

Your Floor Knows Where You Are: Sensing and Acquisition of Movement Data

Philipp Leusmann, Christian Möllering,
Lars Klack, Kai Kasugai, Martina Ziefle
eHealth Group, HumTec / Communication Science
RWTH Aachen University
Aachen, Germany
philipp.leusmann@rwth-aachen.de

Bernhard Rumpe
Software Engineering
RWTH Aachen University
Aachen, Germany
rumpe@se-rwth.de

Abstract—This paper describes the first results on a sensor floor, which can be integrated in home environments to assist old and frail persons living independently at home. The sensor floor works with a dense array of piezo elements. Its purpose is not only to monitor the inhabitant's position within the room but also to analyze impact patterns for later activation of stable rescue procedures in case of fall or other emergency events. Algorithms were developed to gain information on steps of persons in the room from the piezo impulses. The sensors are invisibly integrated in the room's floor, which is part of a living lab (the *Future Care Lab*) developed and built within the eHealth project at RWTH Aachen University.

Index Terms—indoor localization; pervasive health; sensor floor; human tracking; ubiquitous localization; intelligent buildings; ambient assisted living; step detection; gait analysis; movement analysis

I. INTRODUCTION

Electronic health technologies will play an increasingly important role in the coming years, as more and more older people will require medical care and support [1]–[3]. Electronic healthcare (ehealth) technologies support the interaction between patients and health service providers, institution-to-institution transmission of data, and peer-to-peer communication between patients and health professionals [4], [5]. The spectrum of emerging technical applications covers a broad variety of developments, reaching from internal technologies (implants for monitoring physiological signals) over devices integrated into clothes (wearable technologies) to healthcare robots or smart home technologies, which support older people in keeping up their independent live at home [6], [7]. These innovative smart care technologies promise to deliver significant improvements in access to care, quality of care, and the efficiency and productivity of the health sector [8], [9].

Given the increased life expectancy and considering shortcomings in the care sector as well as bottlenecks within the health insurance funds, it is a basic question how older and frail people can stay in their private home keeping up mobility and independence for a longer time. For a successful scenario in which both patients and health care institutions profit from home care solutions, the technology has to be unobtrusive, affordable and reliable. Patients have to be and feel as safe as in a hospital combined with the comfort and the privacy of

his regular home environment.

The *Future Care Lab*, being part of the European Network of Living Labs (ENoLL), serves as a test environment for user centered design of Ambient Assisted Living (AAL) technologies. To examine how patients communicate with smart homecare environments, how they deal with invisible technology, and how the information is to be delivered such that it meets the requirements of timeliness, data protection, dignity as well as medical demands, an experimental space is necessary, which enables to study patients *life at home*.

While a multi-touch wall shifts the primary function of the wall as a room component towards an active, graphical in- and output device for human-computer interaction, the floor functionality has a more concealed role in the room [10]. The unobtrusive monitoring of old and frail persons' movement behaviors is the key application of this room component. A dense network of piezo-electric sensors records each pressure application to the floor followed by a mathematical analysis of pressure events. The goal is to detect characteristic walking patterns, fall events or other abnormal movement behaviors that would indicate an emergency situation. In case that such an emergency situation is detected the system may contact a professional medical personnel. Thus, users do not have to carry an emergency button and to activate the emergency call, which in a lot of cases is not possible, for example when the person is immobile or lost conscience. Meeting requirements of invisible technology, a parquet floor hides this technology.

II. RELATED WORK

Many approaches aim at gaining indoor localization and movement information. They range from wearable sensors like accelerometers and pressure sensors [11], [12], contact free methods using acoustic (microphone) [13] or visual (video camera) [14], [15] sensors to solutions, measuring the contact forces applied to the ground by the user's feet [16], [17]. Each approach offers both, advantages and drawbacks in certain scenarios. Wearable sensors are mobile and can be used in various locations, however they are not invisible and require a high amount of care and maintenance of the user. Acoustic and visual sensors provide very reliable information



but require visible obtrusive technology that may bring up privacy and intimacy concerns, which may help to increase the acceptance of the devices.

Passive infrared sensors [18] as found in motion detectors are widely spread in both private homes and in professional environments. They mainly serve security and amenity purposes and are not designed to provide detailed location information.

Wearing devices featuring Wifi technology and a unique ID (like MAC addresses), can be another method to locate users [19]. However, the possible precision is rather low and it depends on devices to be worn.

The EU-Project EMERGE proposes a method that uses ultra wideband technology. Here, too, devices need to be worn by all tracked persons. Compared to Wifi based localization, a much higher precision of under 1 meter can be reached [20].

RFID tags can be used to locate and identify persons [21]. The RFID tag again requires to be worn, which is difficult to ensure or control and which will be perceived as a disturbance of one's privacy. Localization via ultrasonic sound needs an active device at the person and an additional RF channel to synchronize the elapsed times. An assessment of the measured data leads to a high accuracy [22].

The works of Klingbeil and Wark [23] examine localization in wireless sensor networks and their combination with integrated acceleration sensors. Here, larger devices are necessary up to now, which also must be kept at the tracked person's body. Woodman and Harle [24] follow a similar approach. They use acceleration sensors integrated in shoes which are permanently re-calibrated via WLAN. Doing so, they combine the high relative accuracy of the acceleration sensors with the rougher, but absolute localization of WLAN based methods.

Image based localization systems that use cameras [25] profoundly intrude into peoples privacy. Furthermore, the technical setup is relatively complex as are the necessary computer vision algorithms that process the image material and locate or even distinguish people on the images.

Anne et al. investigated on the combination of WLAN or RFID technology with cameras [26]. The integration of different systems that, on their own, are widely spread, led to good results, especially in a heterogeneous field of users. However, the above mentioned privacy issues remain.

Orr et al. created and validated a system for biometric user identification based on footstep profiles [16]. Here, the ground reaction force of the users foot is measured by load cells and analyzed in order to generate user identification profiles.

Valtonen et al. [27] suggest to use capacitive measurement built into floor tiles to locate humans. This is a passive system with no need for devices on the person. The product 'SensFloor' by the Future Shape GmbH, Germany, localizes persons via proximity sensors that are integrated into a floor mat [17]. The technology also approximates the shape of the object or person on the floor, thus allowing for fall detection.

III. RESEARCH GOAL AND APPROACH

The goal of this research is to develop an intelligent floor that eventually detects characteristics from impact patterns,

both in time and space, like fall events or other unusual movement behaviors indicating an emergency situation for the user. Possible features could be velocity, impact power, impact frequency or impact location.

The approach presented in this paper tries to process data measured by piezoelectric sensors to an interpretable form. These data patterns will then be analyzed to detect impacts made by footsteps and subsequently paths of movement on the floor.

IV. TECHNICAL REALIZATION

The *Future Care Floor* is built using 64 wooden tiles (600 x 600 x 40 mm and 300 x 600 x 40 mm) mounted on a solid steel frame to achieve space for wiring and controller devices beneath. To monitor impact data on the floor, each tile's corner is equipped with a piezoelectric sensor covered in a perpex support structure [28].

After analog preprocessing to limit the voltage to a -2,5 - 2,5 V range and additionally shift the voltage to be all positive in operation amplifiers, the piezoelectric output is quantized using the 10 bit A/D-converters of ATmega1280 microcontrollers on 15 Arduino Mega boards. The sampled data will be transferred to a host computer by a serial protocol wrapped in USB packets.

To interpret the visualized sensor data presented in this paper, it is important to understand the special signal response a piezoelectric sensor gives. While natural understanding of sensors often implies a measurement of weight, a piezoelectric sensor responds to an applied force. For example, when putting a weight on a piezoelectric sensor and leaving it, the response of a piezoelectric sensor will be an impulse. When removing the weight, the piezoelectric sensor will show an opposite impulse. Because of this behaviour, only moving objects will be recognized by the sensors. This means, no further efforts have to be made to remove static objects like furniture from the generated model of the room.

The software for the *Future Care Floor* needs to be divided into two general parts:

- 1) The software running on the arduino *microcontroller* board is responsible to sample sensor data and transfer it to the host computer. It is written in C.
- 2) The raw sensor data is processed and analyzed by software implemented in Java on the host computer.

To achieve the goal of detecting human movement on the floor, multiple steps of processing the raw sensor data need to be performed.

A. Data acquisition at microcontroller boards

As already noted in the previous section, each arduino is sampling data of up to 16 piezoelectric sensors with 10 bit precision and then sends the digital values of all enabled sensors to the host computer in a batch packet, starting with two sync bytes to resynchronize after transfer failures. Additionally, the packet contains meta information about which ports are sent. To maintain data integrity, a CRC checksum is appended to the packet.

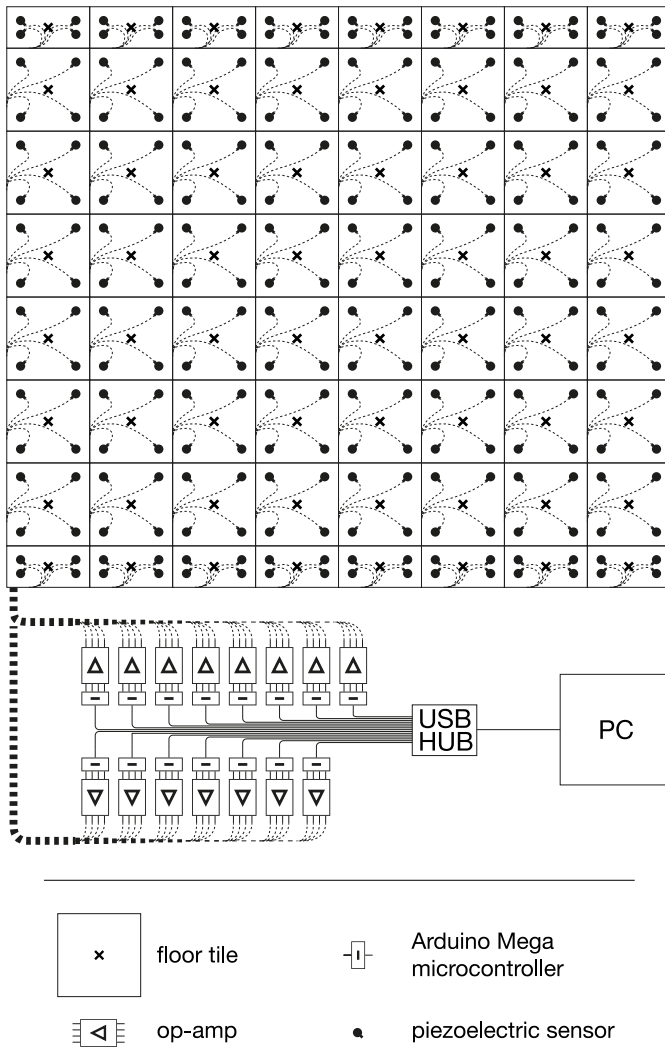


Fig. 1. Overview of floor architecture

For an arduino with all ports enabled, each packet will contain 36 Bytes.

An important aspect of data reliability is the temporal comparability of sensor data. To achieve a uniform pattern, we decided to enumerate all samples from all sensors. On the host computer, all serial reader threads are synchronized after receiving the batch packet, so it can be assumed that all batches are read defacto in parallel.

After being received by the host computer, all values within a batch packet are assigned the same timestamp. Since digitizing 16 analog values on the arduino takes 1,6ms and at the host computer we achieve a data rate of up to 125 batches/s, resulting in a time interval $\Delta(t_n) = t_{n+1} - t_n \geq 8ms$ between two batch packets, with t_n being the time the n-th sample was taken, we think this assumption is sufficiently precise.

B. Data reading and processing

On the host computer it is advisable to reflect the hardware setup, so for each arduino board there is a distinct processing

chain running in parallel threads. For the sake of simplicity, we will only describe one instance of these parallel chains.

For data reading and initial processing, three consecutive FIFO queues are operated. During software design we found, it is crucial to decouple these queues to grant unblocking data retrieval. Thus, for each step we established an autonomous processor thread forwarding the processed data to the next queue.

While the first step is taken by the *SerialReader*, responsible for opening the serial connection and data transfer from and to an arduino board, the second step *SerialDataProcessor* decodes the raw packet into separate *Value* objects. Another feature of the second step is to filter the individual values. Three relevant filters are applied in order:

- 1) *Calibration*: Each sensor shows some value offset in neutral state. This is corrected by using a static lookup table.
- 2) *Low pass*: High frequency components are eliminated from the sensor data by applying a Hanning window function.
- 3) *Relevance checking*: To eliminate noise, values below a absolute certain threshold are filtered out.

See figure 2 for signal comparison before and after filtering.

As *SerialValueListeners* can register to receive data, the third decoupled queue *SerialDataForwarder* will forward filtered *Values* to the listeners.

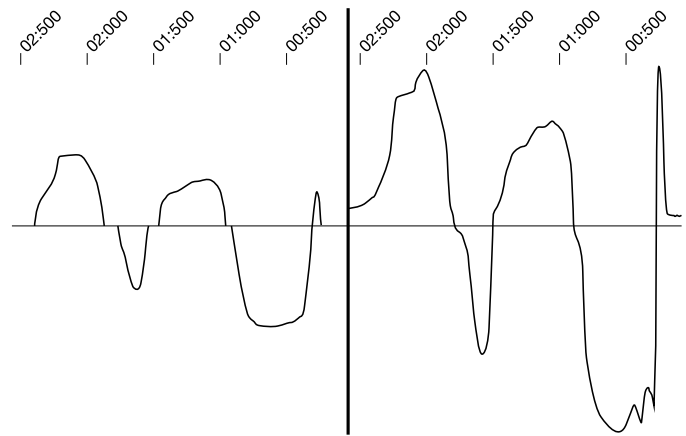


Fig. 2. Comparison between unfiltered (left) and filtered (right) signal of single sensor

C. Transposition into spatial context

While most implemented *SerialValueListeners* are used for graphical display and debugging purposes, the *TileValueAggregator*, itself being a *SerialValueListener*, takes a central role in our system by resolving the spatial distribution of the samples. It does so by mapping discrete sensor samples to their position on the floor, combining them into the tile structure of the floor.

To help data analysis, the *TileValueAggregator* provides many functional operators at floor tile level, amongst which building an aggregated value of all sensors of a tile is the most

important one.

The main purpose of the aggregated signal is to eliminate irrelevant signals from the set of observed values and to simplify the detection of the desired signal. One central problem while analyzing sensor signals of a walking human, was the mechanical interference of directly triggered floor tiles with the respective neighbor sensors either by vibration of the steel framing or friction of the wooden tiles.

Experiments have shown severe differences in the value pattern of directly and indirectly actuated tile sensors: Under most circumstances, all sensors of a directly operated tile show a similar directed value pattern. In comparison only one or two sensors of incidentally influenced tiles were showing values above the filtered threshold.

To compute the aggregation, two different functions have been evaluated: The *average*

$$S_{avg}(t, r, c) = \frac{\sum_{i=1}^n s_i(t, r, c)}{n} \quad (1)$$

where n is the number of the sensors of the tile and $s_i(t, r, c)$ is the i -th sensor value of the sensors of tile at position $[r, c]$ and time t , and the *median*

$$S_{median}(t, r, c) = \begin{cases} s_{\frac{n+1}{2}}(t, r, c) & \text{if } n_{\text{even}} \\ \frac{s_{\frac{n}{2}}(t, r, c) + s_{\frac{n}{2}+1}(t, r, c)}{2} & \text{if } n_{\text{odd}} \end{cases} \quad (2)$$

where n is the number of the sensors of the tile and $s_i(t, r, c)$ is the i -th sensor value in the sorted set of the sensor values of the tile at position $[r, c]$ and time t .

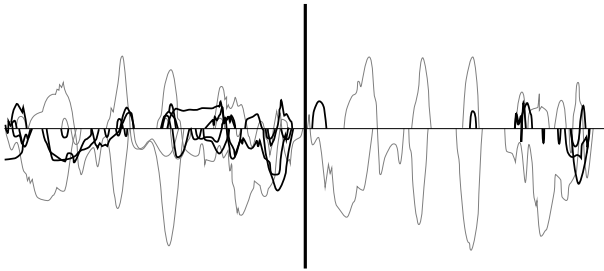


Fig. 3. Graphical comparison between aggregated tile values (S_{avg} left, S_{median} right). Signal of actuated tile plotted grey, adjacent tiles plotted in black

By looking at the graphical analysis of the aggregation functions (see figure 3) the advantages of S_{median} already became obvious. While there is nearly no difference on the features of the signal between both functions, the median function shows less noise.

To find a measure for evaluation of the aggregation function, we specified the Signal-Noise-Ratio (SNR)

TABLE I
COMPARISON OF SNR OF AGGREGATION FUNCTIONS

Run	SNR S_{avg} [dB]	SNR S_{median} [dB]	$\frac{SNR_{S_{median}}}{SNR_{S_{avg}}}$
1	1.0002	1.6177	1.6173
2	1.6269	2.4611	1.5128
3	1.0596	1.5279	1.4420
4	1.0754	1.5221	1.4154
averaged	1.1905	1.7822	1.4969

$$SNR = \log \left(\frac{\sum_{r,c} \begin{cases} S(t, r, c) & \text{if tile}[r, c] \text{ actuated} \\ 0 & \text{else} \end{cases}}{\# \text{ actuated tiles}} \right) \quad (3)$$

$$\frac{\sum_{r,c} \begin{cases} S(t, r, c) & \text{if tile}[r, c] \text{ influenced} \\ 0 & \text{else} \end{cases}}{\# \text{ influenced tiles}}$$

Using this definition, we were able to compare the signal quality of S_{median} and S_{avg} .

While, due to limited time resources, we were only able to evaluate a small amount of test runs, we are convinced of the superiority of S_{median} over S_{avg} . See table I for results.

For all subsequent results the median function is used, while being denoted as S .

An additional feature of the *TileValueAggregator* is to locate the position of an impact within a tile.

For this purpose, a vectorial representation was implemented. Each sensor was assigned a vectorial position of $\vec{s}(t, r, c) = [\pm 1, \pm 1] \cdot |s(t, r, c)| \cdot \alpha$, i.e. the sensor value expresses the vector length, the position of the sensor specifies the sign (for example, the upper left sensor of a tile as a unit vector of $[1, -1]$, the upper right $[-1, -1]$). To detect, whether a vector belongs to an impact or a release, the sign of the single sensor value $s(t, r, c)$ must be evaluated. In our case, we were only interested in position of impacts, which would be a negative sensor value. Finally, an amplification factor α needs to be applied, to normalize the result. This will cause to achieve the maximum amplitude on full sensor impact, even when the actuator will not provide an impact hard enough.

Because of the physical mounting of the sensors directly under the corner tiles without any lever, an impact always influences all sensors of a tile in the same direction. That is, there are no sensors expected to produce a reverse signal of the orthogonal located counterparts. Thus, an approach of highest value was chosen.

To compute the tile vector for an impact, we only took sensor values into account which are within a given range Δ of the smallest value of all sensors of the tile $\hat{s}(t, r, c)$.

$$\vec{S}(t, r, c) = \sum_i \begin{cases} \vec{s}_i(t, r, c) & \text{if } s_i(t, r, c) \leq \hat{s}(t, r, c) + \Delta \\ 0 & \text{else} \end{cases} \quad (4)$$

This technique helped us to improve the resolution of impact location detection from tile level (an area of $3600mm^2$) to the

four quarters of a tile (900mm^2) and an additional circular center area. The validity of these results will need to be asserted in further test runs.

D. Step detection

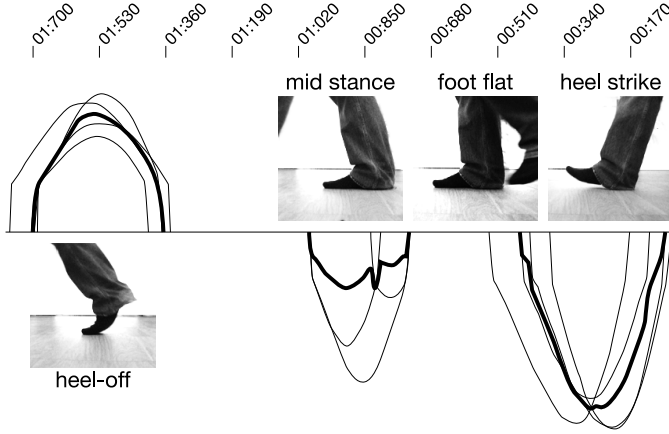


Fig. 4. Plot data of a single step on one tile with respective picture of human step process. Temporal direction is right to left. Aggregated sensor values are plotted bold.

For detecting human steps on the *Future Care Floor*, we decided to follow a relatively simple approach. As visible in figure 4, there are three feature curves in the plot of aggregated sensor signals:

- 1) A dominant *impact curve* resulting from the force of the *initial contact* phase.
- 2) A second, minor *impact curve* resulting from the weight transition during the *mid stance* phase.
- 3) A *release curve* resulting from the negative force while *pre-swing* phase.

While ignoring the *mid stance* curve, we detect *initial contact* and *pre-swing* using the trailing edge of their respective curves. That is, the detect an element in the set of impacts Ω it must be below a certain threshold δ and the derivative must be the first derivative greater than ε after a local minimum:

$$\begin{aligned} \Omega = \{ & (t, r, c) | S(t, r, c) < \delta \\ & \wedge S'(t, r, c) > \varepsilon \\ & \wedge S'(s, r, c) \leq \varepsilon \\ & \forall s < t, s > \hat{p}, \hat{p} = \max(p), \\ & S'(p, r, c) = 0 \} \end{aligned} \quad (5)$$

For release detection we use an inverted form of formula 5 with matching δ and ε .

It is obvious, that the situation becomes increasingly complicated, when, while walking, the person's second foot is also impacting the same tile. Because of the special signal delivered by piezoelectric sensors, the leading edge of the second foot's *initial contact* signal will superposition the trailing edge of the first *initial contact* signal. Additionally, the *pre-swing* phase of the first foot, being temporally very close to the first foot's

TABLE II
STEP DETECTION RATE OF SEVERAL RUNS (DIFFERENT SUBJECTS)

Person (different subjects)	Person weight	Steps performed	Steps detected	Success Rate
A	100	78	71	91%
A	100	46	31	67%
B	58	103	69	67%
B	58	59	30	51%
C	80	50	44	88%
C	80	65	41	64%
C	80	70	50	71%
D	85	74	59	80%
overall		545	395	72%

initial contact phase [29], will also mix into the impact signal. During impact detection, this behaviour results in an interpretable wave, this is not true for release detection. Only the release of the second foot can be detected. Thus, we only depend on the spatial and temporal sequence of impacts for further evaluation.

V. RESULTS

To measure the results of the step detection, we performed several test runs while recording the runs on video. The subjects were asked to walk as natural as possible. The videos were evaluated visually in slow-motion by counting the steps seen on the screen. As the analyzing computer played an audio signal each time a step was detected, these signals were counted as well. The resulting success rates for some test runs are presented in table II.

As can be concluded from these results, the detection rate of steps from different persons is dependent on the individual walking and body characteristics (like weight) of the performing subject. While the test runs were all performed using the same variable properties (e.g. δ and ε in formula 5), which were specified using sample data from subject A, the weight of the subject seems to have a big impact on detection quality. Further tests will be needed to examine the success rate with customized settings. Furthermore, there are plans to evaluate normalization of sensor data to improve the detection rate. An additional factor for suboptimal results is the use of an automated memory model of the implementation language Java. While the live analysis produces lots of data, there are pauses for garbage collection necessary, during which no data gathering and analysis is possible. While efforts in this field have already shown potential for improvement, this also needs to be evaluated more thoroughly.

For the above reasons, the preliminary results are presented as a proof of concept, while there still is plenty of room for further improvements.

VI. CONCLUSION AND FUTURE WORK

The presented work provides an unobtrusive way to monitor people's movement within their personal living space. While the extraction of impact sequences for the purpose of identifying emergency situation was our primary goal, many more applications are possible. In case of the multitouch wall in the

Future Care Lab, for instance, virtual sports programs could be created to maintain fitness for older or frail people. Another benefit is to motivate users to participate in interactive games on top of the *Future Care Floor*.

So, in future projects we will be evaluating systems to automatically process the gathered movement data, allowing us to detect dangerous situations by identifying exceptional paths or special events like downfalls. Possible technologies would, for example, be supervised *machine learning* algorithms. Additionally it could help if the *Future Care Floor* was integrated with further sensors to improve reliability, for example by integration with a context-aware assisted-living system like OpenAAL [30].

Within such a smart approach, also cautionary aspects need to be carefully considered. The omnipresence of information and communication technology may be perceived as a violation of personal intimacy limits, raising concerns about privacy, and loss of control [5], [31]. So far, we have only limited knowledge about the fragile limits between the different poles: the wish to live independently at home and to feel safe, secure, and fully cared on the one hand and the feeling of loss of control and the disliking of intrusion in private spheres on the other. In conclusion, to develop and design a user-centered device in the medical sector further user studies must be run to detect their requirements. Especially, the needs of the elderly, and the chronically ill have to be considered because they represent the major target groups of such devices.

ACKNOWLEDGMENT

We thank Prof. Werner K. Schomburg, Doboplan, Jürgen Löwenhag, Jonas Engels and Dr. Ibrahim Armac. This research was supported by the Excellence Initiative of the German federal and state governments.

REFERENCES

- [1] S. Leonhardt, "Personal healthcare devices," in *Malware: Hardware Technology Drivers of Ambient Intelligence*, S. M. et al, Ed. Dordrecht: Springer, 2005, pp. 349–370.
- [2] S. Weeks, O. Branton, and T. Nilsson, "The influence of the family on the future housing preferences of seniors in canada," in *Housing, Care and Support*, ser. 8, 2005, vol. 2, pp. 29–34.
- [3] P. Wyeth, D. Austin, and H. Szeto, "Designing ambient computing for use in the mobile healthcare domain," in *Online-Proceeding of the CHI 2001*, 2001.
- [4] K. Arning and M. Ziefle, "Different perspectives on technology acceptance: The role of technology type and age," in *Human-Computer Interaction for eInclusion*, A. Holzinger and K. Miesenberger, Eds. Berlin, Heidelberg: Springer, 2009, pp. 20–41.
- [5] S. Gaul and M. Ziefle, "Smart home technologies: Insights into Generation-Specific acceptance motives," in *HCI for eInclusion*, A. Holzinger and K. Miesenberger, Eds. Berlin: Springer, 2009.
- [6] G. Demiris, B. Hensel, M. Skubic, and M. Rantz, "Senior residents' perceived need of and preferences for "smart home" sensor technologies," *International Journal of Technology Assessment in Health Care*, vol. 24, pp. 120–124, 2008.
- [7] K. Kasugai, M. Ziefle, C. Röcker, and P. Russell, "Creating Spatio-Temporal contiguities between real and virtual rooms in an assistive living environment," in *Proceedings of the International Conference Create 10 (CDROM)*, 2010.
- [8] S. Czaja and J. Sharit, "Age differences in attitudes toward computers," *Journal of Gerontology*, vol. 5, pp. 329–340, 1998.

- [9] E. Mynatt, A. Melenhorst, A. Fisk, and W. Rogers, "Aware technologies for aging in place: understanding user needs and attitudes," *Pervasive Computing, IEEE*, vol. 3, no. 2, pp. 36–41, 2004.
- [10] L. Klack, K. Kasugai, C. Röcker, M. Ziefle, C. Möllering, T. Schmitz-Rode, E. Jakobs, P. Russell, and J. Borchers, "A personal assistance system for older users with chronic heart diseases," in *Proceedings of the Third Ambient Assisted Living Conference (AAL'10)*, 2010.
- [11] M. Lüder, R. Salomon, and G. Bieber, "A new online fall detection device," Berlin, 2009.
- [12] S. Mann, "Smart clothing: The wearable computer and WearCam, personal technologies," *Personal Technologies*, vol. 1, no. 1, 1997.
- [13] W. Haines, J. Vernon, R. Dannenberg, and P. Driessen, "Placement of sound sources in the stereo field using measured room impulse responses. lecture notes in computer science - computer music modeling and retrieval." Springer, 2009.
- [14] S. Kahn and M. Shah, "A multiview approach to tracking people in crowded scenes using a planar homography constraint," 2006.
- [15] M. Kourogi and T. Kurata, "Personal positioning based on walking locomotion analysis with Self-Contained sensors and a wearable camera," in *Proceedings of the 2nd IEEE/ACM International Symposium on Mixed and Augmented Reality*, 2003.
- [16] R. J. Orr and G. D. Abowd, "The smart floor: A mechanism for natural user identification and tracking," 2000.
- [17] A. Steinhage and C. Lauterbach, "SensFloor@: ein AAL sensorsystem für sicherheit, homecare und komfort," in *Tagungsband des 1. Deutschen AAL-Kongress*, Berlin, 2008.
- [18] A. A. Galvin and J. K. Guscott, *United States Patent: 4321594 - Passive infrared detector*, Mar. 1982.
- [19] B. Li, A. Dempster, C. Rizos, and J. Barnes, "Hybrid method for localization using WLAN," in *Proceedings of SSC 2005 Spatial Intelligence, Innovation and Praxis*, 2005.
- [20] M. A. Stelios, A. D. Nick, M. T. Effie, K. M. Dimitris, and S. C. A. Thomopoulos, "An indoor localization platform for ambient assisted living using UWB," in *Proceedings of the 6th International Conference on Advances in Mobile Computing and Multimedia*. Linz, Austria: ACM, 2008, pp. 178–182.
- [21] G. yao Jin, X. yi Lu, and M. Park, "An indoor localization mechanism using active RFID tag," in *Sensor Networks, Ubiquitous, and Trustworthy Computing, 2006. IEEE International Conference on*, vol. 1, Los Alamitos, CA, USA, 2006, p. 4 pp.
- [22] H. Piontek, M. Seyffer, and J. Kaiser, "Improving the accuracy of ultrasound-based localisation systems," *Personal Ubiquitous Comput.*, vol. 11, no. 6, p. 439–449, 2007.
- [23] L. Klingbeil and T. Wark, "Demonstration of a wireless sensor network for Real-Time indoor localisation and motion monitoring," in *Proceedings of the 7th international conference on Information processing in sensor networks*. IEEE Computer Society, 2008, p. 543–544.
- [24] O. Woodman and R. Harle, "Pedestrian localisation for indoor environments," in *Proceedings of the 10th international conference on Ubiquitous computing*. Seoul, Korea: ACM, 2008, p. 114–123.
- [25] V. A. Petrushin, G. Wei, and A. V. Gershman, "Multiple-camera people localization in an indoor environment," *Knowledge and Information Systems*, vol. 10, no. 2, p. 229–241, 2006.
- [26] M. Anne, J. L. Crowley, V. Devin, and G. Privat, "Localisation intratiment multi-technologies: RFID, wifi et vision," in *Proceedings of the 2nd French-speaking conference on Mobility and ubiquity computing*. Grenoble, France: ACM, 2005, p. 29–35.
- [27] M. Valtonen, J. Maentausta, and J. Vanhala, "TileTrack: capacitive human tracking using floor tiles," in *Pervasive Computing and Communications, 2009. PerCom 2009. IEEE International Conference on*, 2009, p. 1–10.
- [28] L. Klack, C. Möllering, M. Ziefle, and T. Schmitz-Rhode, "Future care floor: A sensitive floor for movement monitoring and fall detection in home environments," in *1st International ICST Conference on Wireless Mobile Communication and Healthcare - MobiHealth 2010*, 2010.
- [29] K. Götz-Neumann, *Gehen verstehen: Ganganalyse in der Physiotherapie*, 2nd ed. Thieme, Stuttgart, Apr. 2006.
- [30] P. Wolf, A. Schmidt, J. P. Otte, M. Klein, S. Rollwage, B. König-Ries, T. Dettborn, and A. Gabdulhakova, "openAAL - the open source middleware for ambient-assisted living (AAL)," in *AALIANCE conference, Malaga, Spain, March 11-12, 2010*, 2010.
- [31] S. Lalou, "Identity, social status, privacy and face-keeping in the digital society," *Journal of Social Science Information*, vol. 47, no. 3, pp. 299–230, 2008.