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Signal Processing Challenges in Cognitive Assistive Technology

Technological supports for people with disabilities are usually referred to as assistive technology. There has been significant work in developing technologies to support people with mobility and sensory disabilities. Developing these tools for people with cognitive disabilities has not been as widespread. In this article, we briefly outline causes and consequences of cognitive disabilities and then concentrate on smart home technologies. One such challenge in smart homes is the desire to have inexpensive components easily installed and self-calibrating. We briefly mention work in brain-computer interfaces (BCIs).

BACKGROUND

Cognitive disability, sometimes known as an intellectual disability, is the last disability to achieve any significant government attention and is fraught with misconceptions. According to D. Braddock at the University of Colorado, cognitive disability is a substantial limitation in one's capacity to think, including conceptualizing, planning, sequencing thoughts and actions, remembering, interpreting subtle social cues, and manipulating numbers and symbols.

Common consequences of cognitive disabilities include stigma and discrimination, social isolation and emotional problems, difficulty communicating, poverty and unemployment, lack of support for families, a growing digital divide, and institutionalization.

Globally, people with cognitive disabilities are starting to become self-advocates. This is already common among people with sensory and motor disabilities. Key to this effort are the ideas that people come first and that we look at a person with a disability, not at a disabled person. These ideas need to be reflected in the assistive technologies. Why? Most assistive technologies fail because the designers do not take the person using the technology into account. While most of us adapt readily to new tools and technologies, this flexibility is less common among people with cognitive disabilities. Further, our technologies are often part of a fashion statement or a statement on our place in culture. In other words, technologies are part of the social zeitgeist. People with disabilities are aware of many of these issues, and yet the technological devices designed for them are often ugly and set them further apart from the rest of society.

Cognitive disabilities can begin at any age. Those whose causes are genetic, in utero, or occur in early childhood traditionally have been called mental retardation and developmental disabilities (MRDD) and are now being classified as intellectual and developmental disabilities (I/DD). Specific causes can be genetic with key examples such as Down syndrome, Williams syndrome, and fragile X syndrome. The primary cause of cognitive disabilities in utero is fetal alcohol syndrome. Early childhood causes include malnutrition and environmental poisoning, e.g., mercury, lead, and some pesticides. The primary causes of cognitive disabilities in adolescence and adulthood include traumatic brain injury, stroke, and severe mental illness. Alzheimer's disease and other dementia are the primary causes of cognitive disabilities in older adults.

The 2006 distribution of conditions causing cognitive disability in the United States are I/DD (21%) at 4.76 million, brain injury (27%) at 6.03 million, stroke (4%) at .8 million, mental illness (29%) at 6.42 million, and Alzheimer's (19%) at 4.23 million. In total, 22.24 million people are affected [1]. Worldwide statistics are not as detailed, but the estimates range as high as 400 million people.

COMMON ISSUES

The need and access to assistive technologies are related to poverty and unemployment. Most families with children having I/DD live at or below the poverty line. Thus, affordability of technology is very limited. In addition, the wages of support personnel working with people with cognitive disabilities is often just barely above the poverty line. A consequence is that many of these workers, while truly caring for their charges, have limited education and limited engagement with technology. Thus, the caregivers cannot be depended upon to understand and adapt technologies for the individuals they support.

A technological solution, no matter how sophisticated, will not be effective. Adaptability and customization are key to any assistive technology and more so for individuals with cognitive disabilities.

Assistive technologies come in all shapes, sizes, costs, and degrees of technological sophistication. We are considering devices which require some degree of signal processing. We will concentrate on a limited selection of new and emerging devices.

LOCATION-AWARE TECHNOLOGIES

Continuous activity monitoring for health assessment and emergency response is a major application area of location-aware technologies. In particular, homes that are retrofitted with a variety of sensors to monitor and evaluate the activities and

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the state of the residents are becoming the future of distributed health care and delivery. These are called smart homes and are of particular importance for the aging population of the world.

Cognitive and motor function decline due to various forms of dementia or other neurological disorders is estimated to affect over 34 million elderly worldwide [2]. For such conditions, the early detection of symptoms leading to a clinical diagnosis, and timely intervention is crucial. Consequently, the conventional clinical practice of regular semiannual or annual assessment of cognitive decline in clinic visits is insufficient and error prone due to day-to-day fluctuations in subject behavior and performance.

Smart homes can provide the frequent, even continuous, clinically relevant data. These technologies can further be beneficial in assisting with health care delivery to patients at home, monitoring activities such as medication adherence, and completion of necessary daily personal hygiene activities as well as the detection of falls and other emergencies is of interest.

Clearly, identification, localization, and activity classification using unobtrusive sensor networks are fundamental to the design of smart-home monitoring systems. The signal processing and ubiquitous computing communities are already significantly involved in the development of smart homes, and important research outcomes are generated through experimentation at laboratory homes at many institutions. However, it is critical to test technologies in real environments as subjects tend to change behavior patterns in lab environments even though it might be inside a house or an apartment. Researchers at the Oregon Health and Science University (OHSU) have created a living laboratory in which approximately 300 seniors living independently are volunteering to participate in research in their own homes [3].

Cost considerations become as important as clinical accuracy requirements in developing in-home monitoring systems. In order to maximize the impact of the developed technologies in the future of health care, widespread utilization of these solutions is required. Consequently, although expensive solutions for localization exist, these are not necessarily suitable for the problems encountered in ambient intelligence and ubiquitous activity monitoring.

IN-HOME LOCALIZATION

For in-home localization, available solutions include infrared (IR) motion sensors, radio frequency identification (RFID) tags, acoustic- and vibration-based localization, cameras, ultrasound, contact and pressure sensor arrays, and inertial navigation systems. A global positioning system (GPS) is a commonly employed technique for outdoor localization.

There are commercial RFID systems available that provide access to a received signal strength index (RSSI), which can be used as a surrogate for time of arrival in generating indoors triangulation solutions using multiple receivers positioned around the house. In our experience, however, these signals do not exhibit sufficiently high signal-to-noise ration (SNR) and variability throughout a typical house for accurate position and velocity estimation using recursive Bayesian state estimation techniques such as the Kalman filter and particle filters. They are, however, useful with reasonable accuracy for identification since the utilization of temporal information from the subject trajectories can be incorporated into the evidence for this purpose.

Motion and door contact sensors are relatively cheap and could indicate coarse localization information and, combined with identity information from RFID, could be useful for some applications that do not require precise extraction of activity details. In order to get more detailed activity information, these sensors are not sufficient, and body-worn inertial sensors are necessary. This approach has attracted considerable interest. Various event detectors are demonstrated using raw measurements from accelerometers and gyroscopes.

In Figure 1(a) we show how a triangulation model can be built using the RSSI found in some commercial RFID- based tracking systems. Using calibration data collected at a large number of landmark points throughout our lab apartment at OHSU, an RBF-based RSSI distribution map is obtained for each of the two receiver units located at opposite corners of the apartment. The mean value of recorded RSSI values for each landmark is also superimposed. While not shown explicitly in Figure 1, the noise of RSSI measurements at each landmark point is significantly high, with the standard deviation being comparable to the range of the maximum range of variation in average values. Consequently, recursive Bayesian tracking models based on such low quality measurements, even with the help of information fusion from IR motion sensors, cannot meet clinically acceptable accuracy levels of motion and gait analysis; however, for certain other applications, such as emergency monitoring, the performance can be acceptable.

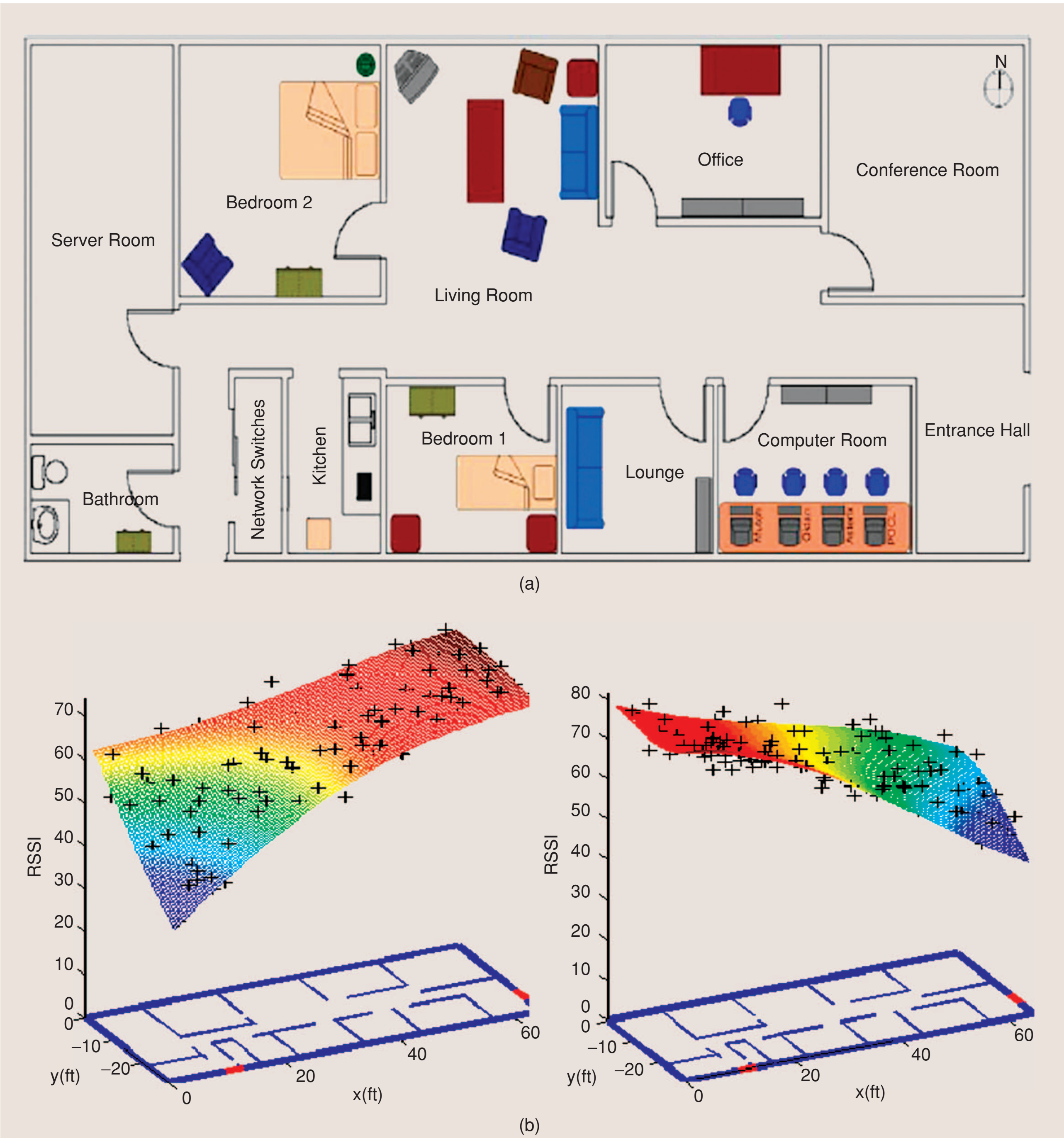
For instance, the RSSI measurement is accurate enough to keep track of identities of multiple individuals sharing an apartment, and, in conjunction with a hidden Markov model (HMM), the walking speed of individuals can be monitored continuously over long periods of time using restricted motion sensors installed in a long hallway with sufficient traffic in the house. Monitoring two people in such a setting is demonstrated in Figure 2. Specifically, for each sequence of motion-sensor firings that occur at time t, the RSSI sequence $\mathbf{r}(t) = [R(t - m\Delta), \ldots, R(t + m\Delta)]$ is used as a feature vector in the following Markov model over sequence of states $\mathbf{q}_i = \{q_{-m}, \ldots, q_m\}$ for the ith individual

$$\begin{aligned}\lambda_i(\mathbf{r}) &= Pr\{\mathbf{r}|\mathbf{q}_i\}\\ &= \pi_{i,q_{-m}} f_i(R(t - m\Delta)|q_{-m}) \prod_{k=-m}^{m-1} p_i(q_{k+1}|q_k)\\ &\quad \times f_i(R(t + (k-m)\Delta)|q_{k+1}),\end{aligned} \tag{1}$$

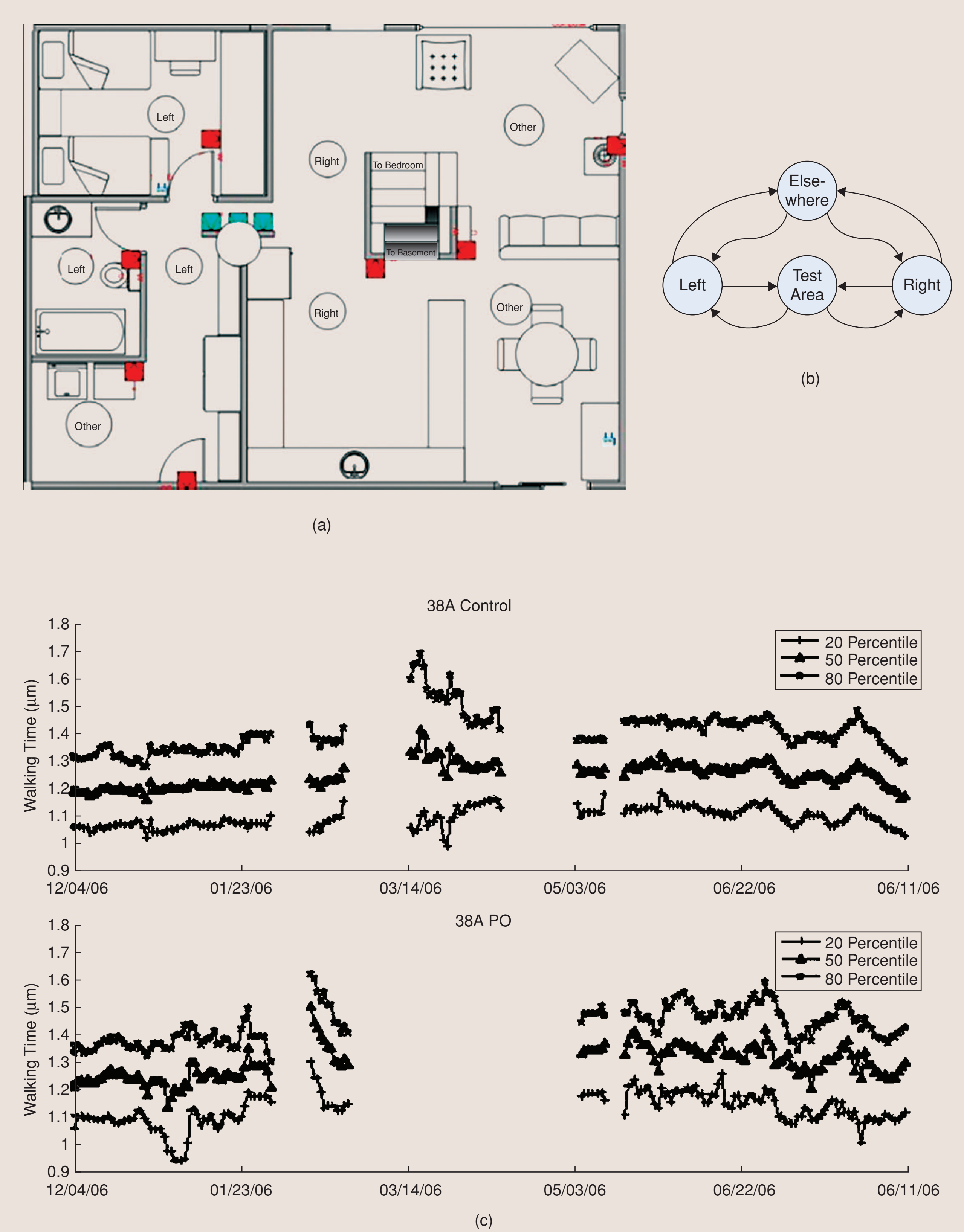
where $\pi_{q_1,i}$ is the prior probability of state q_1 for individual i, $p_i(q_{k+1}|q_k)$ is the HMM state transition probability of individual i from q_k to q_{k+1}, and $f_i(r_t|q_k)$ is the likelihood of measuring an RSSI value of r_t for individual i at state q_k [4].

VIDEO MONITORING

Distributed cameras and the use of advanced video processing and computer vision techniques, although raising questions of privacy, present a convenient solution to the three fundamental problems raised: identification, localization, and activity classification. Specifically for identification, face detection and identification are key. For localization, multicamera-based object tracking based on recursive Bayesian inference combined with proper background-foreground modeling and segmentation and cluster tracking algorithms with occlusion resolution are necessary. The reliable operation of these solutions in multiperson environments (under no operator supervision) is required, and calibration must be convenient for an unskilled technician to be able to set up the system. Furthermore, activity classification requires body modeling and pose estimation via temporal evidence assimilation. Face identification and foreground tracking have been utilized for medication adherence monitoring and fall detection.



[FIG1] (a) A lab apartment and (b) the corresponding calibrated received signal strength indices for two base RFID stations positioned at opposite corners (courtesy of Eric Wan).



[FIG2] Monitoring of walking speed in an apartment with two residents, one diagnosed with Parkinson's disease. The RSSI measurements above are used in conjunction with an (a) HMM model to identify the person passing through the hallway where a sequence of limited-view motion sensors are installed. (c) The walking speed estimates for each individual over a period of eight months is shown as weekly averages.

CALIBRATION

The calibration and modeling of sensor networks that aim to fuse information from a variety of unreliable sources is an important problem that stands in front of the widespread commercial feasibility of solutions such as those illustrated in the previous section. It is important to overcome the temptation to assume mathematical models that lead to simple implementations without careful study. Especially in the case of off-the-shelf, cheap, and unreliable sensors, the signal processing engineers must be cautious and careful in determining model topologies and parameters through rigorous experimental verification, since documentation is not always available at a desired level or detail. For instance, the modeling of even a simple IR motion detector could become a significant challenge if rigorously attempted. It is tempting to assume firing probability models that simply decay as a one-sided Gaussian function of distance that incorporates miss and false firing probabilities, or even incorporate a simple cosine dependency on the relative angular position of the target, as commonly done in binary motion sensor based target tracking literature for theoretical convenience. However, one realizes that when such simplistic models are tested against experimental verification data collected under controlled conditions, they might not be accurate.

Similarly, for vision-based localization and recursive Bayesian tracking, one needs to determine through experimental data under which vision-based measurement error distributions are stationary and how they depend on the state vector of the target being tracked. In the selection of target maneuver models, random walk or constant speed, or constant rate-of-turn type models need to be cautiously employed; preferably, a joint modeling-estimation approach is employed as in the literature on simultaneous localization and mapping (SLAM) in autonomous vehicle navigation. For instance, one can incorporate an adaptive dynamic acceleration model for subject trajectories and the parameters of this model could be included in the state vector to be estimated (i.e., position, velocity, acceleration, and acceleration model parameters). Consequently, the agile trajectories of human motion could be potentially captured with greater accuracy. As an illustration, the joint trajectory-maneuver dynamics for a linear first-order autoregressive acceleration model becomes

$$\frac{d}{dt}\begin{bmatrix} \mathrm{p}(t) \\ \mathrm{v}(t) \\ \mathrm{a}(t) \\ \mathrm{vec}(\mathrm{B})(t) \end{bmatrix} = \begin{bmatrix} \mathrm{I} & 0 & 0 & 0 \\ 0 & \mathrm{I} & 0 & 0 \\ 0 & 0 & \mathrm{B}(t) & 0 \\ 0 & 0 & 0 & \mathrm{I} \end{bmatrix} \cdot \begin{bmatrix} \mathrm{p}(t) \\ \mathrm{v}(t) \\ \mathrm{a}(t) \\ \mathrm{vec}(\mathrm{B})(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \mathrm{w_a}(t) \\ \mathrm{w_B}(t) \end{bmatrix}. \quad (2)$$

Note that this is essentially equivalent to including a latent model that randomly perturbs acceleration dynamics and could be thought of as a hierarchical graphical model for maneuver modeling. The measurement equation for such a filter, assuming sensors that only respond to the position of the subjects, is generally a conditional probabilistic model on the form $P(\mathrm{y}(t)|\mathrm{p}(t))$. Under the reasonable assumption of statistically independent sensor measurements, this joint distribution factorizes. A self-calibrating network would in fact then create and optimize a latent abstract layout for allowable positions as well as trajectories over time based on estimated states. To this end, manifold learning techniques could be employed. This latent representation could minimize calibration requirements during installation, help regularize estimates over time by building a subject-specific prior, and help identify potential sensor failures when atypical measurements arise based on the history of a sensor and its relationship with others in the network.

An increasing body of evidence is accumulating toward the verification of the clinical usability of continuous indoor monitoring data acquired by sensor systems such as those described above. The unreliable nature of the relatively cheap sensors utilized brings together problems associated with high levels of measurement uncertainty (noise), missing data, and unstructured temporal sequences corresponding to natural daily behavioral patterns of multiple known and unknown people (and pets) in the house. These problems associated with the observed phenomena and the sensors pose exciting challenges for signal processing and statistical inference, hence the literature has examples of analysis approached from the perspective of a variety of disciplines including statistical machine learning and data mining.

NEURAL ENGINEERING AND BRAIN COMPUTER INTERFACES

Neural engineering is a branch of bioengineering that draws components from the disciplines of computational and experimental neuroscience, electrical engineering, neural tissue engineering, neurology, and material science. Primary goals include the quantitative modeling of biological neural networks in order to repair or replace damaged tissue and reduce lost function through the design of neuroprosthetics [5]. While cochlear implants have seen successful widespread use worldwide, other applications of interest include the following:

1) visual prostheses, or retinal implants or microwires implanted in the visual cortex
2) cognitive prosthetics in the form of circuitry that restores cognitive function by substituting equivalent circuitry in the brain to mimic local input-output relationships, stimulating circuitry that activates or inhibits local activity, for instance as in deep brain stimulation to suppress tremors in Parkinson's

3) motor prosthetics with direct cortical control through the acquisition of brain activity using invasive microelectrode arrays, electrocorticography, or electroencephalography [6]–[8].

The motor prosthetics application gives rise to the recently popularized area of BCI/machine interface (BMI) that presents numerous challenging problems that are in the domain of the signal processing community. While BCI research is primarily focused on restoring motor capabilities to persons with neurological conditions that lead to reduced or diminished motor abilities, recently emerging applications aim at enhancing and exploiting existing cognitive capabilities of humans as well as presenting an alternative means of seamless human computer interaction.

Research on brain interfaces to enable a direct communication link from the human brain or the peripheral nervous system to external devices, such as robotic manipulators, artificial limbs, or computing devices have been ongoing since the 1960s and 1970s. Significant results in the 1990s have led to the current level of excitement and interest.

Cortical plasticity, the ability of the brain to reorganize itself due to experience and operant conditioning, is an important property that yields the promise of practical BCIs. In particular, it is expected, based on experimental evidence, that over an extended period of usage the brain will be able to interpret the artificial interface as a natural extension of the physical self, thus creating a representation that improves with experience, leading to increased accuracy and task performance [9]–[11]. Open challenges in this domain include the coadaptation of the brain and the interface, development of robust learning algorithms under label uncertainty (since ground truth labels for brain activity are not generally available), and the extraction and selection of most informative features for various modalities and applications.

CHALLENGES

For widespread commercial application and in order to keep installation and maintenance costs low, it is desirable that multimodal sensor nets self-calibrate in two senses: i) learn the layout of the house it is installed in and ii) learn the movement patterns of its residents. These are in fact coupled since the learned layout of the house will be influenced by the distribution of trajectories executed by the residents.

It is not feasible to expect that a very precise calibration of all relative sensor locations and orientations can be made during installation in a short time with little effort. Therefore, from the joint sensor activity, one could infer an abstract layout of the environment based on jointly detected movement patterns. For instance, two motion sensors could discover over time that they might have a common area that they detect and their respective individual exclusive coverage areas, simply by statistically analyzing their joint firing patterns. Similar information could be extracted for any sensor pair. In fact, this information could be used to detect sensor failures.

The purpose of continuous monitoring is to detect unusual events and departures from established patterns even if it is slowly happening. In any case, one needs to build a probabilistic model of likely and routine observation patterns. However, such modeling could be done at some abstract level (using appropriate latent variable approaches) so that even though the daily routines on consecutive days are not precisely identical, the model can indicate that the measured activity patterns are within the normal paradigm. Similar arguments can be made for body-worn or otherwise carried (on a cane) inertial sensors.

Developing new signal and image processing techniques is often driven by specific problem classes. Assistive technology for people with cognitive disabilities provides a very challenging class of problems for statistical signal processing. In this article, we have only touched on a few of the possibilities. From learning on manifolds to statistical inference and data fusion, the applications are broad and the problems challenging.

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