Accelerometer Based Real-Time Activity Analysis on a Microcontroller

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***Abstract*—In this article we present a new algorithm implemented on a microcontroller for the classification of human physical activity based on a triaxial accelerometer. In terms of long term monitoring of activity patterns, it is important to keep the amount of data as small as possible and to use efficient data processing. Hence the aim of this work was to provide an algorithm that classifies the activities "resting", "walking", "running" and "unknown activity" in real-time. Using this approach memory intensive storing of raw data becomes unnecessary. Whenever the state of activity changes, a unix time stamp and the new state of activity, as well as the number of steps taken during the last activity period are stored to an external flash memory. Unlike most accelerometer based approaches this one does not depend on a certain positioning of the sensor and for the classification algorithm no set of training data is needed. The algorithm runs on the developed device Motionlogger which has the size of a key fob and can be worn unobtrusively in a pocket or handbag. The testing of the algorithm with 10 subjects wearing the Motionlogger in their pockets resulted in an average accuracy higher than 90%.**

Keywords-Accelerometer; human activity recognition; activity classification; physical activity monitoring; pervasive computing.

I. INTRODUCTION

Physical activity on a regular basis is very important to maintain a good physical and mental state of health. It has positive effects on all body functions and leads to a feeling of well-being. Various studies prove that the risk of cardio vascular diseases such as angina pectoris, stroke, cardiac infarction, circulatory disorder, etc. is up to 50% lower for physically active people [1]. According to [2], physical activity should be one of the highest priorities for preventing and treating disease and disablement in older adults. Hence effective interventions to promote physical activity in older adults deserve wide implementation. Apparently for many people it is difficult to estimate the amount of their own physical activity. The WHO assumes that about 60% of the world's population is not reaching the recommended amount of activity. The ratio is even higher in the leading industrial countries (e.g. North America and Europe). It is recommended to do at least about 150 minutes of moderate physical activity (e.g. walking, cycling, sports, etc.) throughout the week. There are multiple ways of accumulating the total of 150 minutes per week. The concept of accumulation refers to meeting the set goal by performing activities in multiple shorter bouts of at least 10 minutes each, spread throughout the week then adding together the time spent during each of these bouts: e.g. 30 minutes of moderate-intensity activity 5 times per week [3].

Most people are not able to estimate their amount of physical activity and do not achieve the recommended amount of activity. As a consequence they cannot benefit from the positive effects of physical activity. [4] showed that providing simple information about physical activity and comparing it with others motivated the participants of a study to be more active and to lead a healthier life style. As physical activity mirrors the overall health status of a human being, objective data about one's daily dose also allows long term trend analysis and can be helpful in the early detection of diseases. It is one of the challenging research areas of pervasive and ubiquitous computing to provide unobtrusive and automatic recognition of human activities. To achieve pervasive monitoring within concepts as suggested in [5] and [6] it is inevitable to have a reliable technique that can be used under the conditions of daily living and is accepted by potential users. Microcontroller based systems are the first choice for such applications as they are cheap and can be designed in small dimensions for an unobtrusive use.

A. State of the art

There are several approaches to measure activity of humans. Most information about a person's motion can be derived from computer vision based approaches. The gold standard is a motion laboratory with a tracking and motion capture video systems, three-dimensional modeling software and a force sensing ground to measure time-dependent pressure distributions. Obviously the described setup is limited to a laboratory use and requires considerable time effort to prepare, carry out and analyze a measurement and is thus not suited to be used mobile or in a real home setting.

In literature smart home environments or the application of sensors in a home environment are also used to obtain activity data of a person. Most approaches use systems based on

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infrared sensors, ultrasonic sound, video or radio frequency technologies either separately or as a combination.

One of the first publications using IR is a system called Active Badge [7], [8]. They developed a small device (55mm x 55mm x 7mm) that transmits a 0.1 seconds lasting infrared signal with a range of 6 meters every 15 seconds. The signals are received by a sensory network and sent to a processing unit. As every Active Badge sends out a unique infrared signal, the processing unit can distinguish between different Active Badges and their position. An infrared system based on PIRs (Presence Infrared Sensors) is presented by [9]. They prepared two smart homes with PIRs, which were positioned in a way that they could oversee certain areas of interest, e.g. bed, armchair, entrance, sink and cabinet. The sensors fire whenever they detect movement in their sector. In [10] a system based on ultrasonic sound is presented. Here the participants of a study were wearing small devices called Active Bats transmitting ultrasonic sound. Ultrasonic sound receivers are integrated in the ceiling of the test environment and connected to a sensor network. If a request is sent by the basis computer, the requested Active Bat answers and its position can be calculated from the runtime of the ultrasonic signal to the different sensors in the ceiling. An inverted functional principle is presented in [11]. Examples for the use of computer vision techniques to augment home based sensorized environments were published by [12], [13] and [14]. Radio Frequency Identification (RFID) tags and readers are used in several activity recognition systems because of their durability, small size and low costs. It can be distinguished between systems that are based on fixed readers and tagged moving objects as shown in [15] and systems with mobile readers worn by the user. The iGlove and the iBracelet that are presented in [16] are examples for the latter ones. Regardless of which approach is used for activity monitoring in a smart home environment, it is always limited to a certain setting. However, physical activity takes place mainly outside the living environment. Hence monitoring techniques for physical activity should be able to address the demand for mobile operating mode. The use of GPS as a tracking system has the advantage of being relatively cheap while working on a large fraction of the earth's surface. However, the accuracy is not high enough for activity recognition and signals are not available in buildings [17]. GSM can also be used for mobile activity monitoring as shown in [4]. However, the presented approach is very dependent on the number of GSM cells in an area which lead to unsatisfying accuracy results caused by bad network coverage. Body-fixed accelerometers offer an appropriate alternative for the mobile assessment of daily physical activities [18].

In the past many accelerometer based systems for the recognition of human activity have been developed. They differ in the number of acceleration sensors used, the way sensor information is processed and the usage scenario. Some aim to classify activities of elderly people [19], [20] whereas others are used to analyze motion of elite athletes [21]. There are systems to recognize a wide set of daily physical activities such as lying, sitting, standing, walking and running [17]-[20], [22]-[34] and systems for a fine grained analysis of a certain physical activity, e.g. walking along a corridor, upstairs or downstairs [36],[37]. All of the cited systems are based on the standard method for classification that can be described as follows:

1. Recording of training data
2. Feature extraction
3. Feature selection (e.g. with the principal component analysis (PCA))
4. Training of the classifier
5. Recording of test data
6. Evaluation of the classifier

Features of the measured acceleration that are used in many cases are

- Arithmetic mean [23], [24]
- Standard deviation [23], [24], [30]
- Signal entropy [24], [30]
- Signal energy [23], [24], [30]
- Correlation between the axis of two or all accelerometers [23], [24]
- Signal magnitude area (SMA) [22], [28]
- Autoregressive coefficients [25], [28]
- Frequency derived features [36]

Most groups used the Weka toolkit or MatLab for their work. These platforms offer the most common classifiers that were employed as listed in the following:

- Decision tree (DT) [22], [23], [36]
- K-Nearest-Neighbor classifier (k-NN) [23], [29], [33]
- Support Vector Machine (SVM) [23], [24], [25], [27], [34]
- Neural network [26], [28], [30]

Most classification methods require a training of the classifier. As shown in [23] the classifier results in a worse accuracy if it was trained with a data set that was not obtained from the user. Of course, the accuracy can be improved by training with a data set from the user but this leads to additional complexity in system use and is not feasible for most potential users. Apart from [22] all projects process the acceleration data on a PC or gaming console. This requires considerable raw data storage effort for the body worn devices or local restriction to the reception of the used radio transmission technique.

All of the systems presented above investigated the use of one or multiple accelerometers attached to a subject's body in a defined sensor orientation. This offers the possibility to use the gravitational acceleration to determine the horizontal angle of certain body parts. For example, an upright chest can be used to classify "sitting" of a non-moving person whereas a horizontal orientated chest indicates "lying". However, in respect of an everyday long time monitoring, it is desirable to bother subjects as little as possible. Systems that require laborious attachment of sensors will hardly be accepted by potential users.

B. Task description

The aim of the presented work was to develop a system that is suitable for pervasive monitoring of physical activity in daily life. The obtained information can be used to a) provide the user a feedback aiming to motivate him to more physical activity if needed and b) to analyze health and activity trends in the long term which is especially interesting in the field of elderly care. To reach these goals it is necessary to develop a system that is capable of an accurate classification and suited for an easy everyday use. This implies a couple of technical demands that must be considered when developing the system architecture. The monitoring device should be of small dimensions and have a rechargeable battery lasting at least one day. In order to keep costs reasonable the device should be implemented with standard components. To be as user-friendly as possible and to avoid bothering the user, the monitoring device should not need to be attached in a certain orientation to any part of the user's body. To achieve a high acceptance it is more desirable to develop a device that can be worn unobtrusively and arbitrary in any pocket of the user's clothing. In respect of an efficient energy and data management we propose that the activity classification should take place on the device itself and not on a PC. Thus the recognition of activities must be done in real time and instead of acceleration raw data only the recognized activity states are saved together with a time information. The aim of the presented work was to distinguish between the activity states "resting", "walking", "running" and "unknown activity" on a microcontroller in real-time with an algorithm that does not need any user specific training. Additionally we wanted the algorithm to be capable of detecting and counting steps.

II. SYSTEM CONCEPT

A. Hardware architecture

The hardware architecture of the device Motionlogger as shown in Fig. 1 is a further development of the layout presented in [38]. The recognition of physical activity bases on the data of a triaxial accelerometer (1). We use the SMB380 from Bosch Sensortec. The sensor is connected to an ATmega 644 where the data processing takes place. The microcontroller is mounted on a NanoLOC AVR module (2) that also comes with a 2.4 GHz radio module, which can be used for data transmission. As for further analysis it is important to assign recognized activity states to a time information we integrated a real time clock (RTC) (3) that has a separate power source lasting for at least 1 year to prevent the need for a new setting of the clock if the main power source (6) got empty. Hence, after setting the RTC once, the microcontroller can request a correct time whenever needed. The microcontroller can store activity states together with a unix time stamp either on a micro SD card (4) or a Flash EEPROM (5). As we save data as txt-file on the micro SD card, it can be read out by any computer. All ICs are supplied with power by a rechargeable battery (6). Finally an iPod connector (7) is used as interface for data transfer, to recharge the battery and to program the microcontroller. The assembled Motionlogger is shown in Fig. 2.

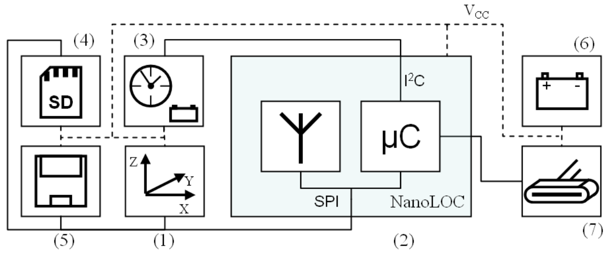

Figure 1. Hardware architecture of the Motionlogger.

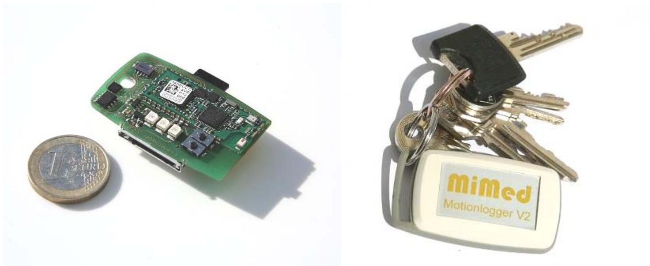

Figure 2. The Motionlogger.

B. Acceleration data

As it is our goal to classify physical activity independently of the orientation of the Motionlogger relative to the user's body, we calculate the resulting vector $\left|\vec{a}(t)\right|$ from the X-, Y- and Z-axis acceleration values:

$$\left|\vec{a}(t)\right| = \sqrt{a(t)_X^2 + a(t)_Y^2 + a(t)_Z^2} \tag{1}$$

In rest position $\left|\vec{a}(t)\right|$ always equals the gravitational acceleration. If a person is wearing the Motionlogger in his pocket, walking results in acceleration patterns as shown in Fig. 3. In contrast to most previous approaches this pattern is not influenced by the orientation of the measuring device. The sensor has a second order analogue filter that defines the maximum bandwidth to 1.5 kHz. In order to reduce signal noise a digital filter (moving average) can be activated for further reduction of the bandwidth. We selected a bandwidth of 50 Hz and set the sensor range to +/- 8g.

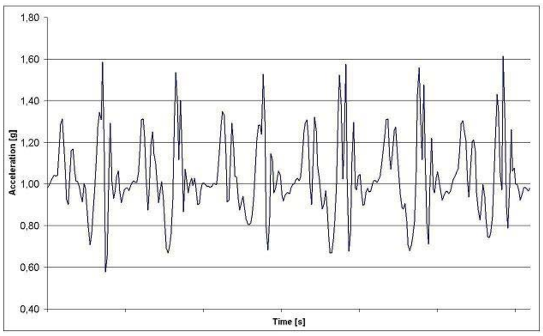

Figure 3. Resulting acceleration pattern for walking. (Independent of the Motionlogger's orientation)

C. New approach for activity classification

Acceleration patterns like the one shown in Fig. 3 slightly differ for different individuals who are performing the same activity. However, as walking is a cyclic motion sequence the performed movements of one individual and thus the individual acceleration patterns start to repeat after one double step (= two steps). Even if a person has a hobble in his gait the periodic repetition of a certain motion sequence can be detected. The same rule applies for running. Walking and running only differ in the frequency of the periodic repetitions. If a person wears the Motionlogger in a pocket of his trousers the measured acceleration pattern shows asymmetry if a "left foot step" is compared to a "right foot step". But after two steps (= double step) the pattern repeats. By analyzing whether and when a certain acceleration pattern repeats (see Fig. 4) it can be detected whether the subject is performing a cyclic motion sequence. To do so, the first values of the sampled data are used as reference pattern Y that is compared to the rest of the sampled data X. The first consistency of the reference pattern with a later acceleration geometry corresponds to the duration of one double step t_{DS}. To recognize whether the cyclic motion is "walking" or "running", the duration between the similar patterns has to be analyzed. To perform continuous activity recognition in real time the proposed classification method must operate in certain time slots. Every time slot starts with the sampling of acceleration data and ends with the analysis of the buffered data as shown in Fig. 5. For every time slot its own individual reference pattern Y is used. It is obtained from the first 50 acceleration values of the sampled data. During the analysis no further data is sampled. The output at the end of the analyzing window is the recognized activity state for one time slot (sampling + analyzing), which has a duration of 5.7 seconds.

D. Implementation of the classification

This section describes the implementation of the data processing and activity classification as illustrated in Fig. 6. First it is checked whether the difference between the maximum acceleration value of the sampled data a_{max} and the minimum acceleration value a_{min} is higher than a defined threshold a_{thres}. If not, the activity state is classified as "resting".

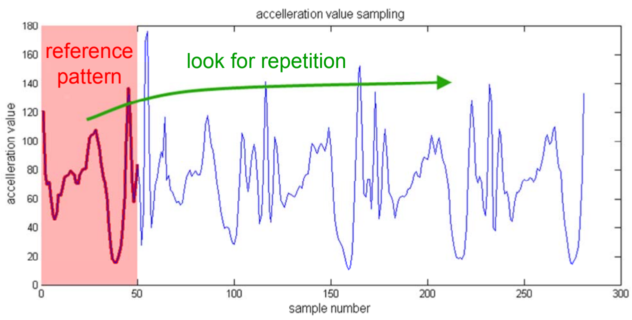

Figure 4. Approach: Looking for repetition of the reference pattern.

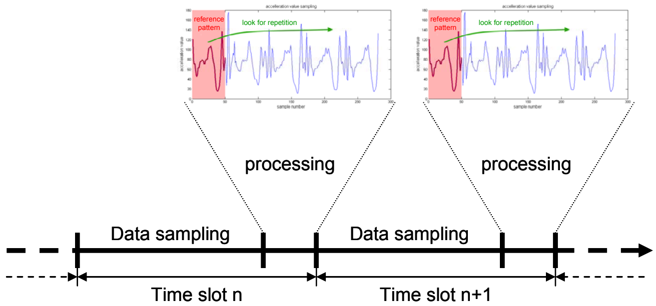

Figure 5 Sequential data sampling and processing in time slots

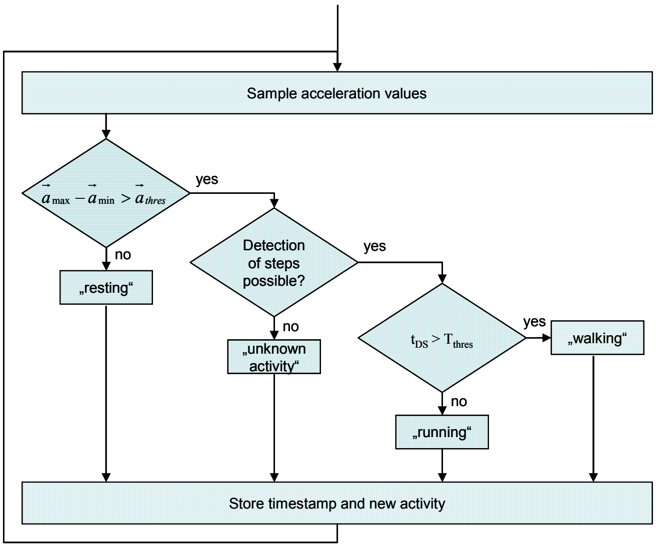

Figure 6. Flow chart of the data processing

If

$$\vec{a}_{max} - \vec{a}_{min} > \vec{a}_{thres} \quad (2)$$

is true, the data is processed further and analyzed for a repetition of the reference pattern in that sample. In order to detect steps the sample is not only analyzed for one but for multiple repetitions of the reference pattern. If there are multiple repetitions in similar time distances of t_{DS}, it is assumed that the activity state is either "walking" or "running". Otherwise the activity is classified as "unknown activity". To distinguish between "walking" and "running", t_{DS} is compared to threshold value T_{thres}. If

$$t_{DS} > T_{thres} \quad (3)$$

is true, the activity is classified as "walking", else as "running".

E. Detection of steps

As described above the acceleration data are analyzed for a regular repetition of the reference pattern in order to detect double steps and their duration t_{DS}. This is done by using the normalized cross correlation function $NCCF_{X,Y}(u)$, which is a measure for the similarity of two patterns. It returns a value between -1 and 1 whereas the latter one implies that the compared patterns X and Y are congruent. The NCCF is often used for image-processing applications and defined as

$$NCCF_{X,Y}(u) = \frac{\sum_{t \in D_X} ((Y(t) - \overline{Y}) \cdot (X(t+u) - \overline{X_{D_X}}))}{\sqrt{\sum_{t \in D_X} (Y(t) - \overline{Y})^2 \cdot \sum_{t \in D_X} (X(t) - \overline{X_{D_X}})^2}} \quad (4)$$

Fig. 7 shows the graph of 285 sampled acceleration values. The first 50 values serve as reference pattern Y. The results from the NCCF are printed in the graph underneath. It shows a first local maximum after 60 samples which corresponds to the first detected double step. In the upper graph it can be seen that the reference pattern Y fits the acceleration pattern X quite well. The same appears after 121 and 179 samples. It can be seen that the distance between the local maxima of the NCCF und thus the duration for a double step t_{DS} are very constant for normal walking.

To recognize double steps the algorithm searches for maxima of the NCCF > 0.6. After the first repetition of the reference pattern (double step) is detected it is checked whether there are further repetitions in areas of multiple distances of t_{DS} (see Fig. 8). If there are further maxima > 0.6 within these regions the activity is classified as “walking” or “running”, depending on the value of t_{DS}.

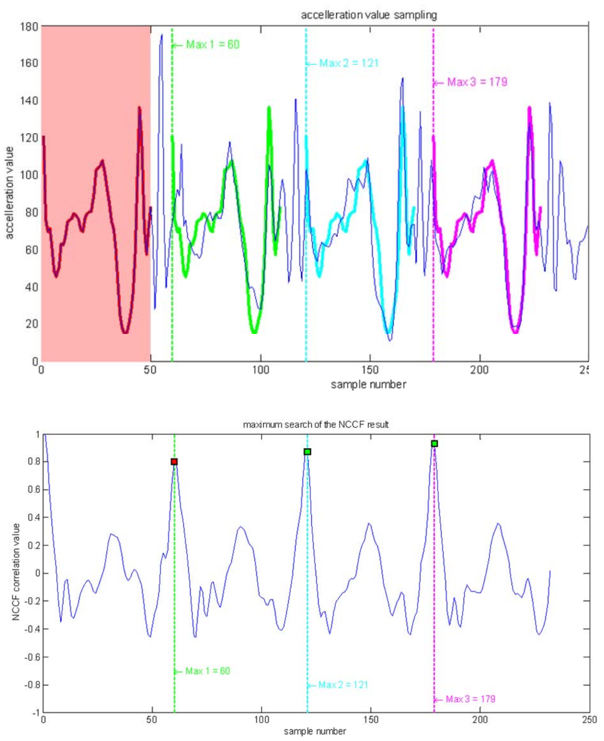

Figure 7. Local maxima of the NCCF (downer graph) mark the repetition of the reference pattern in the upper graph.

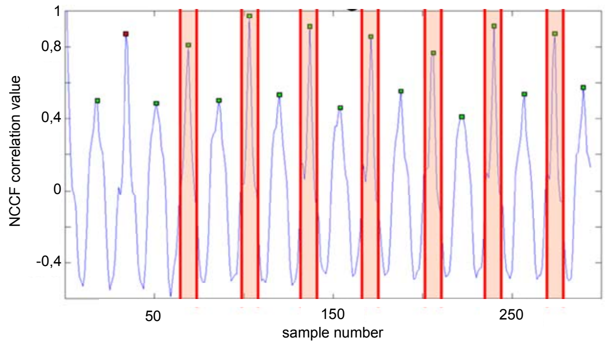

Figure 8. Searching the NCCF output for periodic maxima. The distance between the marked areas of interest is t_{DS}.

III. System Evaluation

A. Experimental Setup

To evaluate the accuracy of the developed activity monitoring system we conducted an experiment with 10 subjects (3 females and 7 males). The oldest subject was 55 and the youngest 22 years old (average: 25 years). Shoes varied from sneakers to sandals with high heels. One of the subjects had a hobble in gait because he was wearing an orthosis due to an Achilles' tendon tear. Each of the subjects had to perform the activity states “walking”, “running” (not the subject with the high heels sandals) on varying ground (outside) and “resting” (sitting or standing) for at least two minutes. Additionally the subjects had to perform an undefined activity (moving but not “walking” or “running”), which in most cases was fulfilled by playing with a Wii gaming console. During the Experiment the subjects wore a Motionlogger with the described classification algorithm in a pocket of their trousers and were filmed for a later analysis of the classification results.

B. Experimental Results

Altogether we obtained more than 50 minutes of recorded activities consisting of 527 classified time slots. Each classified time slot was compared to the activity state shown on the recorded video. The activity state “walking” was detected highly reliable with 100% true positives. The activity state “running” only showed 88% true positives. All results of the evaluation are shown in the confusion matrix in Table 1. The resulting sensitivity and specificity of the algorithm are shown in Table 2.

TABLE I. CONFUSION MATRIX

		activity			
		walking	**running**	**unknown**	**resting**
classified as	**walking**	1,000	0,011	0,028	0,000
	running	0,000	0,872	0,018	0,000
	unknown	0,000	0,117	0,890	0,077
	resting	0,000	0,000	0,064	0,923

TABLE II. ACCURACY OF ACTIVITY CLASSIFICATION

	sensitivity	specificity
walking	1,000	0,987
running	0,872	0,995
unknown activity	0,890	0,947
resting	0,923	0,981

IV. CONCLUSION

In this article we presented a new algorithm for the classification of physical activity in real time based on the data of a triaxial acceleration sensor. The algorithm does not need any training and recognizes the activity states "resting", "walking", "running" and "unknown activity" independently of the sensor's orientation on the human body. If the recognized activity state is "walking" or "running" the number of performed steps is counted. The algorithm was implemented to run on an ATmega 644 microcontroller. For evaluation we used the device Motionlogger. Ten subjects wore the device arbitrary in a pocket of their trousers and performed the above mentioned activities. Altogether more than 50 minutes of activity data were recorded during the experiment. The approach achieved the sensitivity 1 and specificity 0.99 for the activity "walking".

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Within the research consortium of the Bavarian Research Foundation (BFS) „Fit4Age“ a team of scientists and engineers affiliated to 13 departments of the Bavarian universities Erlangen-Nürnberg, München, Regensburg and Würzburg works together with 25 industrial partners on the development of products and services for the aging society.

The scope of the research consortium is to develop technology based solutions which will help elderly people in their future living environment comprising home and workplace as well as in communication and transportation. Eventually not only elderly people but also all social groups should profit from these solutions.

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