength and performance of cardiovascular system. Note that the "age" x-axis is not to scale as the middle section is typically wider than the "early life" and "elderly" parts

network was used for communication with the occupant by a smart phone. Hardware that was integrated included a humidifier, aroma and oxygen dispensers, temperature and lighting control, and sound monitoring. Then, an information fusion system was developed for appropriate, timely response of the environmental parameters relating to the sleeping state of the occupant, and to identify possible sleep disorders according to the sleep disorder classification in [59].

4 Future perspectives and research challenges

The technologies related to vital signs, walking/falling, joints, sleeping and autonomic computing were carefully chosen as high-impact ones that can help the elderly live in their own homes while being noninvasively, nonintrusively and seamlessly monitored. These smart home technologies can help the elderly maintain or slow the rate of degradation of their functional capacities as they age. As stated in the WHO *Active Aging—A Policy Framework* [76, 77], these low-cost, user-friendly interventions will create a supportive home environment and healthy lifestyles for the good health and well-being of the elderly. More specifically, the clever use of information and communication technologies systems (or smart medical home technologies) can help the elderly improve or at least slow the degradation of their functional capacity as they age. In this way, their functional capacity stays above the disability threshold, as illustrated in Fig. 22.

Below, we describe and discuss several future perspectives and challenges related to the research work described earlier in Sect. 3.

4.1 Walking

We have shown that with simple, low-cost, inertial sensors—accelerometers and gyroscopes—plus low-power wireless communications and signal processing, it is possible to determine the *walking age* of an individual. These results demonstrate the feasibility of measuring and classifying walking-related signals. The relationships and correlations among walking signals, health and certain types of diseases would provide ample opportunities for future work. For example, using a larger population of the subjects (especially elderly persons from different age groups, ethnicity, gender, physical attributes, etc.), research in the topics below would provide rich information to develop the relationships and correlations among walking signals and various health/fitness or lifestyle metrics.

- Determine the best positions to attach the five sets of sensors on the each leg (two sets), each arm (two sets) and torso (see Fig. 23 for an illustration of on-body sensors—yellow/green in *smart socks*, *smart handbands* and a *smart belt*, to acquire walking signals) [78].
- Use five sensor systems to determine unilateral (local) versus bilateral motion, coordination between hands and feet and their relation to walking metrics such as speed and tilt or sway.
- What are the effects of different surfaces such as carpet, wooden floor, tile, grass and concrete on the walking signals?
- What are the impacts of different normalization metrics such as age, sex, height, weight, leg length on the classification results?
- Determine step characteristics such as how long each foot stays on the ground, lifting of feet, ground contact force (with a wireless force sensor in soles of shoes—can later be extended to create smart shoes with more sensors) and step lengths.
- What are the characteristics of initiation and stopping of walking and how do they impact the walking signals?
- Examine the possibility of using walking signals (such as variances of walking gait), as an early diagnostic method for some diseases such as Alzheimer's, proper functioning of musculoskeletal system and internal organs such as heart and lungs.
- Use walking signals to predict susceptibility to falling since falls are often the by-product of other health issues related to, for example, cardiovascular weakness, changes in medication, beginning of dementia, gradual muscle degeneration, or poor balance.
- Use the walking signals to obtain new insights related to degradation in walking characteristics and to develop tailored measures and guidelines to reduce or prevent those risk factors.
- Use walking signals such as gait, stride, and pace measurements and autonomic computing to detect subtle changes in walking patterns. Such changes can then be transmitted to healthcare professionals to detect early health problems.
- Use motion analysis with inexpensive sensors and computing as a new *vital signs monitor*, similar to blood pressure reading, to provide more clues about the health of the elderly.

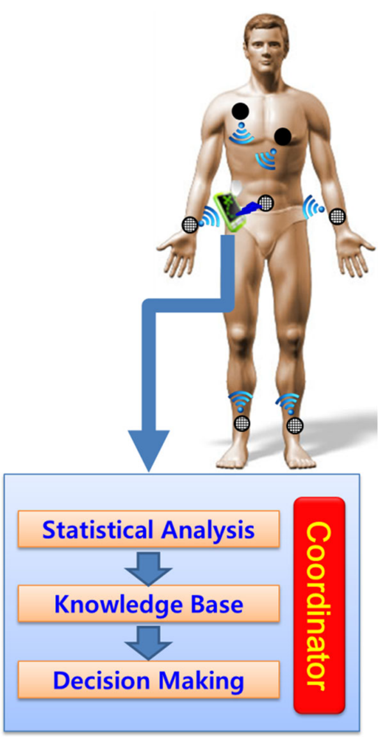


Fig. 23 System architecture (sensors, communications and autonomic computing) for some on-body sensors with low-power wireless communications. The *five bottom* sensors shaded cross-hatched can be for the "*smart walking analyzer*" system. Sensors in *solid black* can be for vital signs related to heart signals, blood oxygenation level and temperature, for example

4.2 Joints

As mentioned earlier, the increasing lifespan has stimulated much research and technology development in user-friendly, wearable sensing (and actuating) systems for the elderly. As we age, there is usually a degeneration of our musculoskeletal stability and there are increasing numbers of injuries. Joints, especially the knee joint, are commonly injured. Here, we described a smart knee monitor to help physiotherapists and kinesiologists acquire real-time, knee-related parameters to help in assessing the rehabilitation process. Future work can include the following.

- More extensive field testing of the knee monitor.
- Integrate the sensing and electronic components into a more compact unit so they are easier to wear, more lightweight with sensors that are of lower power consumption so battery lifetime is longer or there is a longer period between recharging.
- Implementation of a neural network to train the device so feedback can be provided on the accuracy of knee exercises during rehabilitation.
- Improve graphical user interface and include biofeedback using the extensive set of sensors. For example, if the injured person is incorrectly performing the exercises, then biofeedback can be used to instantly provide an alert so the incorrect way does not become the learned method. If the incorrect method is learned, then usually, it is extremely difficult to unlearn it.
- Implement additional requirements from input of the specialists including physiotherapists, kinesiologists and orthopedic clinicians.
- Automate the data collection to remove the human element.

The research work on walking and joint signals measurement is in contrast to existing sophisticated gait laboratories that are expensive to setup and operate. Such laboratories equipped with high-speed cameras and pressure-sensitive walking surfaces, etc., require highly trained personnel and are in a laboratory setting that are quite different from normal walking environments such as sidewalks, roads, trails or grass. In contrast, the low-power, inexpensive sensors and electronics used here are compact, noninvasive, user-friendly and provide valuable walking and joint information in real time. They present easy-to-use solutions to monitor and quantify systematic human locomotion or gait in normal everyday environments. These wearable sensors can also be used to promote and encourage physical activity and exercise that would help in the reduction in chronic health issues such as obesity, heart diseases or stress. For the elderly, both types of walking and joint sensors can become important tools in assessing risk to falling and eventually fall prevention.

4.3 Sleeping

A smart sleeping environment including a variety of sensors (environment and vital signs), actuators, wireless communications and computing infrastructure was described. The smart sleep environment system included a check-up questionnaire so the bedroom can be customized to the sleeper's needs. It was shown that among the external actuators, enhanced oxygen in the bedroom atmosphere had the largest impact on early start of deep sleep and remaining in deep sleep for a larger fraction of the sleeping period.

Future work will include the following aspects of our smart sleep environment system.

- Incorporating more user-friendly, "plug-and-play" sensing devices for vital signs such as blood pressure, breathing, brainwaves and movement, and correlate results with sleep quality.
- The impact of additional environmental conditions such as carbon dioxide, noise level and soothing noises on sleep will be investigated.
- Conduct more tests on a larger population of test subjects and increase collaborations with clinicians. This will involve gathering parameters related to sleep, analyzing data from sensors, asking questions of the sleeper and integrating answers with collected data to improve sleep environment and sleep quality.
- Use sleep data and information from sensors to supply diagnosis criteria with high reliability and provide recommendations based on diagnosis criteria for sleeping problems.
- Investigate correlations among the results from the system (with enhancements) described here with existing methods for sleep monitoring and analysis.

4.4 Autonomic computing

Here, we discuss issues related to the software solution for the U-Healthcare smart home [78–80]. The software should be built on models that captures sensory data of the smart home environment as well as those related to the health/well-being/fitness of the elderly (see Fig. 23 for system architecture related to on-body sensors). Then, using data and information fusion techniques, autonomic computing is embedded in an autonomic decision-making system (ADMS) [81]. ADMS is then used to manage or provide recommendations for various situations that can arise in the smart medical home—both with respect to the environment as the individual—with minimal human intervention. Autonomic computing refers to an "intelligent" computing environment that can dynamically manage itself according to specified policies, rules and objectives.

As described in [81, 82], autonomic computing in ADMS indicate systems that are self-*, for example, self-managing, self-tuning, self-healing, self-protecting, self-adapting, self-configuring and self-organizing. Such a software system can make decisions on its own using high-level policies and objectives that have been customized for the elderly based on their specific needs and health/fitness in collaboration with medical specialists. Note that ADMS will not replace medical specialists. Rather, it will perform time-consuming tasks so the elderly can have the same continuous care in a comfortable environment and can perform their daily activities similar to what they would experience in a dedicated and sophisticated nursing home or long-term care facility. For the smart medical home, a schematic illustration of the ADMS architecture is shown in Fig. 24.

The ADMS, for example, data and information collected by the sensors are sent through a communications link to the computer that runs the ADMS. Information is processed and aggregated and then transformed into knowledge and stored in the knowledge data base (KB). At specific times or on request, the knowledge is used to reason about the situation of the home or the elderly and then determine whether any action is needed based on the objectives.

The ontology for the ubiquitous healthcare elderly smart home is shown in Fig. 25. Ontologies can be used to describe the real-world situation. Knowledge is represented as a set of concepts and the relationships among them. It can be used to model the relationship between elderly activities, health signals and context data (semantic representation of real-world knowledge in computer language) in the smart medial home. The model consists of the following three steps with associated details in each step succinctly described next.

First, are the requirements for a semantically rich knowledge base that captures concepts and relationships. Data are shared among the monitor, analyze, plan and execute functions. And there is context and situation awareness and identification. Semantic is supported, new facts are inferred, and the knowledge base is dynamically updated with new information/knowledge. Second is SHOM (Smart Home Ontology Model). Here, OWL (Web Ontology Language) is used to define classes and relations between them. It can use OWL-DL (Description Logic) to ensure decisions for specific concepts/situations. Third is decision making. Initially, data are gathered through health/fitness and environment sensors. Then, the data are filtered, aggregated and fused. Next, information is inferred using a first-order engine.

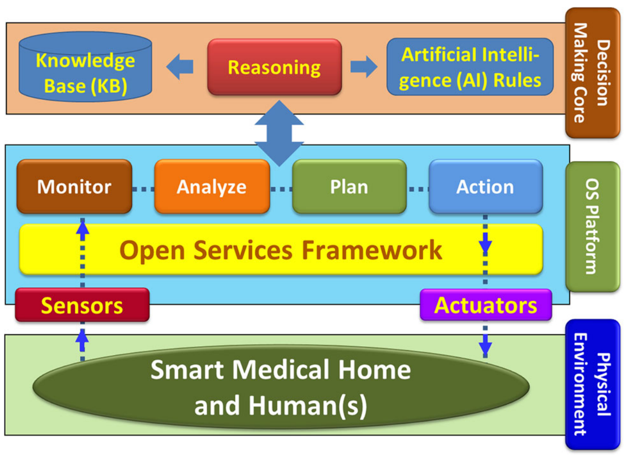
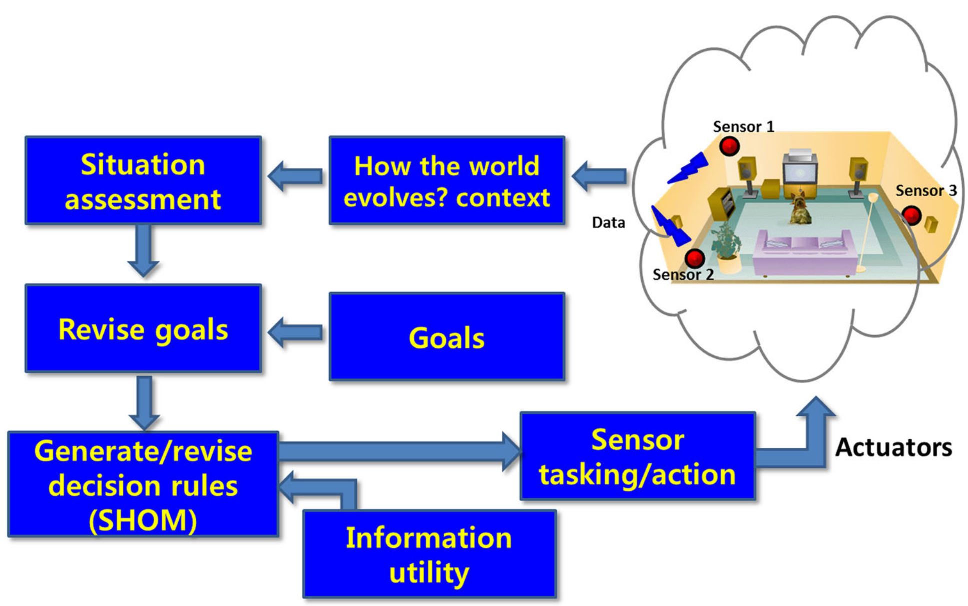


Fig. 24 Schematic illustration of autonomic decision-making U-healthcare smart home

4.5 Research challenges

Below, we illustrate some of the research challenges starting from hardware up to healthcare in Fig. 26. More specifically, there are many challenges in developing the hardware infrastructure of sensors and actuators with short-range communications capabilities. At the higher system and computing level, there are challenges in developing more "intelligent" wired and wireless home networks and

Fig. 25 Schematic illustration of ontology model for U-health smart home



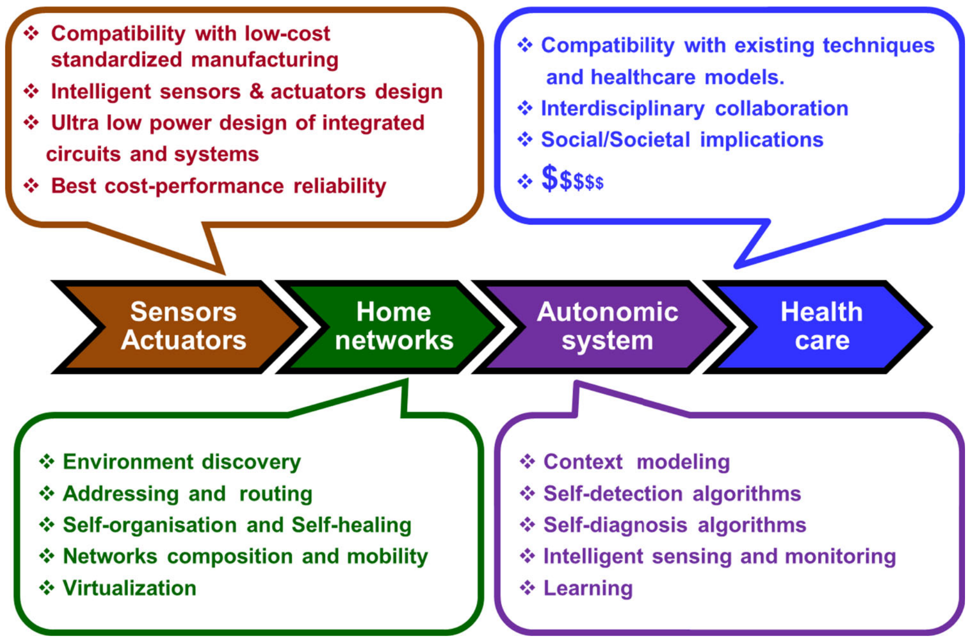


Fig. 26 Schematic illustration of the research challenges—hardware infrastructure of sensors and actuators; wired and wireless home networks; autonomic system for making the home "intelligent" and healthcare issues

the autonomic system for making the home "intelligent." When these challenges are solved in collaboration with medical specialists, we can enjoy improved quality healthcare at reduced costs. Next, we provide some additional details in the case of sensors.

For on-body sensors, some of the key research challenges are energy efficiency, responsiveness and robustness. Sensors may sometimes have to operate several years without battery replacement, so low-power consumption and high-energy efficiency are important performance parameters. More efficient batteries as well as methods for energy harvesting or improvements in the efficiency of existing harvesting techniques can help solve the energy requirements for sensors. Since sensors have to report their data to a central node, robust, secure energy-efficient protocols are needed.

From the sensing perspective, periodic *sleep and wake-up* of the sensors can help to improve battery lifetime or time between recharging events, while concurrently ensuring that important monitoring events are not missed. The low-cost, easy-to-use sensors must function reliably in different environments. The global performance of a sensing activity from a suite of sensors should not be sensitive to individual sensor failures, so robust data fusion is very important in the wireless sensor network. That is, the wireless sensor network must be much more capable than simple sum of capabilities of sensors. Therefore, robust techniques in fusing data and extracting information will be important and are urgently needed. This will necessitate the efficient collaborative use of computation, communication and storage resources. Also, the sensors must exhibit graceful performance degradation when faults are present. The triad of cost–performance–reliability represents key factors when developing or deploying sensors for elderly healthcare.

5 Concluding remarks

The tremendous development and applications of information and communications technologies in the past few decades have had a significant impact on our daily lives. These impacts include instant communications, smart devices, powerful and small-sized computers, digital imaging systems and "intelligent" consumer products such as refrigerators, washing machines, stoves and heating/cooling systems. The manufacturing advances and technologies that propelled these applications are now being harnessed for novel environmental and biomedical sensors and actuators, which, when combined with ICT, will allow for smart medical homes for the elderly.

A major goal of the smart medical home is to allow the elderly to live independently and safely in a familiar home setting. Through noninvasive, non-intrusive and timely monitoring, it will be possible to take care of the elderly's health and well-being with a significant reduction in healthcare costs. This is possible because many aspects of elderly well-being and safety can be automated, and early detection of health problem can lead to early treatment and better health status. It will also be feasible to improve chronic and geriatric care at home and to bring healthcare to remote locations and in poor countries through the convergence application of information and communications technologies, sensors/actuators, biotechnology, medical knowledge and autonomic computing.

To date, there have been significant advances and progress in sensing—actuating, communications and information systems. There has also been much progress in the medical aspects of healthcare. However, more efforts are needed on the synergistic integration of sensing–actuating systems and information and communication technologies with computing and computation for elderly U-Healthcare applications such as smart medical homes. With smart medical homes, the elderly can enjoy comfort and safety in familiar surroundings, improved quality of service and quality of life, and the healthcare costs will be reduced. This will further result in reduced stress and burden to family members, adding to the multitude of benefits of smart medical homes for the elderly.

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