Capacitive proximity sensing in smart environments

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\textbf{Abstract.} To create applications for smart environments we can select from a huge variety of sensors that measure environmental parameters or detect activities of different actors within the premises. Capacitive proximity sensors use weak electric fields to recognize conductive objects, such as the human body. They can be unobtrusively applied or even provide information when hidden from view. In the past years various research groups have used this sensor category to create singular applications in this domain. On the following pages we discuss the application of capacitive proximity sensors in smart environments, establishing a classification in comparison to other sensor technologies. We give a detailed overview of the background of this sensing technology and identify specific application domains. Based on existing systems from literature and a number of prototypes we have created in the past years we can specify benefits and limitations of this technology and give a set of guidelines to researchers that are considering this technology in their smart environment applications.

Keywords: Evaluation, capacitive proximity sensing, smart environments, guidelines

\section{1. Introduction}

The notion of ubiquitous computing has always been associated with sensing human activity in different environments. This enables a semi-autonomous adaption of the surroundings based on the recognized activities. There is a large variety of sensing technologies that can be used to measure the physical effects of activities. Many generate some sort of noise or sound that can be picked up by microphones. This can be used to recognize position [1], translate speech to commands [2], or enable medical applications such as lung function testing [3]. Another group of activity tracking systems rely on wearable accelerometers that follow the movement of various body parts for tracking activities of daily life [4], controlling entertainment applications [5] or realizing gestural interactions [6]. However, the most commonly used technology are visual systems, such as RGB and depth cameras that apply various image analysis operations to recognize human activity. Examples include the reconstruction of environments [7], associating motion patterns to activities of daily life [8], or full-body gesture recognition [9].

An entirely different method is capacitive sensing that measures the influence of conductive objects on electric fields. Its first application dates back to the early 20\textsuperscript{th} century. The Theremin is a musical instrument controlled by the movement of two hands without touch [10]. The human body is primarily comprised of ionized water and thus has specific electrical properties including conductivity. By sensing its influence on the field parameters and applying signal processing, we are able to recognize various human activities. Compared to the previously described technologies, capacitive sensing has some unique features that provide benefits in particular applications. The generated electric field propagates through any non-conductive material, thus the sensors itself can be applied unobtrusively. The energy consumption and required processing power are small. This enables applications based on batteries and photovoltaic cells and integration into embedded systems. Most notably, they have a high versatility that is achieved by modifying electrode material, geometry,
excitation frequency and voltage according to the desired application. The technology has been used to create invisible systems for localizing persons in indoor environments [11], create interactive systems from plants [12], detect respiration rate from a distance [13], or create large area interaction zones in free air [14].

This work provides a classification of capacitive proximity sensors within smart environments. We begin with a detailed overview of the technological basis, establishing the physical background and existing varieties of sensor systems. We discuss the influence of different geometries and materials and outline suitable data processing methods. This leads to the identification of relevant application domains that are supported by this technology and provide an evaluation based on existing systems and different prototypes we have created on our own. Furthermore, we can provide a comparison to other sensing technologies that are popular for systems in smart environments. Based on this we are able to determine advantages and drawbacks, leading to a set of guidelines supporting developers in creating applications using capacitive proximity sensors.

2. Capacitive Proximity Sensing

![Capacitive sensing procedure](image)

Any living organism produces a small electric field that is caused by cell activity and ionic currents in the nervous system [15]. Measuring this electric field requires sensitive sensors and is typically limited to close proximities. The human body is mostly composed of ionized water and differences in the proportion of water in specific types of body tissue are causing distinct electrical properties that can be distinguished. The response of a living organism to an external electric field is called bioimpedance [16]. Thus, we can either use external electric fields and measure the influence of the human body moving within, or couple the body to an electric transmitter and measure the resulting field.

2.1. Physical properties

A complete overview of the electrostatic principles of capacitive proximity sensing can be found in the book by Baxter [17], chapters 2 and 6. We will give a very brief introduction to this topic in the following section. The basic process of capacitive proximity sensing is symbolized in Figure 1. A sensing electrode is periodically charged and discharged, measuring the time it takes to discharge completely. If a conductive object enters the field the energy that can be stored is increased, leading to a longer discharge time. Looking at generic formulas, determining capacitance between parallel plates this behavior can be described analytically.

\[ C = \frac{Q}{V} \]

\[ C = \varepsilon_0 \varepsilon_r \frac{A}{d} \]

The capacitance is directly proportional to the plate area \( A \) and inversely proportional to the distance \( d \) between the plates, with \( \varepsilon_r \) being the relative static permittivity of the dielectric between the plates. Sensor electronics are grounded with the body acting as ground itself. The sensor plate is continuously charged using a constant voltage \( V \). A higher capacitance leads to the system to holding a larger charge \( Q \). The conductive object acts as second plate and thus increases the capacitance \( C \) by reducing the distance \( d \).

2.2. Capacitance measurement

![Three measurement modes for capacitive proximity sensing](image)

A classic work in the field of capacitive proximity sensing that will be referenced occasionally in this work is the dissertation “Electric Field Imaging” by Joshua Smith that aggregates the works performed using capacitive proximity sensors by the MIT Media...
Lab in the 1990s [18]. One of their contributions was the introduction of different measurement modes for capacitive sensing [19]. They are shown in Figure 2. Transmit mode uses a transmitting electrode that is coupled to a conductive object, typically the human body. The properties of an electric field generated with respect to a receiving electrode will therefore depend on the distance of this body, thus extending the achievable range. Shunt mode also uses receiving and transmitting electrodes that generate a field between each other. However, as there is no coupled body, any conductive object will ground the field, thus reducing the amount of energy stored. This setup works with various transmitters on a single receiver. This generates a larger amount of “virtual sensors” using limited hardware [20]. The third measurement mode is loading mode. A single electrode creates an electric field grounded by any suitable object in the environment. Thus, any approaching grounded object increases the capacitance of the system. This is measured periodically.

The most ubiquitous use of capacitive sensing technology is projected capacitance touch screens that are used in the majority of finger-controlled devices. They use various layers of transparent electrodes or nanowires to detect the mutual capacitance created by objects entering the created field [21]. Some varieties support “floating touch” that tracks fingers in gloves or fingers that are hovering above the surface [22], [23].

We can distinguish three different projected capacitive sensing methods, as shown in Figure 3. Touch sensing uses densely distributed sensors that are tuned to project a weak electric field, in order to detect one or more objects touching the interactive surface. The sensors have to be close to the surface. Floating touch uses densely distributed high-sensitivity sensors that are able to register both touches and very near objects (< 2cm) to enable usage using protective gear or additional navigation feature. The sensors have to be close to the surface. Proximity sensing uses sparsely distributed sensors that are able to create a stronger electric field. This field propagates further into the environment, allowing us to detect larger objects that are in proximity of the sensor electrode. Achievable distances vary from 30 cm up to 150 cm and the sensors may be applied below thick non-conductive material.

### 2.3. Electrode materials

A major factor that has to be considered when designing a capacitive sensing application is the material of the electrodes attached to the sensor. It should be chosen according to the available space and surface properties, i.e., if the interaction device has a flexible surface, conductive thread could be used, if it is solid and opaque, the application of solid metal electrodes is viable. Additionally, there are several transparent materials available. While we traditionally associate solid metals to antennas, transparent conductive layers have been in use for decades now, e.g., in car windows or solar technology. They use metal oxide layers, polymer layers, or most recently carbon nanotubes [24]. Transparency is most important for displays that use projected capacitive touch systems. They use a multi-layer design of insulated transparent electrodes that are able to detect the movement of several objects close to the surface [21]. A recent work by Grosse-Puppendahl et al included an evaluation of different electrode materials in terms of their spatial resolution at larger distances between object and electrode [25]. They benchmarked both ITO and PEDOT:PSS. The first is a thin layer of indium-titanium-oxide, a highly conductive metal layer that possesses good optical properties. PEDOT:PSS is a conductive polymer that has a lower conductivity and slightly less appealing optical properties. The test procedure uses differently sized electrode and a metal tube as grounded test object that is set to different distances from the electrode. The results are shown in Figure 4. They conclude that copper has the best properties, but ITO is a suitable alternative in applications that require optical clarity. PEDOT:PSS
works well at smaller distances, but the resolution deteriorates faster.

Figure 4 Spatial resolution of different materials at various distances [25]

2.4. Electrode geometry

Another important factor when designing capacitive sensing applications is the geometry of the electrodes. The potential layouts include simple straight wires, plate electrodes, and complex multidimensional structures. The latter are optimized for a specific task, e.g. finger detection on touch screens [26]. They are designed to measure the mutual capacitance between intersecting sending and receiving electrodes. If a sensible excitation and measuring process is used, multiple nearby objects can be tracked reliably and with high precision. Examples are the two layers of perpendicular straight line electrodes, as used by the first iPhone, or interlocking diamond shapes that create a good spatial coverage [27].

Applications using capacitive proximity sensing are typically less concerned about intricate designs, but instead use varying electrode sizes and placement over a larger area. There are numerous factors that can influence this geometrical layout. These can be put into the following categories:

- number of objects
- object size
- desired spatial resolution

Going back to the example of touch screens, we want to detect a larger number of small objects (usually up to 10 finger tips). To select small items on the screen a high spatial resolution is required. The result is a fine multilayer grid that uses mutual capacitance to simplify multi-object recognition, a fine electrode spacing to achieve a high spatial resolution, and thin or transparent electrodes to guarantee good optical properties. A similar rationale can be applied to other applications. Looking at the smart couch by Gross-Puppendahl et al., the aim is to detect the presence and posture of one or more persons on a couch [28]. This requires recognizing large body parts such as head, torso or limbs. There is no fine-grained spatial resolution required and it is assumed that a maximum of two persons are on the couch. The number of electrodes can be reduced accordingly. Furthermore, as the electrodes are placed below the upholstery it is necessary to register objects at a larger distance.

Figure 5 Electrode placement below upholstery [28]

The resulting electrode placement can be seen in Figure 5. To distinguish two persons and different sitting positions, four electrodes are placed below the sitting area. In the back, there are two electrodes spread over the entire width to determine the presence of the upper body close to the backrest. The electrodes in the armrests register a resting head or arm and are primarily used for detecting lying positions. In consequence, this setup is suitable for recognizing multiple sitting persons, infer information about their sitting position and recognize lying persons. Regarding those postures, the results of the evaluation are good [28].

A third example for electrode placement is the TileTrack system by Valtonen et al. It is a capacitive person tracking system using floor tiles [29]. The system uses transmit mode, with the transmitting electrodes placed below the floor tiles and the receiving electrodes placed in the walls of the area. The main goal of the system is the localization and tracking of persons on the surface. Thus, the electrodes should completely cover the floor area to establish a good transmission link to the bodies. This is shown in Figure 6. The receiving electrodes have to ground the field transmitted by the whole body. Valtonen et al. picked wire or plate electrodes that reach from floor level to a height of 190cm and cover most typical body sizes. While the system has some limitations with regard to applicability in larger rooms, the de-
sign rationale is appropriate for narrow rooms or when only movement close to walls has to be detected. Regarding these constraints, the resolution achieved in their evaluation is sufficient for most applications.

**Figure 6** TileTrack electrode placement showing floor tiles and two types of receiving electrodes [29]

### 2.5. Sensor Kits

In this section we give a short overview of capacitive proximity sensor development kits that are available on the market and can be freely used by researchers. There are numerous toolkits available by suppliers of touch technology that can be used for proximity sensing, however they are not specifically tailored for that purpose. A first example of this category is the CY-3271 starter kit by Cypress Microsystems [30]. It contains a single capacitive proximity sensor on a multifunctional board that is attached to a RF (radio-frequency) wireless communication board via an I2C interface. Multiple of those kits can communicate with a single base station connected to a PC. A second example is EVAL-AD7147, an evaluation board for capacitive touch sensing by Analog Devices [31]. It can interface 13 capacitive touch sensors and communicates to a PC via USB. The data acquired by the touch sensors can be used to realize capacitive proximity sensing, e.g. in a smart couch [32].

Various research groups working with capacitive proximity have created specifically tailored hardware. In many cases the schematics of the electronics and precise descriptions of the hardware have been provided for the research community. The MIT group around Smith has shared extensively, providing schematics of the different hardware iterations, thus allowing other researchers to recreate the system [18]. The design of a high-sensitivity sensor based on a spread spectrum operating concept was shared by Carnegie Mellon University [13]. However, recreating those systems requires considerable knowledge in electrical engineering and creating circuit boards, thus preventing less technically proficient user groups from experimenting with the technology.

**Figure 7** CapToolKit (left) and OpenCapSense (right) rapid prototyping toolkits

In 2007 Wimmer et al. developed CapToolKit, a rapid prototyping toolkit for capacitive proximity sensors, that is provided pre-assembled as off-the-shelf package [33]. Based on open source hardware and software it provided researchers with the opportunity to easily create own applications without developing hardware. The system is shown in Figure 7 on the left. In cooperation with Wimmer, Grosse-Puppendahl et al. created an improved toolkit, called OpenCapSense [25] that was released in 2013. In addition to higher processing capabilities and improved sensitivity, it supports all three sensing modes described in section 2.2.

Several groups rely on one of those toolkits to create capacitive proximity sensing applications. Some examples include activity recognition using tables and shelves [34], augmented wrist-worn devices [35], or sleep-phase recognition by application on slatted frames [36].

### 2.6. Data Processing

**Figure 8** Abstracted sensor data processing pipeline

In order to acquire usable data from any digital sensor, an analog signal has to be measured and processed. A simplified, typical processing pipeline for this is shown in Figure 8. The basic structure is also applicable to the processing of capacitive proximity sensor data. The analog signal is the capacitance of an electric circuit that can be digitized using different methods, e.g. by using the quantized discharge time of the circuit. In the following section some typical steps of raw data processing and high-level pro-
cessing for capacitive proximity sensors are presented and discussed.

2.6.1. Raw data processing

Raw data processing of capacitive proximity sensors is primarily intended to compensate for sensor noise and environmental influences. Noise is an inherent property of any measurement system and describes random unwanted data that is added to a signal. Environmental factors can have a strong influence on the signal of a capacitive sensor system. These include temperature, humidity, composition of the air, or grounded objects in close proximity. There are numerous additional preprocessing steps that can be taken, including different multiplexing methods that may be required in some hardware settings, or signal quantization that reduces the outgoing data to a distinct set of values, in order to simplify post-processing. These will not be further discussed in the scope of this work.

Table 1 Baseline calibrations terms and methods

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial calibration</td>
<td>First set-up of baseline at system start, e.g. by taking the average over various samples</td>
<td>Required for any application</td>
</tr>
<tr>
<td>Static baseline</td>
<td>Baseline that does not change at run-time</td>
<td>For static environments</td>
</tr>
<tr>
<td>Dynamic baseline</td>
<td>Baseline that changes over time</td>
<td>For non-static environments</td>
</tr>
<tr>
<td>Drift</td>
<td>Change of system response to environmental factors at run-time</td>
<td>-</td>
</tr>
<tr>
<td>Drift compensation</td>
<td>Methods to account for occurring drift, by changing the baseline value</td>
<td>Non-static applications</td>
</tr>
<tr>
<td>Recalibration</td>
<td>Change of the baseline value at a specific point in time given a set of rules</td>
<td>Non-static applications</td>
</tr>
</tbody>
</table>

Noise reduction

In order to reduce noise, typically some sort of filtering is applied. Filtering describes a set of methods that attenuate the parts of a signal that are not relevant in a given application. In capacitive proximity sensing the most common variety is high-frequency noise that is added to the signal. Therefore, low-pass filtering can be used to reduce this influence. This variety of filter attenuates high-frequency signals, while letting low-frequency signals pass. The most typical examples are average filters that take various samples and calculate an average value, and median filters that are sorting a set of samples and select the median element. Each of those filters has a variety of adaptations that are too specific to discuss in this limited scope. Some varieties are discussed in the specific prototype sections.

Baseline calibration

A very important aspect of capacitive raw data processing is signal calibration. The generated electric field is subject to changes over time, if either intrinsic parameters change or the environment is modified. Some specific examples include the electronic components heating up, the environmental temperature changing, or objects being moved in and out of detection range. Additionally, the capacitance of the measurement system may be considerably higher than the measured change in capacitance. This effect is called parasitic capacitance. Therefore, it is essential to have a well-calibrated and adaptive baseline. This is defined as the sensor signal acquired from the environment without the presence of any recognizable object. Again, there are numerous methods to adapt and configure the baseline. We have collected a few common terms and methods and give some pointers regarding their application in Table 1. If a dynamic baseline is used, a set of rules will have to be defined that determines at which points in time the baseline has to be recalibrated, what specific methods should be used, and the set of parameters that control the methods. One simple example is defining a threshold level that triggers a baseline calibration. If the signal increases above this threshold, we assume an object is present. If the signal returns below this threshold, the object was most likely removed. If this new signal is different from the existing baseline, we can assume that the environmental parameters have changed and trigger a baseline reset.

2.6.2. High-level processing

High-level processing assumes that we already have calibrated and normalized sensor data that is used in further steps. The goal of any capacitive sensing application is the acquisition of information about a detectable object, e.g. its current position, the material used, or the shape. In order to get this information we need to use knowledge about the object and intrinsic properties of the sensor system. In this section we will discuss methods to combine data from various sensors using the system properties, how to track the position of an object using different methods, and how to recognize specific features. An
overview of the methods in abridged form is given in Table 2.

Table 2 Overview of high-level processing methods for capacitive proximity sensors

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor data fusion</td>
<td>Combining sensor data into a shared representational format</td>
</tr>
<tr>
<td>Uniform fusion</td>
<td>Sensor data fusion that combines all data into a single common format</td>
</tr>
<tr>
<td>Heterogeneous fusion</td>
<td>Sensor data fusion that combines groups of data to serve multiple purposes</td>
</tr>
<tr>
<td>Object tracking</td>
<td>Continuous identification of an object within the systems range</td>
</tr>
<tr>
<td>Single object tracking</td>
<td>Methods to realize object tracking for a single detectable object</td>
</tr>
<tr>
<td>Multiple object tracking</td>
<td>Methods to realize object tracking for multiple objects</td>
</tr>
<tr>
<td>Feature recognition</td>
<td>Identifying certain parameters of an object within the system range</td>
</tr>
</tbody>
</table>

Sensor data fusion

Sensor data fusion describes “the theory, techniques and tools which are used for combining sensor data, or data derived from sensory data, into a common representational format” [37]. Using the combined information from various capacitive proximity sensors we are able to generate high-level information that exceeds the capabilities of a single sensor. We can distinguish uniform fusion that uses the information from all involved sensors in a common way and heterogeneous fusion that combines groups of involved sensors that serve multiple purposes, yet are attached to a single system. A simple example for the latter is a single sensor with a large electrode that detects the presence of a body from a farther distance and then a combination of various small electrodes that track single fingers.

Sensor data fusion often requires using additional information we possess about the system. A classic example is the precision or bias of the sensor. Various methods, e.g. the class of Kalman filters, use weighted information from several sensor sources [38]. If we know that in an ensemble of sensors one is less precise than another, the weighting factors can be adapted accordingly.

One of the most important additional information we use when fusing data of capacitive proximity sensors, is the geometric layout of the system. This describes position and size of all electrodes that are integrated. Using this information is crucial when trying to localize an object. There are numerous methods that enable us to determine the location of multiple objects or additional dimensions of the position. However, it is possible to use other sources of information in the fusion process. For example, if the electrode material may result in a different response they should be treated accordingly by adapting their weight in a fused data representation. Another example is the shape of the electrode that may result in different responses. The specifics of sensor data fusion are depending on the specific application and the desired common representation that is most suitable for subsequent calculations.

Object tracking

An important class of data processing methods is object tracking. In computer vision applications this can be defined as “the problem of estimating a trajectory of an object in an image plane as it moves around a scene” [39]. The analogy to capacitive applications is viable if we consider a 3D space and a distinct interaction area instead of a scene. Capacitive proximity sensors can register the presence of grounded, conductive objects in their range. However, as this presence is determined indirectly using the influence on an electric field it is not possible to get the actual distance between sensor and object and the resulting sensor value. The created electric field is only analytically descriptive for very specific, theoretical classes of objects [17]. Nonetheless, we are able to get a relative distance measurement. If we combine this proximity value using geometric information about the electrode location we can infer the relative position of an object in the sensing area. The weighted average algorithm uses the position of the electrode centers and sensor values as weight to detect an object location relative to electrodes [40]. Another method is trilateration that uses the fixed location of three or more points and the known distance between object and fix points. This is used in many radio-based localization applications. In case of capacitive proximity sensing this position is determined relative to the locations of the electrodes, using the proportional differences of the sensor signal. A more complex example for direct calculation was presented by Smith, who formulated the issue of detecting multiple objects as a forward problem and used numerical methods to estimate the position and orientation of two hands [18].

A second class of object tracking methods relies on numerical solution to a probability distribution instead of direct geometrical calculations. The initial assumption is a uniform probability of object presence at any point in the area covered. The methods then follow a few basic steps, as shown in Figure 9. At first the probability is updated based on the current sensor readings and a priori knowledge we pos-
cess about the system. Afterwards, we try to fit the objects into the resulting probability distribution. It is not guaranteed that this process will find an object. In case of failure the process starts again. If an object is found the probability update uses the current object location in the update algorithm, thus starting with a non-uniform probability distribution.

![Diagram](image)

**Figure 9** Generic pipeline of probability based methods of capacitive proximity sensing

One example for this type object recognition was presented by Grosse-Puppendahl et al. [41]. Based on a model suggested by Smith, it is assumed that an object may be present anywhere. According to current sensor readings regions are removed where no objects can be present. Finally an object is fitted into the remaining space. This method additionally uses particle filters to track locations over time and is able to follow multiple objects.

Throughout the years various methods have been proposed that support multi-object tracking using capacitive sensors. Touch screens often use inversion of the sender signal to reliably detect the positions of multiple points. However, this method can’t be used in proximity applications [42]. Some of the previously presented methods support the tracking of two or more objects. There are still several limitations, particularly if not only the object location should be tracked, but also various other features such as rotation. This is still an area of ongoing research, leading to the next area of high-level processing - feature recognition.

**Feature recognition**

Feature recognition is primarily used as a term in image processing, traditionally in computer-aided design applications to classify specific geometric properties of an object but also picture analysis, e.g. in facial analysis [43], [44].

In the domain of capacitive proximity sensing, feature recognition can be defined as the acquisition of non-location information from any detectable object. An important feature in industrial applications is the material of an object [17]. With regards to registering additional features a system was presented by Wimmer et al. - Thracker [45], a prototype augmenting a regular monitor with capacitive proximity sensors. In addition to recognizing hand position the system is able to detect grasp gestures, which can be used to select items on the screen and perform pick and drop operations. Capacitive sensors can also be used to distinguish between persons and a children’s seat on the passenger side of a car [46].

The methods to recognize the features can be diverse, ranging from typical machine learning algorithms, to model-based approaches. An incomplete list is given in Table 3. In order to keep this work contained we refrain from a deeper discussion at this point.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data-driven methods</td>
<td>Directly associate input data to output features using various methods, e.g. machine learning and training data</td>
</tr>
<tr>
<td>Model-driven methods</td>
<td>Input data is manipulating a pre-defined model of the system that is latter mapped to the output</td>
</tr>
<tr>
<td>Neural networks</td>
<td>Computational models using a network of neuron-like objects that are often used in machine learning</td>
</tr>
<tr>
<td>Pattern recognition</td>
<td>Methods that look for certain patterns in a set of input data</td>
</tr>
<tr>
<td>Semantic mapping</td>
<td>Methods to realize object tracking for a single detectable object</td>
</tr>
</tbody>
</table>

3. Application Domains in Smart Environments

In this section we give an overview of potential application domains for capacitive proximity sensing. While the focus is on smart environments, we do not use the narrow definition that only considers home environments. Instead we look at all sensor- and actor-augmented environments that use contextual information to provide additional services to its inhabitants, visitors and users. We discuss a number of prototypes based on capacitive proximity sensors that cover these application domains and have been presented in previous publications of different authors. They are briefly summarized in Table 4, including details on the measuring layout and information about the data processing that has been used.
3.1. Indoor localization

Reliably localizing and tracking multiple users is one of the main challenges of smart environments. The position of a user is important for systems that require contextual information in periodic intervals. In many cases basic motion sensors are able to deliver sufficient information, if a single person should be followed. The tracking of multiple persons typically requires more sophisticated solutions. This is equally important when the system needs to distinguish between users and non-critical actors in the environment, such as pets.

Various indoor tracking and localization approaches have been proposed in conjunction with Ambient Intelligence. There are even specific competitions with the intention of comparing the different methods’ performances against one another [47]. Three categories of localization methods can be distinguished, active marker-based solutions, passive marker-based solutions, and marker-free solutions. Both active and passive marker-based solutions require a person to carry some type of tag in order to enable localization. This is a disadvantage in certain applications as the cost is higher and some users may forget the tags. Marker-free solutions are capable of localizing persons independently of whether they are carrying additional accessories. This latter category includes using microphones for the detection of subtle noises caused by movement [1], or different camera-based approaches [48]. The three main criteria used to compare these localization solutions are the total provisioning costs per area, their reliability, and the amount of persons that can be tracked and distinguished. One example system based on capacitive

Table 1 Overview of related capacitive proximity sensing systems mentioned in this work

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Application Areas</th>
<th>Measuring Layout</th>
<th>Data Processing</th>
</tr>
</thead>
<tbody>
<tr>
<td>SensFloor [11]</td>
<td>System for indoor localization and fall detection as floor underlay</td>
<td>Indoor Localization</td>
<td>Loading mode, variable number of sensors based on area size</td>
<td>Individual coding of zones on floor - analysis of activity based on trajectories</td>
</tr>
<tr>
<td>TileTrack [29]</td>
<td>Indoor localization using transmitters below floor and receiver electrodes</td>
<td>Indoor Localization</td>
<td>Transmit mode, large transmitter electrodes below floor, different receiving electrodes</td>
<td>Location by calculating center-of-gravity on most active tiles</td>
</tr>
<tr>
<td>Touché [53]</td>
<td>Swept-frequency sensing to detect different types of touches on a conductive material</td>
<td>Smart Accessories</td>
<td>Swept-frequency sensing, single electrode</td>
<td>SVM classification using features in different frequency ranges</td>
</tr>
<tr>
<td>Botanicus Interactus [12]</td>
<td>Using plant tissue as conductive material as application for swept-frequency sensing</td>
<td>Smart Accessories</td>
<td>SVM classification of touches that are transferred to input events</td>
<td></td>
</tr>
<tr>
<td>Active capacitive sensing [54]</td>
<td>Conductive textile electrodes to sense different parameters of the human body, based on location</td>
<td>Physiological Sensing</td>
<td>Loading mode, single electrode attached to body part</td>
<td>Different filtering methods, based on electrode position, activity classification using LDA</td>
</tr>
<tr>
<td>Spread spectrum sensor [13]</td>
<td>Single electrodes using a spread spectrum technique for improved sensitivity</td>
<td>Physiological Sensing</td>
<td>Loading mode, single electrode placed remotely</td>
<td>Spread spectrum technique to improve SNR, amplitude measurement for respiratory rate</td>
</tr>
<tr>
<td>School of Fish [14]</td>
<td>Array of shunt mode sensors that can track 3D position and orientation of two hands</td>
<td>Gesture Interaction</td>
<td>Shunt mode, flexible array of sensors</td>
<td>Modeling hands as collection of spheres and fit into area based on sensor values and position</td>
</tr>
<tr>
<td>Thracker [45]</td>
<td>Four electrodes placed around display that can sense spatial position of hand in front of display and certain gestures</td>
<td>Gesture Interaction</td>
<td>Loading mode, four electrodes placed spatially around display</td>
<td>Position based on distance to electrodes or gesture based on nearest object to electrode</td>
</tr>
<tr>
<td>GestiC [63]</td>
<td>Shunt mode array enabling near distance gesture interaction above sensing area</td>
<td>Gesture Interaction</td>
<td>Shunt mode, four or five receiver electrodes</td>
<td>Positioning based on single proximity values and HMM-based gesture recognition</td>
</tr>
</tbody>
</table>
sensing is the previously presented TileTrack. It uses a combination of transmit mode and center-of-gravity calculation between different floor tiles to calculate the position of multiple persons [29]. A second, already commercialized system is SensFloor that uses an integrated solution of capacitive sensors and wireless communication hidden below a floor covering. It is able to detect the position of several users and other parameters such as falls, based on analyzing activity above single sensor areas or the movement trajectories over time [11].

3.2. Smart Appliances

Smart appliances are devices that are attentive to their environment [49]. This is usually achieved by integrating different sensors and actuators to provide additional functions and services to a user. Some examples include intelligent furniture that can register occupation, internet-connected household items, and single-purpose devices that provide reminder services. An overview of several examples was created by Park et al. [50]. One recent example of smart furniture is a system for object localization using smart drawers and RFID technology, presented by Nickels et al. [51]. Another example is activity recognition realized by various simple sensors that can be easily integrated into furniture [52]. Sato et al. have presented Touché, a swept-frequency capacitive sensor that distinguishing various types of touches on any suitable surface and medium [53]. Some examples include recognizing different hand postures in liquids and touching several body parts to control mobile devices. Their system is based on analyzing a broader range of frequencies that have a unique effect on the resulting capacitance. Using a classification method, they are able to distinguish several categories of events. A prototype based on this technology is an interactive art installation that is controlled by touching different parts of a plant [12]. Capacitive sensing provides the ability to add interactive features to many appliances and can be placed unobtrusively.

3.3. Physiological sensing

We previously introduced bioimpedance as the response of a living organism to an external electric field, caused by the human body being mostly composed of ionized water [16]. Capacitive proximity sensors can use this effect to measure various physiological parameters that are related to movement of different body parts, including internal organs, most notably the heart. Cheng et al. have presented a system that allows measuring motions and shape changes of body parts using capacitive sensors embedded in garment [54]. They are able to measure the swallowing and breathing rate. One example for an industrial application is non-contact electrocardiogram (ECG) sensing in cars, intended to recognize drowsiness in drivers. Using three electrodes it is possible to detect the heart rate or even acquire a full ECG through various layers of clothing [55]. MacLachlan presented a system that registers the respiratory rate of a person lying on a bed from a distance of up to 50cm using a single electrode and a highly sensitive sensing method based on spread spectrum methods that are commonly used in wireless communication [13].

Capacitive proximity sensing is a powerful technology that is able to gather physiological information over a distance, while being unobtrusively integrated into various appliances. For applications that require this information, e.g. to determine the state of alertness or fitness of a user, it is a viable alternative to body-worn sensors that could be considered more disturbing by the user.

3.4. Gestural Interaction

Gesture recognition enables the detection of meaningful expressions of motion by a human body, including the hands, arms, face, head and body [56]. If these expressions are translated into machine commands the result is gestural interaction. The most expressive and explicit form of gestures are performed by the hands, further distinguished into free-air gestures and touch gestures. The latter typically involves one or more fingers interacting with a surface. If multiple fingers are used the interaction pattern is also called multi-touch.

Apart from the capacitive touch technologies shortly presented in section 2.2, there are also numerous other means of realizing finger tracking on surfaces. Jeff Han showed a low-cost system based on frustrated total internal reflection (FTIR) of infrared light. This system tracks ten or more objects in real-time on large surface areas [57]. Acoustic systems are another popular technology in this domain. Surface acoustic wave (SAW) uses the signal decrease of ultrasonic waves as they pass through an object touching the surface to infer its location [58].

Throughout the years there have been various attempts to enable the tracking of gestures in free air.
Capacitive proximity sensors have been first presented almost 100 years ago by the Russian physicist Leon Theremin, who invented the eponymous touch-free electronic instrument [10]. The theremin uses two electrodes to control pitch and volume of a generated sine wave. Capacitive hand tracking has been a research interest at MIT in the 1990s [14] and has been investigated recently by other groups, enabling touch control even through thicker non-conductive materials [33], [40]. Camera systems based on visible light are popular in this domain. They either rely on markers [59] or use methods based on discovering the hands without markers, e.g. by detecting the skin color [60].

In the last few years there have been two commercially successful and popular systems that track gestures using infrared light for depth sensing. The Microsoft Kinect is using an infrared projector and camera to enable whole body gesture tracking of multiple persons at a longer distance [61]. The second device is the Leap Motion that enables fine-grained tracking of fingers and hands in a smaller area above the device. It is based on two cameras and infrared diodes that are illuminating the interaction area [62].

Capacitive touch screens are ubiquitous in most finger-controlled devices ranging from smartphones, small tablets to small notebooks.

4. Prototype systems

In this section we discuss the application of capacitive proximity sensors in smart environments, based on various prototypes that we have created in the last few years. The main purpose of this section is to show how the technology can be used in the different application domains and give practical examples on choosing specific designs and methods. Each system is described and sorted into one or more application areas. We outline how they are linked to the domain of capacitive proximity sensing in terms of measuring method, electrode layout and data processing. We also discuss technical and usability evaluations that have been performed for each prototype. A short overview of the presented prototypes is given in Table 5.

4.1. CapFloor

CapFloor is a capacitive system for indoor localization and fall detection that is based on a grid array of sensing electrodes placed below a floor covering [64]. A sketch of the system is shown in Figure 11. The grid is comprised of insulated wires that are placed orthogonal to each other. The sensors are placed on two sides of the room and operate in loading mode. CapFloor can be placed below any non-conductive material, like wood, tiles and PVC, if the distance between the wires and the floor surface is not too high (< 5cm). It can discriminate between a foot being above an electrode or a whole body. Combining this information from various sensors we are able to get a reliable localization of lying and standing persons. As we are using only two sides of the room for sensors it is possible to cut the wires on the adjacent sides without considerably affecting the signal. This simplifies the installation in non-rectangular rooms.

Accordingly, CapFloor can be used in various application scenarios. Indoor Localization in the home domain can be useful in energy saving and fall pre-
vention by appropriately activating and deactivating the environment lighting. It can also be used in security-restricted areas to detect unauthorized movement.

The fall detection should be used in a system that has various levels of escalation. It is not easy to distinguish between a person doing exercises on a floor and a person that has fallen down. Accordingly, the system should query if the person is well and not autonomously call for outside help unless necessary.

4.1.1. Data processing

Using long wire electrodes may result in considerable noise and influence from outside electric fields. Therefore, CapFloor requires preprocessing to reduce the noise and achieve a more robust high-level data processing. The localization uses a weighted average algorithm that calculates the position based on active electrodes and their location within the room.

The fall detection is using a time-series analysis of the aggregated values of the sensors that are currently registering an object. This method is using the assumption that the overall sensor response is roughly equivalent to the shape of the object that is closest to the surface, resulting in a higher capacitance of the overall system. Here we are using the plate capacitor model again. This effect is shown in Figure 12.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Application Areas</th>
<th>Measuring Layout</th>
<th>Data Processing</th>
</tr>
</thead>
<tbody>
<tr>
<td>CapFloor</td>
<td>Capacitive system for indoor localization and fall recognition based on electrode grid below the floor.</td>
<td>Indoor Localization</td>
<td>Loading mode, variable number of sensors based on area size</td>
<td>Binary activity association and using geometry for positioning. Monitoring of overall value for falls.</td>
</tr>
<tr>
<td>Smart Bed</td>
<td>Capacitive sensors placed below mattress able to determine sleeping postures and breathing rate.</td>
<td>Smart Appliances, Physiological Sensing</td>
<td>Loading mode, four sensors on each side of bed</td>
<td>Posture fitting using a static model. Fourier analysis for breathing rate recognition.</td>
</tr>
<tr>
<td>The Capacitive Chair</td>
<td>Office chair equipped with capacitive sensors to distinguish different typical work postures and stress levels.</td>
<td>Smart Appliances, Physiological Sensing</td>
<td>Loading mode and shunt mode, eight sensors, heterogeneous sensing capabilities</td>
<td>Model fitting using a dynamic model. Fourier analysis for breathing rate recognition.</td>
</tr>
<tr>
<td>Active Armrest</td>
<td>Heterogeneous system for finger gesture recognition and arm rest identification for automotive applications.</td>
<td>Smart Appliances, Gestural Interaction</td>
<td>Loading mode, heterogeneous layout</td>
<td>Finger positioning using direct calculation. Binary arm presence detection.</td>
</tr>
<tr>
<td>MagicBox</td>
<td>Mobile 3D gesture interaction device using an array of electrodes.</td>
<td>Gestural Interaction</td>
<td>Loading mode, six wireless sensor nodes</td>
<td>Geometric positioning of hand relative to plane. Adapted mouse methods for gesture recognition.</td>
</tr>
<tr>
<td>CapTap</td>
<td>Table capable of analyzing 3D gestures and knocks to realize tactile interaction in a living room.</td>
<td>Smart Appliances, Gestural Interaction</td>
<td>Loading mode, 24 capacitive sensors and a single touch registering microphone</td>
<td>Image-based hand and arm registration. Independent touch detection. Tracking of multiple objects.</td>
</tr>
</tbody>
</table>

The sum $s$ of all $n$ sensor values $r$ is the closest equivalent to the system capacitance and therefore a viable measure. If the overall value is above a threshold $v_t$, a person $p_j$ is lying on the floor.

$$s = \sum_{i=0}^{n} r_i$$,  \( p_j = \begin{cases} 1, & s \geq v_t \\ 0, & s < v_t \end{cases} \)

In order to increase the robustness, this threshold has to be exceeded for a certain amount of time $t_m$. In consequence a fall $f$ is recognized if the following equation is not 0.

$$f = \prod_{j=0}^{t_m} p_{t_f}$$

![Figure 12 Shapes of a standing and lying person on top of the CapFloor grid](image)
4.1.2. Evaluation

Figure 13 Floor mats with integrated CapFloor system used at the EvAAL 2011 competition [64]

The CapFloor system was evaluated in the scope of the Indoor Localization Track of EvAAL 2011, where it participated out of competition [47]. This was necessary due to constraints of the competition that made it impossible to equip the whole area. In Figure 13 we can see a picture of the demonstration setup installed in the living lab where the competition was held. The wires are integrated into different mats that can be quickly placed in the environment. It was tuned to localize a single person and performed reasonably well in the covered areas, recognizing the position of this person with a precision of approximately 20cm. The resolution of the system is depending on the chosen density of electrode wires. While there is a certain measure of proximity, it is not possible to register objects that are more than a few centimeters away from the wires. Later iterations of the system use higher voltages and shunt mode measurements to improve the tracking reliability and enhance the fall detection.

4.2. Smart Bed

The Smart Bed is a regular bed frame that has been equipped with capacitive proximity sensors, in order to determine occupation, posture and sleep phases [36], [65]. A sketch can be seen in Figure 14. The electrodes are comprised of copper foil and attached to the flexible wooden panels of the slatted frame. Therefore, the electrodes are sensitive to both proximity and applied pressure, resulting in a superposed combined sensor value that is considerably higher as proximity measure alone. The electrodes are symmetrically distributed, with four attached to each side of the two person bed. The system is able to determine different sitting and lying postures of one or two persons, including less regular lying positions such as diagonal or orthogonal to the long side of the bed. Using an analysis of the movement gathered from the variation in the sensor signal, the sleep phases can be analyzed, similar to accelerometer-based applications that are available for smartphones [66].

The Smart Bed can be used for various purposes. A main scenario is a connection between the occupation detection, a home automation system and a timer, in order to activate ambient lighting if the person is getting up in the night, presumably to visit the restroom. Accordingly, in a single person household the lights could follow a user through the apartment by autonomous switches, in order to conserve energy. In the domain of personal health the Smart Bed is able to give the user a feedback on sleep quality, based on the sleep phase measurement performed in the night. Another potential application is to use the acquired pressure distribution as indicator for unsuitable lying postures that may be harmful to the back over a longer period of time [67].

4.2.1. Data processing

Figure 15 Data processing components [36]

The different components of the Smart Bed data processing are shown in Figure 15. Raw sensor data is distributed to three different modules, the calibration which is determining the initial parameters for
the sensor data fusion, the drift compensation that alters those parameters according to long term trends and finally the sensor data fusion module that processes the data and does feed it to the occupation & position detection.

![Figure 16 Calculating centers of pressures and deviation](image)

Occupation and position are calculated by dividing the two person bed into left and right and individually calculating for each side the total sensor values, assumed center of pressure using weighted average and the standard deviation (Figure 16). The same calculation is performed in between the two sides to detect two person activities or a single person lying on both sides. Using these six intermediate values we can map various poses. If all activity is on one side and the horizontal deviation is low, we can assume that one person is sitting. Additionally the intermediate values can be used to calculate more information, e.g. the exact location a person is sitting at.

The data processing for the sleep phase recognition is based on measuring the sensor data variations in order to analyze movement. Discriminating between sleep phases using movement is a common approach that has been used in the past [68]. Using a sparse set of sensors it is possible to recognize movement by comparing subsequent sensor readings and associate it to the sleep phases using different activity profiles.

4.2.2. Evaluation

![Figure 17 Sleep movement data over three hours in one night](image)

The Smart Bed posture recognition is able to successfully distinguish eight typical sitting and lying states, such as a “person sitting on the right side of the bed”. Using adaptation of the intermediate values it is possible to optimize these states and for example calculate a more precise sitting position on a certain side of the bed.

Regarding the detection of sleep phases there has been an evaluation and benchmarking over three nights [65]. The Smart Bed was able to achieve comparable results to smartphone applications that implemented the movement based methods presented by Salmi and Leinonen [68]. Figure 17 gives an example of movement recordings using the capacitive proximity sensors over one night. The activities are grouped into distinct chunks that are later associated to the sleep phases. Future developments for the Smart Bed include an integration of respiratory rate measurement that can be used to improve the sleep phase recognition and also can potentially detect anomalies that may be indicative of a certain health risk.

4.3. The Capacitive Chair

![Figure 18 Smart office chair sketch - eight electrodes three in backrest, three on seat and two in armrests](image)

The Capacitive Chair is a regular office chair equipped with eight capacitive proximity sensors that can register different sitting postures, work-related activities and the respiratory rate [69]. Seven solid copper electrodes placed below the covering are augmented by a single conductive thread electrode that is placed in a mesh on the backrest. In the past smart chairs have used pressure sensors to infer posture and occupation [70]. By combining presence and proximity sensing it is possible to directly infer postures where parts of the body do not touch the surface, e.g. if the body is arched towards the front, or if an arm is raised from the armrests. Additionally, larger-sized electrodes in the backrest measure the breathing rate by measuring the movement of the chest.

The Capacitive Chair aims at providing different services to typical office workers and office managers. Using the occupation detection it is possible to advise for some type of physical activity, if the time
spent in front of the screen was too long. The system can also advise the user to change to a more back-friendly posture or regularly switch the stance to achieve a healthier lifestyle. Using the breathing rate measurement, we are able to get some measure of the stress level associated to the current working situation. By adapting the environment, it is possible to improve the working atmosphere and reduce stress. The Capacitive Chair uses a multi-faceted data processing approach. A machine learning algorithm is associating the sensor values to different typical sitting positions, inspired by a recent study of sitting positions for modern device usage [71]. An adaptive body model that is fitted to the current sensor values allows for fine grained adaptation of those postures. Using a time-series analysis of the sensor data, we can identify how active a person is currently working. Finally, a frequency domain analysis is used to determine the current breathing rate [69].

4.3.1. Data processing

![Figure 19 Screenshot of the Capacitive Chair application showing the fitted 3D model on the left, posture detection on the upper right and the recognized posture on the lower right](image)

In Figure 19 we can see a screenshot of the Capacitive Chair debug application. On the left side is a 3D model that is fitted to a chair model according to the current sensor values. On the right side the classification probabilities are on the top and the classified posture on the bottom.

All processing methods use filtered and normalized sensor data. The difference in shape, material and size of the electrodes necessitates slight adaptations to noise filtering and data processing. As an example only the conductive thread backrest electrode is used in the breathing rate detection.

The 3D model is a simplified human joint model comprised of 13 connected components. Based on the current sensor readings, single parts or groups of components are fitted to a model of the chair. The process is a mix of posture mapping, as found in the smart bed and direct modification of the links between the single components [69].

![Figure 20 Conductive thread weaved into mesh of Capacitive Chair backrest](image)

We use a SVM classifier that was trained using data collected by several persons, matching the input from eight sensors to ten potential output postures. An early observation is that certain postures are difficult to distinguish given the limited number of sensors and the similarity of the postures on the rigid chair. A higher number of sensors could be used to distinguish the different poses more reliably.

To register the working situation, we are using the variance in sensor values over time. This relates to the quantity of movements on the chair. Using thresholds over specific time frames we are able to distinguish “inactive work” and “active work”.

The breathing rate measurement is operating on a single conductive thread electrode that is integrated into a mesh on the backrest. The setup is shown in Figure 20. Consequently the surface of the electrode is large and able to pick up the chest movement. Using a Fast Fourier Transformation the signal is transformed into the frequency domain. We are looking for significant signal portions in frequency areas that can be associated to breathing, between 0.2Hz and 3Hz.

4.3.2. Evaluation

The Capacitive Chair has been evaluated in two distinct studies. The first aimed at testing the aggregated recognition of working activities with several persons over various days. The second study was testing the posture recognition with various users that the system supports distinguishing two different working situations. We have performed a test over 3 days between December 4th, 2013 and December 6th, 2013 on a typical work day in the office. The resulting activity logs were used to generate a chart as shown in Figure 21.
We can see some phases of “not at chair” - usually for lunch break or meetings. The time spent on the chair is either classified as active work, such as writing and typing, or inactive work, such as reading.

In the second evaluation we were testing the posture recognition of the chair in a short study with 10 participants. Our system was tuned to distinguish three poses and a non-pose, sitting upright, sitting hunched, “slouching on chair” and a disturber position close to the chair. The persons were given a short introduction in which the different postures were shown. Afterwards, the persons were asked to move into those postures. When testing the disturber position the subjects were asked to rattle at the chair, stand close, move it around and thus generate arbitrary potential sensor readings. Each class was tested for 10 seconds, collecting 200 samples. Overall the results were very convincing. Of the 40 measurements series only two were not achieving 100% accuracy. The upright and disturbance positions were classified correctly for all candidates. A single candidate had an 86% rating on the hunched posture. Another candidate had a 55% rating on the slouching position. The average of correctly classified postures is 98.5%.

4.4. Active Armrest

The Active Armrest is a prototype demonstrating unobtrusive gestural interaction in the domain of automotive applications [72]. The interior of modern cars can be considered a smart environment as it includes an ensemble of sensors and actuators that adapt the system behavior according to user preference.

Many cars use touch screens or jog dials to control primary and secondary car functions [73]. Capacitive proximity sensors allow integrating interactive areas into different existing surfaces of a car, e.g. an armrest. The Active Armrest is using a set of eight sensors that are separated into two groups, as shown in Figure 22. There are two larger electrodes in the back of the armrest that are dedicated to recognizing the presence and distance of an arm. In the front of the armrest there is an array of six small electrode sensors, in order to register finger gestures. The basic idea is to disallow interaction when the arm is resting and enable it once it is lifted. The Active Armrest supports swiping gestures of a single finger and static holding gestures of two fingers. This allows controlling various typical automotive applications, e.g. navigation applications or comfort settings that can be controlled in a similar fashion.

4.4.1. Data processing

As we already mentioned, the Active Armrest electrodes are put into two groups. The data processing for both groups is distinctly different. In order to detect the presence of the arm using the two-electrode group a simple threshold on the accumulated values is used. The six sensor array in the front (touch area) is using a weighted average method to calculate finger positions. Additionally, a threshold is used to distinguish one and two fingers. The resulting data processing pipeline is shown in Figure 23. The
finger tracking and gesture recognition will be inactive until it is ensured that no arm is present.

4.4.2. Evaluation

In order to evaluate the Active Armrest the prototype shown in Figure 24 was built. An aftermarket armrest was equipped with an OpenCapSense toolkit. The demonstration application is based on the SenseKit debug software supplied with the toolkit. As of now there is a simple USB connection to a nearby PC.

Figure 24 Active Armrest prototype, left - outside view, right - detail view of electronics

Figure 25 Active Armrest demo software, left - finger tracker, right - OSM based navigation application

The MagicBox was our first attempt to create an interaction device based on capacitive proximity sensing. It is using an array of six individual wireless capacitive sensors that communicate to a central station [76]. The aluminum foil electrodes are sized 10cm x 6cm. A sketch is shown in Figure 26. The system is able to track the position of a single hand in three dimensions at a maximum distance of approximately 20 cm. It uses different methods to infer gestures from the hand movement.

It is intended as a generic interaction device that can potentially be hidden below non-conductive surfaces. As it can be used without touching it is also applicable in sterile environments. A suite of demonstration applications has been created that showcase typical scenarios for the MagicBox. This includes multimedia applications, e.g. image viewer and media player, but also a 3D object viewer intended as demonstrator for potential medical applications, allowing a surgeon to check MRT or CT images in a sterile environment, without touching any surface.

4.5. MagicBox

4.5.1. Data processing

The first data processing step of the MagicBox is the planar localization of the hand, following the weighted average algorithm previously presented. In order to calculate the distance of the hand from the
plane we are using a piecewise linear interpolation, that resembles the response curve of a single sensor [76]. An example interpolation is shown in Figure 27.

An addition of the MagicBox is a generic gesture recognition module, based on methods similar to mouse gesture recognition adapted for three dimensional locations [77]. Using the developed debug software, we can define an arbitrary set of potential gestures and adding training data, as shown in Figure 28. The module is looking for matches based on the most recent set of locations.

4.5.2. Evaluation

The MagicBox prototype is based on the Cypress First Touch starter kit [30] and combines six capacitive sensors communicating wirelessly to a single base station. They are put together with a USB-rechargeable power supply into a casing. The prototype electronics, including the six wireless boards and sensors, battery and power supply PCB are shown in Figure 29.

The different iterations of the MagicBox have been evaluated in conjunction with various demonstration applications. A usability study with 18 persons led to general approval of the system [76]. Two of the applications used in this study are shown in Figure 30. On the left is a 3D object viewer that has to be controlled by a combination of menu navigation and direct manipulation of the screen content. On the right side there is an image viewer that was controlled by gestures to trigger the next/previous images or perform zooming operations. The most common positive remarks gathered in this study can be roughly put into three groups:

- The device is very intuitive to use
- The idea of interacting this way is novel and interesting
- It is easy to control applications with those gestures

Likewise we identified three main groups for negative comments about the prototype:

- The device is not very precise
- The interaction speed is slow
- It can be tiring for the arm

Later iterations have improved on some of the weaknesses by using a more sophisticated gesture recognition system and higher sensor refresh rates. Accordingly, there were fewer complaints about interaction speed and precision [77]. However, the final complaint about the device being tiring for the arm, requires a different approach, that we investigate in the final prototype presented in this work.

4.6. CapTap

The CapTap is a large area interaction device unobtrusively integrated into a living room table. It is comprised of 24 capacitive sensors and a single microphone for touch registration. As capacitive proximity sensors on their own struggle to distinguish close objects and touching object this device supports reliable detection of different touch events [78]. 
the domain of free-air gestural interaction there are two prevalent challenges. The physical demands of prolonged interaction with such systems is high [79], [80]. Additionally, it is difficult to adapt selection events to gestural input. The latter is typically realized using time- or position-based gestures [79], [81]. There is no trivial solution to these challenges and any approach has to take into account the specific application scenario. Several systems are trying to provide specific GUIs, while others include additional input devices assisting the interaction [82], [83].

CapTap presents an approach to improve the interaction speed of invisible input devices based on capacitive proximity sensors. We have combined a method to detect touches using a microphone with a capacitive hand tracking system.

4.6.1. Data processing

The hand localization of the CapTap is based on a novel image-based approach that reconstructs a grey scale image from the capacitive sensor values and then applies various image processing methods to fit the hands and arms of the user into the resulting image. An example for fitted palms and arms can be seen in Figure 32. We are analyzing the image moments and pixel intensities within different regions that are created by using a threshold on the reconstructed image, enabling a 3D localization of two or more arms and palms. These properties are stabilized using a Kalman filter. A single contact microphone connected to an USB audio interface is attached on the bottom of the table in order to register touch events. Using acoustic classification methods, similar to TapSense [84], we are able to distinguish taps, double taps, knocks, double knocks, finger swipes and hand swipes. The data from both sensing devices is fused together, to create a rich interaction that combines gestures performed in different elevation levels, swipe gestures on the surface and several touch events that can be used for selection events [78].

4.6.2. Evaluation

The CapTap prototype is integrated into a common living room table. On the left side of Figure 33 we see the 24 electrodes made of non-etched circuit boards. A sensor is attached to each. The contact microphone and audio interface are shown on the right side.

The overall abstracted layout of the prototype is shown in Figure 34. The capacitive sensors are controlled by three OpenCapSense boards. The microphone and audio interface are placed within the table together with a Mini-PC. This PC performs all necessary calculations, including an analysis of the audio signal and the image-based palm and arm recognition.

Figure 35 Tracks generated by Kalman filtered palm position, a sine wave (A), a rectangle (B), a circle (C), and a diagonal swipe (D)
In a study with 10 users we wanted to identify if the touch-based selection events will improve the interaction speed of users compared to time-based selection and how reliable our touch recognition system is [78]. While taps and hand swipes could be detected with very high reliability (recognition rate higher 97%), particularly double knocks were more difficult to classify, as the gesture was more individualized than anticipated (recognition rate 60%). This can be overcome by either including more persons in the training of the classifier or providing a personalized calibration of the table. The hand tracking performed well in three dimensions. Figure 35 shows examples of several tracks that have been recorded and the registered view of an overhead camera that was placed above the table. The interaction speed when using tap selection was on average about 15% faster than time-based selection (selection-time 300ms). The test was randomized and targets were chosen according to Fitts’ law.

<table>
<thead>
<tr>
<th>Name</th>
<th>Application Domains</th>
<th>Environmental Influences</th>
<th>Detection Range</th>
<th>Processing Complexity</th>
<th>Unobtrusiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacitive proximity sensing</td>
<td>Indoor localization, smart appliances, physical sensing, gestural interaction</td>
<td>Electric fields, conductive objects</td>
<td>Near distance (&lt; 100cm)</td>
<td>Few high dynamic range data sources</td>
<td>Invisible integration possible</td>
</tr>
<tr>
<td>Capacitive touch sensing</td>
<td>Smart appliances, physical sensing, gestural interaction</td>
<td>Electric fields, conductive objects</td>
<td>Touch</td>
<td>Few binary sensors</td>
<td>Thin cover above electrodes</td>
</tr>
<tr>
<td>RGB cameras</td>
<td>Indoor localization, smart appliances, physical sensing, gestural interaction</td>
<td>Occlusion, external lights</td>
<td>Far distance (&gt; 10m)</td>
<td>Complex image processing based on resolution</td>
<td>Pinhole lenses</td>
</tr>
<tr>
<td>Infrared cameras</td>
<td>Indoor localization, physical sensing, gestural interaction</td>
<td>Occlusion, external infrared light</td>
<td>Medium distance (&lt; 5m)</td>
<td>Complex image processing based on resolution</td>
<td>Infrared source and camera</td>
</tr>
<tr>
<td>Ultrasound sensing</td>
<td>Indoor localization, physical sensing, gestural interaction</td>
<td>Acoustic occlusion, absorbing materials</td>
<td>Medium distance (&lt; 5m)</td>
<td>Few low dynamic range data sources</td>
<td>Emitter and senders with exposed pinhole speaker, microphone</td>
</tr>
<tr>
<td>Microphone arrays</td>
<td>Indoor localization, smart appliances, physical sensing</td>
<td>Environmental noise, absorbing materials</td>
<td>Medium distance (&lt; 5m)</td>
<td>Very high dynamic range data sources</td>
<td>Exposed pinhole microphones</td>
</tr>
<tr>
<td>Radiofrequency sensing (RF)</td>
<td>Indoor localization, smart appliances, gestural interaction</td>
<td>Other RF devices</td>
<td>Far distance (&gt; 10m)</td>
<td>Few low dynamic range data sources</td>
<td>Hidden emitters and senders possible</td>
</tr>
</tbody>
</table>

In the previous sections we have presented background information on capacitive proximity sensors, suitable application domains within smart environments, existing capacitive systems and a number of our prototypes. In the following section we are building on this collected information to perform a meta-analysis of the acquired data. This includes discussing benefits and limitations of the technology, as well as comparing it to competing technologies. Finally, we provide a set of guidelines for parties interested in developing capacitive proximity sensing applications in this domain.

5.1. Smart environment sensor technologies

In order to categorize capacitive proximity sensing in the domain of smart environments, it is necessary to include a comparison to other sensing technologies. Cook and Das discussed various sensors that are relevant for smart environments [85]. From this selection we have chosen systems that have a broad applicability and have been used in various smart environment applications. Those have been chosen from the domains specified in Section 3. Thus, they are potential competition for capacitive proximity sensors.

Capacitive touch sensing, as opposed to capacitive proximity sensing relies on an electrode being
touched instead of an object being in proximity. Its use is ubiquitous in touch screen applications.

RGB cameras are a class of image sensors operating in the same frequency domain as the human eye. They are capable of processing different colors.

Infrared cameras operate in light frequencies that are invisible to the human eye. This allows for application in dark environments, as it is possible to project infrared light into the scene without disturbing the user.

Ultrasound sensing uses mechanical waves just above the audible limit of human hearing. The waves propagate similar to sound signals and one can perform reflection measurements or time-of-flight methods.

Microphone arrays measure signals in the range of human hearing, and thus work with audible signals, such as human speech.

Radiofrequency (RF) sensing uses signals in a range between several hundred kHz up to 5GHz, typically used for wireless communication. Commonly the signal strength or time of flight is used to gather information about the environment.

A short overview can be found in Table 6. We have included a comparison of suitable application domains, environmental influences, detection range, processing complexity and unobtrusiveness of the technology. We considered two sources for those criteria. The first is the collection created for the EvAAL competition that compares different technologies in the domain of Ambient Assisted Living, which has several overlaps with smart environments [47]. They investigate various aspects related to user acceptance, including the need for unobtrusive systems and concerns about processing complexity. Wilson discusses numerous aspects of sensor technology in his book including the importance of the sensor environment and potential criteria for distinguishing sensors [86].

5.2. Classification of capacitive proximity sensors

Most technologies are capable of supporting multiple application domains. Some non-intuitive examples include WiSee that enables whole-body gestural interaction using WiFi signals [87] or MoGees that uses a single microphone to enable gesture interfaces on various surfaces [88].

Capacitive sensors are disturbed by conductive objects and electric fields, whereas cameras struggle with occlusion and specific light sources. A line of sight is required, even though some materials are transparent for different light. Microphones are prone to dampening materials and environmental noise registered by the sensors. RF signals propagate well through most materials and only other RF sources may be disturbing.

Regarding the detection range we are considering applications in buildings, whereas it is not usually necessary to measure properties of objects that are very far away. In this criterion we also include deteriorating sensor readings in a certain distance. RF and visible light cameras have the best range. Infrared cameras have deteriorating quality, particularly when using static pattern projection. Ultrasound also gets less precise when exceeding a certain distance, due to the wave properties and single measurements. Capacitive proximity sensors struggle to measure objects that are far away from the sensing electrode, as their influence on the electric field might be below the achievable resolution.

It is not trivial to find a good measure for the processing complexity associated to sensing technologies. We are using a simplified model, taking the dynamic range of a sensor and the number of sensors typically required. Dynamic range is the interval between the smallest detectable value and the largest detectable value. Microphones have a high dynamic range measuring over a larger frequency scale, whereas touch sensors only have two states. Ultrasound sensors usually measures simple amplitudes in time-of-flight systems and thus do not require complex processing. Processing camera images in both visible and infrared requires complex operations on large data arrays and is difficult to perform in real time for simple embedded systems.

Finally regarding unobtrusiveness, capacitive sensors and RF sensors can be applied completely invisible. Cameras, microphones and ultrasound need a direct line-of-sight or mechanical connection to the measured property and are thus more challenging to hide. However, some applications can be very unobtrusive, e.g. the CapTap prototype (4.6) that uses a microphone attached to the opposite side to register acoustic events on a surface, or pinhole cameras that are barely visible to the naked eye.

5.3. Benefits

Given the information collected in the previous section, we can now discuss the specific benefits of capacitive proximity sensing. We are using three different groups for categorization: versatility, unobtrusiveness, and processing complexity. Some exam-
amples within these groups are shown in Table 7. In the following sections we will discuss those groups in detail.

Table 7 Overview of capacitive proximity sensing benefits

<table>
<thead>
<tr>
<th>Name</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Versatility</td>
<td>Flexible electrode design, scalability, different sensing methods</td>
</tr>
<tr>
<td>Unobtrusiveness</td>
<td>Invisible application, non-disturbing frequency range</td>
</tr>
<tr>
<td>Processing Complexity</td>
<td>Small number of sensors, variable dynamic range</td>
</tr>
</tbody>
</table>

5.3.1. Versatility

A main benefit of capacitive proximity sensors is the versatility in which they can be applied. With flexible choice of electrode materials, size and geometry, it is possible to create individual applications. Example electrode materials include transparent metal oxide layers, woven conductive thread, copper wires, PCB boards, and simple aluminum foil.

Additionally, the sensor systems are highly scalable. By choosing appropriate voltages and frequencies, it is possible to add a high number of sensors to a single object. Using smart measurement windows and multiplexing methods, sensors can be placed close together and electrodes may act as both sender and receiver.

The sensing methods presented - loading mode, shunt mode and transmit mode - enable a variety of different sensing patterns. The human body can be used as both sender and receiver and sensors can be designed that have very low power consumption.

In conclusion, it is possible to add capacitive sensing to most everyday objects with a variety of potential applications. Regarding electrode materials, our prototypes use flexible (4.2) or solid electrodes, conductive thread (4.3), wires (4.1), shielded (4.6) or non-shielded layouts.

5.3.2. Unobtrusiveness

Electric fields are not usually perceived by persons, unless they are of exceptional strength. Furthermore, they propagate through many materials in our environment, including most plastics, wood, and tile. Thus, we can apply capacitive proximity sensors invisibly without a strong effect on the measurement. Application below several centimeters of covering is possible, if the electrodes are designed properly for large distance sensing.

The frequency range in which the sensors operate is not in an interval that disturbs other electronic systems. Thus, it is feasible to use capacitive sensing even in environments, where non-disturbance is a requirement. Additionally, the frequencies used are not considered biologically active, and the field strength is low.

![Figure 36 Electodes and sensors hidden below mattress of Smart Bed](image)

It is possible to equip most conductive objects directly with capacitive proximity sensors and hide them below non-conductive objects with minimal spatial requirements. Our Smart Bed (4.2) and Active Armrest (4.4) prototypes are using sensor sets that are completely invisible from the outside and communicate wirelessly to a PC only using a power supply. Figure 36 shows the electrodes and sensors attached below the mattress of the Smart Bed.

5.3.3. Processing Complexity

An appropriate analogy to a capacitive proximity sensor is the photodiode. As opposed to light intensity we are measuring capacitance instead. While the information gained from such a measurement is limited, the processing power required to analyze the signal is low. Performing signal analysis on an array of 24 capacitive sensors, as in the CapTap prototype (4.6) is comparable to processing the image of a 6x4 pixel camera. Therefore, it is easy to create highly integrated systems with low-powered processing units. While it is possible and in many cases beneficial to use complex data processing algorithms for object detection, a similar result can be achieved with less complex methods.

In many applications it is even viable to opt for a quantized capacitance measurement. In case of a touch sensor, a single binary measure is sufficient. However, it is also possible to select multiple levels and reduce the dynamic range to easily computable values of 4 or 8 Bits. Depending on the chosen algo-
rithm, this dynamic range reduction can occur either in pre-processing or high-level processing.

With the exception of the Capacitive Chair (4.3) and the CapTap that require frequency domain operations, our prototypes use simple data processing methods that can be suited for embedded systems. One of the presented examples is the weighted average algorithm for object detection. Regarding model-based data processing, even very simple cylindrical models, such as the one used for the Smart Bed, are capable of reliably predicting the postures relevant in real world applications. In general, the low requirements for data preprocessing, allows dedicating more resources to high-level data processing algorithms if the specific system is resource constrained.

The OpenCapSense toolkit that is the base for most of our prototypes has a fairly powerful microcontroller that is able to implement all of the processing steps. This enables highly integrated, low-power capacitive proximity sensing prototypes that can be used in smart environment applications.

5.4. Limitations

Table 8 Overview of capacitive proximity sensing limitations

<table>
<thead>
<tr>
<th>Name</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environmental influence</td>
<td>Static electric fields, dynamic electric fields, temperature, humidity, conductive objects</td>
</tr>
<tr>
<td>Physical range</td>
<td>Small differences in capacitance, reduction due to influences, physical limitations</td>
</tr>
<tr>
<td>Object detection</td>
<td>Small number of data points, a priori knowledge</td>
</tr>
</tbody>
</table>

Despite the potential benefits described in the previous section, there are various limitations of capacitive proximity sensing that we can put into the groups of environmental influence, physical range and object detection. A short overview is given in Table 8. They will be detailed in the following sections.

5.4.1. Environmental Influence

One of the main limitations of capacitive proximity sensors is their sensitivity towards environmental influences. Any factor that modifies an electric field will also affect the measurement of a capacitive sensor. The current environmental parameters, including temperature and humidity are having a considerable effect on the atmosphere in which the electric field propagates. However, those changes are usually over a longer period of time and can be countered using drift compensation, as described in Section 2.6.1.

More challenging are other electric devices in the environment that emit strong electromagnetic fields. While persistent sources, such as permanent electric installations can usually be compensated using a galvanic isolation, there are other non-obvious challenges. As an example, we noticed that certain plasma TVs are able to disturb the measurement and increase noise levels considerably. This change is even varying according to screen content. A minor effect is the presence of high-frequency fields that are getting more prevalent in modern IT equipped environments. Instead of the 2.4GHz and 5GHz ranges that are often used in wireless communication, capacitive proximity sensors can operate in the range of a few kHz to one MHz.

An additional issue might arise when placing sensors close to each other. The created electric fields may disturb the measurement if some electrodes are charged and create fields to adjacent electrodes while they are discharged for measurement. Consequently, specific charge-discharge cycles or multiplexing methods have to be used to counter this effect.

A major challenge is dealing with conductive objects that are placed in the immediate sensing environment. It is difficult to distinguish the object we want to register from any disturbing object, if their influence on the electric field is similar. Long term data analysis may help in performing a successful recognition.

The CapFloor prototype (4.1) is most seriously affected by environmental influences, given the small size of the electrodes relative to the interaction area and the changing environment on top of the floor. We are using a strong noise reduction algorithm and drift compensation to create a more stable result while reducing the detection range.

5.4.2. Physical Range

Figure 37 Reduced angular resolution on smaller, distant objects

The physical range of the generated electric field is one of the main limiting factors of capacitive proxim-
ity sensing. In order to register objects that are further away, we have to increase the electric field strength sufficiently. This is easier the larger the electrode is, as its potential capacitance is higher. However, this also leads to distant objects having an ever smaller influence on the overall capacitance, and we need more precise measurement circuits and longer measurement times to improve the signal-to-noise ratio. Additionally, looking at smaller objects the angular resolution will decrease as shown in Figure 37. This makes it more difficult to get a precise localization as the immanent noise leads to an angular error. While this can be compensated using more sensors, the far distance would require us to use large electrodes that have to be placed further apart resulting in a huge area that would have to be equipped with sensor electrodes.

The achievable resolution and detection distance is not comparable to vision based systems and has to be taken into consideration when designing the specific application. A balance between electrode size, physical range and achievable resolution has to be found.

The size of the MagicBox (4.5) does not allow an integration of very large electrodes. Instead we are optimizing the available space, in order to achieve hand detection in a distance between 15 and 20 centimeters.

5.4.3. Object Detection

![Figure 38 Same response to differently sized objects (left), distinct response to varying materials of same-sized objects (right)](image)

Object detection using capacitive sensors can be explained using a camera analogy. A single electrode system is equivalent to a single photo sensor. The light intensity measure is comparable to field capacitance. Accordingly, we can’t distinguish if the measurement is caused by a weak source in close proximity or a strong source at a further distance. As a practical example, a single capacitive sensor can’t decide if one hand is close to the sensor or two hands are further away. This effect is a challenge for object detection and we have to combine the information from various sensors to get a good idea about object shape and size. Due to the presented challenges in physical range and electrode size, capacitive proximity sensing systems do not have the same level of scalability as cameras, where millions of photo sensors can be placed in very small areas.

Additionally, the effect of an object on the electric field is not always closely correlated to the object dimensions, but instead based on conductivity, material and other factors. We may get the same response to different objects at varying distances, or a different response for same-sized objects at a specific distance, if they are made of unlike materials. This effect is shown in Figure 38.

The Active Armrest (4.4) supports gestures for one and two fingers that are distinguished using a simple threshold. If another object is entering the field or the person has larger fingers the system will fail to properly separate gestures. Accordingly, some other compensation methods or a calibration should be used.

5.5. Guidelines

After discussing the limitations and benefits of capacitive proximity sensors, the final section of this chapter will give some general guidelines on their application. The first step of this process is a decision if capacitive sensors technology is suitable for the given application. This part should be driven by three questions.

What do I need to measure in my application scenario?

Capacitive proximity sensors can measure the presence and properties of conductive, grounded objects. This includes the various application scenarios shown in the previous sections. However, if the application requires measuring properties of unsupported objects that are non-conductive, a different technology should be chosen.

What sensing technologies are supporting the required measurements?

It may be the case that multiple technologies support the measurements required in this specific applications. Cameras often can provide similar recognition as capacitive sensors, e.g. in indoor localization applications. In this step all potential sensing technologies should be collected.

Are capacitive proximity sensors beneficial for my scenario?

An evaluation of the candidates is the final step and should lead to a decision about the most suitable sensing technologies. If the distance is too high for capacitive proximity sensors or enough processing
power is available and lighting conditions are static, cameras might be more suitable. This should be driven by the different benefits and limitations of the technologies.

If there is a decision in favor of capacitive sensors the next step is to design the specific electrode layout. Similar to technology selection we can use a few basic questions to get an idea of what layout to use.

**How many sensors are required to get the measurement?**

The number of sensors required is depending on the area we want to cover, the specific object parameters that have to be determined and the desired resolution. The electrodes are inherently limited in size, as a single sensor can only charge and discharge to a specific maximum capacity. Therefore, if a large area has to be covered more electrodes and sensors are necessary. If we just want to measure the presence of a hand a single electrode may suffice. If orientation and position are interesting we need to combine measurements from various sensors. We used six electrodes for the MagicBox (4.6) as it is only tracking a single hand on a limited surface. Most prototypes (4.2, 4.3, 4.4) use eight sensors as this turned out to be a good compromise providing sufficient data that can be collected by a single sensor kit. CapTap (4.6) uses 24 sensors as we wanted a high resolution over a larger area and CapFloor is scaled to room size and may use a high number of sensors.

**What should be the size and geometry of the electrodes?**

This is closely related to the previous question. If the application is not restricting the available space, the electrode should be approximately of the same size as the object that is to be detected. This generates the highest difference in capacitance when the distance is changing. The Active Armrest (4.4) uses six very small electrodes for finger tracking and two larger ones for registering the arm presence. CapFloor (4.1) uses wire electrodes that are spread throughout the room to maximize coverage. The hand tracking devices (4.5, 4.6) are equipped with hand-sized electrodes and the body sensing devices (4.2, 4.3) use as much of the available space as possible.

**What is the best electrode material to use?**

Copper is always a good first choice to create electrodes. If elasticity is necessary we can use copper foil and solid copper if that is of no concern. For transparent electrodes we will have to use one of the previously presented materials, such as ITO. If electrodes have to be integrated into cloth, conductive thread is a good candidate. Any conductive material will act as an electrode, thus the application and budget should be the primary driver of this decision. The Active Armrest and CapTap (4.4, 4.6) are not constrained and use solid copper electrodes. CapFloor (4.1) uses copper wires. MagiBox (4.5) integrates the sensors into a thin casing, thus we used aluminum foil. As we wanted the electrodes of the Smart Bed (4.2) to deform along with the slatted frame we used copper foil. The Capacitive Chair (4.3) uses a number of solid copper electrodes but also includes a single conductive thread, as it could be integrated into the mesh structure of the back rest.

**Does my application require any shielding?**

Shielding prevents detecting objects approaching from a certain direction. If the application requires this additional hardware, because it is anticipated that other objects might disturb the measurement, shielding should be used. The only prototype that uses shielding is the CapTap (4.6), as various electronic devices are integrated into the table and we wanted to minimize disturbance.

Finally, if the hardware is designed as desired the different variations of data processing have to be chosen and configured according to the application.

Using baseline calibration is beneficial in the vast majority of applications. Having a distinct starting point simplifies all further steps of high-level data processing, such as normalization and setting of different thresholds. This step may only be omitted in very stable environments and if the system has sufficient a priori information to operate on raw data. Drift compensation should be handled in a similar fashion. The common methods are not computationally expensive and having a stable baseline over time allows the same algorithms to be applied in a more robust fashion. These steps are performed for all our prototypes. The method and configuration of noise reduction are strongly depending on the specific case.

Some form of noise reduction might be required in most applications. Yet, according to the type of noise a variety of methods can be used. If outliers are an issue, a median filter is appropriate; if a smoother signal is desired, an average filter can be used. None of our prototypes are affected by outliers, but we use different forms of adaptive average filters that attenuate environmental influences but react quickly on fast changes in sensor values.

Regarding high-level data processing there are numerous variations of methods presented in this work. Data-driven machine learning algorithms are a good method if we have a small set of potential outcomes, e.g. the postures that could be recognized on a chair or couch. We partially use these methods in
the Smart Bed (4.2) and exclusively regarding the posture classification of the Capacitive Chair (4.3). If our application has many potential outcomes, e.g. the thousands of potential locations in a hand tracking system, it is typically beneficial to use a model-driven approach, as used in all other prototypes (4.1, 4.4, 4.5, and 4.6). However, these models may be supported by data-driven algorithms, such as particle filters. One example is the Swiss-Cheese object tracker by Grosse-Puppendahl et al. [41]. The data processing examples shown in the previous sections give an idea of the decision rationale in various application domains.

In conclusion, capacitive proximity sensors are a viable, or even, ideal solution for a considerable number of different applications in smart environments. However, a certain level of preparation is required in the design process to create a system that benefits from the technology.

6. Conclusion

On the previous pages we have evaluated capacitive proximity sensing technology in smart environments. After presenting a basic overview of the technological principles we have identified and detailed several application domains that are relevant in this context. Using a set of self-designed prototypes and various devices created by other researchers, we showed how to apply capacitive proximity sensing to create viable systems in these domains. Afterwards, we discussed the benefits and limitations of the technology using a set of criteria to compare it to other widely used sensor systems. In the end we have given some guidelines that should aid interested parties in deciding for or against the technology.

Capacitive proximity sensors already have shown their great potential in various applications. However, it is foreseeable that the story does not end here. There are various trends that may lead to an increased relevance for capacitive proximity sensors in the future. A necessary step is a smarter, more adaptive sensor that is able to react independently and intelligently, with regards to changes in the environment. This enables usage in self-organizing sensor networks that are becoming more prevalent in modern smart environments.

A particular driver of innovation in the past years is the increased number of rapid prototyping systems, such as 3D and circuit printers that enable researchers and developers to quickly test out novel concepts. Conductive ink allows turning arbitrary surfaces into electrodes. Combining these techniques and attaching suitable capacitive proximity sensors let us create novel smart appliances with hidden interactive parts that enable interaction beyond the scope of what has been presented so far.

The technology will always be bound by the laws of physics, restricting the potential applications to a specific spatial range. However, this should not discourage interested parties from experimenting with this technology, using the available toolkits or custom designs.

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