BodyANT: Miniature wireless sensors for naturalistic monitoring of daily activity

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ABSTRACT

In this paper we present a novel wireless sensor node design, called BodyANT. BodyANT has a miniature outline of 20x10x3mm and reaches almost 5 days of battery operation when continuously transmitting acceleration data at 32 Hz. We evaluate the performance of BodyANT in an extensive set of laboratory and naturalistic experiments over multiple days. Our sensor node implementation showed robust performance for up to eight simultaneously operating nodes. We deployed three BodyANT nodes in a study of daily activities in combination with two further devices, a heart rate monitor, and a GPS receiver and analysed the network performance over multiple recording days. The data loss per sensor node in the experiment was 3.3% on average. We present and discuss detailed results on data losses per user activity.

Our results demonstrate the feasibility of using BodyANT for long-term activity monitoring and recognition applications.

1. INTRODUCTION

Body-worn sensors are a primary source of information for health and well-being coaching and personalized services. While these services essentially benefit from continuous wearer state and fine-grained activity information, unobtrusive monitoring during everyday life remains a challenging task. In daily routine, most activities are too complex and variable to be captured by one sensor alone. Instead, a complementing network of several distributed nodes is needed to monitor activities. However, these body sensor networks (BSNs) become more complex and cumbersome compared to a single sensor, even when the network relies on wireless communication links.

For successful BSN deployment, nodes must comply with a number of requirements regarding day-long use in natural environments. Most critical technical challenges are related to sensor size, weight, cost, wireless operation, and runtime between recharges. Moreover, for a wireless BSN, the entire network must operate robustly, even in potentially harsh situations, such as during physical activity, interfering radios, and obstruction by body parts. While a spectrum of sensor node implementations have been proposed (see our discussion of related approaches in Section 2), the challenges for on-body use of sensor networks persist. Continued sensor node developments are needed that address BSN validation in naturalistic monitoring scenarios. For monitoring of daily activities using BSNs, it is essential to confirm a robust wireless data transmission performance. Particular routines, such as working in an office may involve sitting body postures, activities close to furniture with metal parts, and other radio services that all interfere with the BSN data transmission. Similarly challenging conditions exist, e.g. for traveling in trains, and outdoor activities. Nevertheless, transmission performance has not been widely analyzed in frequently observed activities and contexts during daily routine.

In this paper we present a new wireless sensor node design, called BodyANT. With a miniaturized node outline and a size-matched coin cell battery, we optimized the BodyANT system for on-body use in day-long monitoring applications. The device achieves a runtime of several days while continuously transmitting sensor data within a BSN. While these properties are excellent among on-body solutions, our BodyANT design builds on standard off-the-shelf components and inexpensive production techniques.

1.1 Paper contributions

The focus of this work is to introduce BodyANT and demonstrate its applicability for monitoring of daily activities. We confirm applicability by presenting results from different laboratory experiments and from our monitoring study of totally 81 hours during seven days. In particular, the paper provides the following contributions:

1. Our BodyANT sensor node design is presented, which can be integrated with many different sensing modalities. The system consists of sensors, a controller to capture and process sensor data, and a wireless transceiver based on the ANT protocol. The implementation considered in this work incorporates a 3-axis acceleration and temperature sensor in a BodyANT node outline of 20x10x3mm.

2. We analyzed the sensor node performance regarding network scalability, runtime between recharges, and

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data reception rates in separate laboratory and daily activity monitoring experiments. Our evaluation showed that a network of multiple nodes can perform continuous sampling and robust wireless transmission at 32 Hz for up to ten days from 230 mAh coin cell batteries, when used for 12 hours each day.

3. We demonstrate the BodyANT network operation under naturalistic everyday life conditions of different wearers and typical node placement on the body. In this study, we included our BodyANT sensor nodes (at wrist, leg thigh, chest), a heart rate monitor (at chest), and a GPS sensor (at upper arm). We evaluated wireless transmission and recognition performance in frequently observed activities, body postures, and contexts.

In Section 2 we summarize different approaches and applications in BSN node design and highlight their performance. Moreover, we review previous works that addressed daily activity monitoring using on-body sensor data. The BodyANT design is presented in Section 3, and our laboratory performance evaluation in Section 4. Subsequently, Section 5 presents evaluation and results of our daily activity monitoring and performance evaluation.

2. RELATED WORK

Unobtrusive on-body monitoring requires a lightweight, miniature battery comparable to the dimensions of state-of-the-art BSN node designs. To this end, coin cell batteries have a most suitable form factor, while setting constraints regarding the energy to operate low-power wireless sensor nodes. Platform metrics of sensor nodes include also size and weight, battery runtime between recharges, processing capabilities, number and type of sensor modalities, as well as RF communication characteristics [5]. Sensing modalities are related to specific on-body monitoring applications and include e.g. environmental conditions such as air pressure and temperature, or physiological processes such as heart rate and body motion. Among others, body motion was shown to be a vital source of information to recognize daily activities [3, 9].

Different wireless sensor node designs for on-body monitoring have been proposed in the literature. Due to the large space of platform characteristics and possible sensing scenarios a comprehensive comparison of existing node designs is challenging. For this reason, we included in the review existing wirelessly transmitting sensor node designs that have been demonstrated for on-body monitoring in naturalistic environments, in particular for body motion.

2.1 On-body wireless node designs

A miniature wireless sensor node should be as small and lightweight as possible to not interfere with a wearer's daily activities. To compare different node designs we consider the node outline including the antenna dimensions. Wireless nodes using RF protocols operating in the 315-916 MHz ISM band require large centimeter-long antennas, compared to the sensor node PCB. Examples of these ISM band developments include uParts [4] and Mica2Dot [5]. Large antennas constrain node usage in naturalistic environments, especially when worn at limbs. Moreover, these ISM bands require region-specific node implementations to comply with local RF regulations. Wireless nodes which operate in the global 2.4 GHz ISM band facilitate the use of miniature chip antennas, e.g. MITes [20] and BSN nodes [12].

Depending on the application focus different mechanical sensor node designs have been proposed in the literature. BSN nodes [12] and Mica2Dot nodes adopted a connector board-based design where different sensor boards can be stacked on the node, e.g. a 3-axis accelerometer board. This allows a flexible design at the expense of size and mechanical robustness due to board interconnects. Eco nodes [16] are most similar to our design in size (12x12x5mm) and weight (2 g), and allow to connect other sensors via an expansion port. Wireless accelerometer MITes [21] are part of the MITes platform [20], a set of different wireless sensor nodes used for naturalistic data collection in homes. Wireless accelerometer MITes have a node outline of 30x25x6mm including an additional daughter-board to capture 3-axes acceleration.

Battery life of a wireless sensor node is important when targeting at day-long monitoring of daily activities. The time between battery recharges depends on multiple parameters including, but not limited to, battery capacity, type of RF communication, message rate, number and type of sensor modalities. Using a 560 mAh battery, Eco nodes operated for 7.56 h and Mica2Dot nodes for 3.18 h [16]. Power consumption of both platforms does not permit continuous day-long operation with size-matched batteries. Wireless accelerometer MITes have been shown to operate for 20.5 h on a 230 mAh battery at 200 Hz sampling rate [21].

uParts [4] were designed for large scale use. The platform employs low-end components including a PIC12F675 microcontroller, transmitter, and binary output ball switch sensor. In combination with a duty cycling of 36 s it allows for coarse-grained activity sampling.

Applications of these wireless on-body nodes include physiological monitoring (BSN node) [12], recognition of different gym activities (MITes) [19] and activities in a home setting (MITes) [10], infant monitoring (Eco) [16], interactive dance performance (Eco) [14], and human behavior monitoring in a conference environment (uParts) [4].

Few wireless sensor devices using the ANT communication protocol were previously documented in scientific literature. Most notably, a bioimpedance and ECG device was introduced [18, 22] and a posture measurement system for patients recovering from hip surgery was proposed [11]. Nevertheless, a spectrum of commercial devices exists[a].

2.2 Activity monitoring using on-body nodes

In previous works on daily activity monitoring data was often acquired using data logging or other wire-bound devices, e.g. [3,6,9]. Wire-bound devices are not affected by data loss in the wireless transmission channel, but require additional procedures to synchronize data streams recorded with multiple logging devices. In contrast to these data loggers, the

[a]See: http://www.thisisant.com/pages/ant/interoperability-matrix

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use of wireless nodes allows for continuous multi-modal information fusion from sensors located at different parts of the body.

Huynh et al. [9] used a stacked data logging device to record daily routines. The wearer was required to upload the recorded activity data every 4 h due to the limited memory capacity of the logging device. Bao et al. [3] used data logging devices that required four AAA-sized batteries, rendering the device rather obtrusive for long-term recording. Intille et al. [20] used wireless accelerometer MITes in the semi-naturalistic home environment of the PlaceLab. In [20], wireless characteristics of the MITes were evaluated regarding transmission range and robustness to environmental noise. However, no evaluation of wireless transmission performance was reported when attached to the human body.

The influence of positioning wireless nodes at different body parts during static sitting and standing postures in indoor environments was found to marginally influence the message reception rate [13]. Combinations of multi-modal wireless sensor nodes, e.g. accelerometer and wireless heart rate monitor, were used for recognizing activities in semi-naturalistic environments [10] and for gym exercises [19]. Activity-specific data transmission performance of wireless on-body nodes in naturalistic environments was not specifically analyzed in these works.

3. SYSTEM DESIGN

BodyANT is a new wireless sensor node design based on standard off-the-shelf components and the ANT communication protocol. While using standard components our design goal was to minimize form factor and node energy requirements to use BodyANTs during day-long monitoring of everyday activities. The node dimensions are 20x10x3 mm with a weight of 1 g without battery. Size and weight allow to unobtrusively wear the node inside a shirt-sleeve or trouser leg. Figure 1 shows a BodyANT node equipped with a 3-axis acceleration sensor.

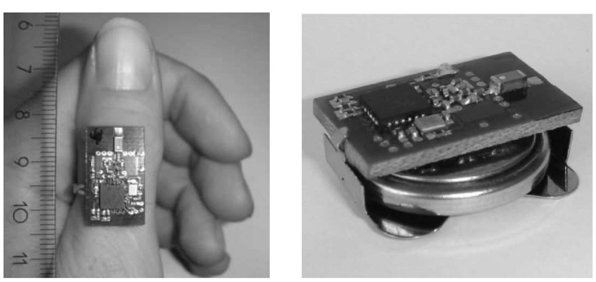

Figure 1: BodyANT node. Left: Node dimensions compared to a thumb. Right: Node attached to a coin cell battery and holder.

BodyANT comprises sensor and host parts. The design is simple, yet flexible as the node's sensor part can be modified to provide different sensors according to application needs, without altering the design concept and host part. Figure 2 illustrates the BodyANT system design.

The host part comprises of a Nordic nRF24AP1 radio transceiver and an Atmel ATmega88V microprocessor. Radio

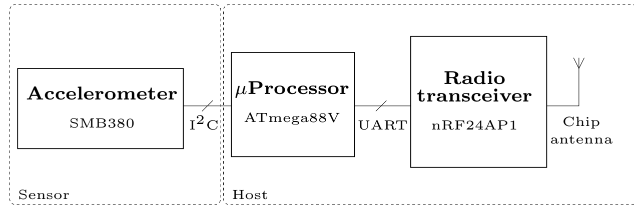

Figure 2: BodyANT node system design: Host and sensor parts communicate via I^2C, microprocessor and transceiver via serial interface.

transceiver and microprocessor communicate via UART. The Nordic radio transceiver is a low-power version that embeds the ANT protocol. ANT is an adaptive TDMA communication protocol, operating in the 2.4 GHz ISM band. It is equipped with mechanisms to minimize message collision and features 1 Mbps RF data rate, 20 kbps true data throughput with up to 125 RF channels. The microprocessor ATmega88V integrates 8 K Bytes Flash program memory, 512 Bytes EEPROM, 1 K Bytes SRAM, programmable USART, SPI, I^2C (TWI), 8-channel (10-bit) ADC, and up to 23 IO ports.

Our BodyANT node implementation consists of a total of 35 standard off-the-shelf components. The BodyANT considered in this work is equipped with a Bosch SMB380 3-axes (10-bit) digital accelerometer with optional temperature output. Acceleration can be measured with a bandwidth of up to 1.5 kHz in ranges of $\pm 2g/\pm 4g/\pm 8g$ corresponding to a resolution of 4.0 mg/7.8 mg/15.6 mg.

With the selected components our design requires no additional voltage regulation. Power supply voltage ranges from 2.4 to 3.6 V. The node switches to power down mode when the battery voltage falls below 2.4 V to ensure controlled system behavior. A stable clock cycle is provided using a 16 MHz crystal as clock source for both the radio transceiver and microprocessor. When active, the microprocessor periodically reads sensor values and sends messages to the radio transceiver according to the ANT message protocol. The transceiver continuously broadcasts the messages at a predefined message rate. If not activated, the microprocessor and radio transceiver are kept in power save mode.

Only few configuration parameters are needed to set up an ANT communication channel, including RF frequency and message period. The broadcast message payload is 64 bits of which 54 bits are used in this implementation: three 10 bit values for 3-axes acceleration readings, 8 bit for temperature, 8 bit for battery voltage, and 8 bit for a sequence counter. Individual nodes can be identified by a protocol-specific channel identifier. To receive data that has been transmitted from BodyANT nodes we used a commercially available ANT-USB dongle. In addition to the default sensor sample transmission mode, our implementation includes a wireless programming mode to change system parameters, such as the message rate, during runtime.

4. LABORATORY SYSTEM EVALUATION

Wireless nodes for monitoring daily activities require day-long battery life and sufficient system scalability to use mul-

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tiple wireless nodes simultaneously. To evaluate the performance of BodyANT regarding these two criteria, we conducted two dedicated laboratory experiments. Wireless transmission performance was measured by data loss rate r_d. We defined the data loss rate as one minus the ratio of samples received N within time period ΔT at sampling rate f_s:

$$r_d = 1 - \frac{N}{f_s \cdot \Delta T} \quad (1)$$

The BodyANT node configuration parameters used in the experiments are: system clock f_{CPU}=2 MHz, system sampling rate f_s=16 Hz, and a battery of 230 mAh (VARTA CR2032). ANT protocol-specific configuration parameters were set to: message rate f_{msg}=32 Hz, transmit power level P_{Tx}=0 dBm, bidirectional transmit channel type, broadcast data type, and default public network.

We used a sampling rate of 16 Hz to capture daily activity dynamics of postures and movements. In addition, each node transmits sensor readings twice to increase robustness against occasional loss of single messages. We used ANT bidirectional transmit channels to exploit the protocol's message collision avoidance capabilities. A simple unidirectional TDMA communication protocol would assign fixed time slots to each transmitter and could cause considerable data loss due to interference of simultaneously transmitting nodes. Interference can occur periodically as a result of individual transceiver clock drift. This requires additional synchronization and collision detection capabilities in order to minimize data loss.

As our goal is to maximize battery life the ANT broadcast data type is used which consumes the least amount of RF bandwidth and power. The experiments were conducted in the same laboratory premises where BodyANT nodes were placed on a wooden surface in the receiver's line-of-sight (LOS). The nodes were equally spaced and oriented in a row. To receive transmitted messages from the nodes an ANT-USB receiver was attached via USB to a notebook. Messages were recorded using the Context Recognition Network Toolbox [2] running on a notebook. Data loss rate was computed from the recorded data.

4.1 System scalability

Typically multiple sensor nodes are used in parallel to monitor human activities. Maximum number of simultaneously operating nodes depends on the RF protocol bandwidth and node message rate. We evaluated message and data loss rate for our design by operating two to eight BodyANT nodes simultaneously. The receiver's LOS distance was 1.80 m which corresponds to the human body height. Messages were recorded for 1 h for each set of N nodes (2≤N≤8).

Figure 3 illustrates the mean data loss rate. The mean data loss rate was less than 0.06%, while simultaneously operating two to eight nodes. This indicates a robust operation of our node design. The number of simultaneously operating nodes could be even increased if each node is assigned a dedicated RF frequency (as it has been done, e.g. for accelerometer MITes [20]). However, the receiver must be configured with a list of transmitter RF frequencies beforehand, which significantly constrains flexibility for BSN deployment.

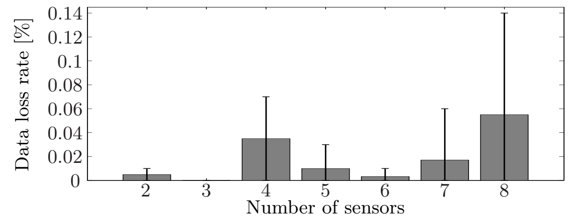

Figure 3: Data loss rate for simultaneous operation of two to eight BodyANT nodes. Min-max values show node-specific variations.

4.2 Battery life

The battery runtime between recharges is crucial as we aim at monitoring of daily activities over periods of days. Node shutdowns due to insufficient battery life results in loss of potentially vital episodes of daily activities.

We define battery life of a single node as the time between the transmission of the first and last message before the node switches to power save mode. We evaluated BodyANT battery life by operating three nodes simultaneously. In this evaluation we included power consumption contribution of the ANT protocol build-in message collision avoidance mechanism.

BodyANT node battery life was measured to be 116±3 h during which 12.7±0.8 million messages were transmitted. We attribute the variances to dynamics in the medium and transmission protocol as well as electrical variations in the node transmission hardware as the nodes were populated and assembled by hand.

Switching to Tx-only channel type further increased the battery life by a factor of two. However, when using multiple nodes simultaneously message collision cannot be handled automatically, e.g. when transmitting on the same RF frequency. This may lead to data losses of up to several minutes if nodes start transmitting at the same time.

Compared to existing wireless node implementations, our design further extends battery runtime performance. uParts were reported to operate for weeks on a 130 mAh battery at a message interval of 36 s using Tx-only transmission mode [4]. However, uPart node's ball switch sensor allows for coarse-grained daily activity sampling only. In addition, very long message intervals significantly increase battery efficiency [15]. This benefit was not exploited for BodyANTs in this investigation, however, it may further extend battery runtime.

5. DAILY ACTIVITY MONITORING

We evaluated the performance of BodyANT for daily activity monitoring in a naturalistic monitoring study of seven days. We summarize here first quantitative results for transmission performances during daily routines based on the acquired experimental data.

5.1 Activity recording setup

We selected a body-worn recording system consisting of three BodyANT nodes, a heart rate monitor chest-belt (HRM), and GPS device. The latter two are commercially available

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from Suunto[b]. A Q-Belt Integrated Computer (QBIC) from ETH Zurich [1] was used to record data from all sensors. The data was wirelessly transmitted to the QBIC system using the ANT protocol, and a single-hop star network topology. Two ANT-USB receivers were attached to either side of the QBIC belt. The data recording and alignment on QBIC was performed using the Context Recognition Network Toolbox [2]. In addition to the sensor readings, reception timestamps and message sequence counters were transmitted to ensure data stream alignment. Figure 4 shows the entire on-body sensor system.

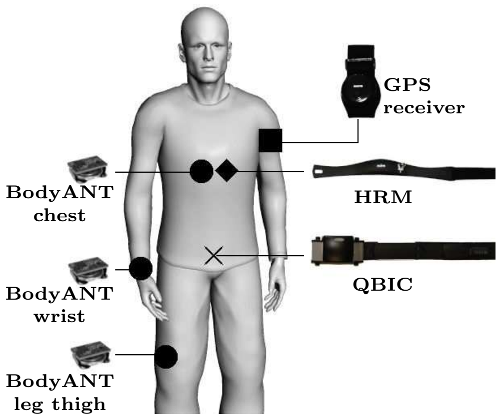

Figure 4: Wearable system used for recording daily activity. The QBIC belt computer served for acquiring, time-stamping, and storing sensor network data.

We adopted the same parameters for the BodyANT configuration as in the laboratory experiments, detailed in Section 4. As the majority of motion patterns in daily life are symmetric only the dominant body side was equipped with BodyANTs. BodyANTs where attached at dominant wrist, dominant leg thigh, and at HRM (chest position) to record arm, leg, and upper body motion, respectively. Similar sensor positioning has been frequently used for motion and activity monitoring, e.g. in [8]. The HRM provided heart period data (RR intervals) by measuring time duration between consecutive QRS complexes. The GPS device provided speed and distance by evaluating the GPS satellite signal. The heart period and GPS messages were transmitted at 5 Hz.

Two ANT receivers were used in this setup to split the traffic among the nodes. While this has been an initial precaution to avoid system failures, we observed during the experiments that the components work very robustly and are not restricted to this configuration.

5.2 Recording procedure

The sensor system was worn by two male users (aged between 25 and 33 years) during several days for at least 12 hours each day. Daily routine during the study included various activities. Most time was spent on office work (2389 min), attending meetings and lectures (220 min), transitions between office and home (738 min), as well as eating (329 min) and personal hygiene (33 min). The system was attached in the morning after getting up and continued to be worn until late in the evening.

The users maintained a manual log of daily activities. They were asked to specifically note activities that extended for several minutes or longer, as well as to specify transition and locomotion activities. In total we acquired 81 hours of sensor data during seven days from both users. In a post-recording step the data was inspected and manual user annotations were added to the dataset.

5.3 Total network transmission performance

The total data loss of the wireless sensor system in our recordings was 3.3%, i.e. within a period of 10 s only five of 160 transmitted samples were not received (cf. Eq. (1) in Section 4). Figure 5 shows the sensor node-specific total data loss rate in different loss duration intervals. The intervals denote the time during which no data was received.

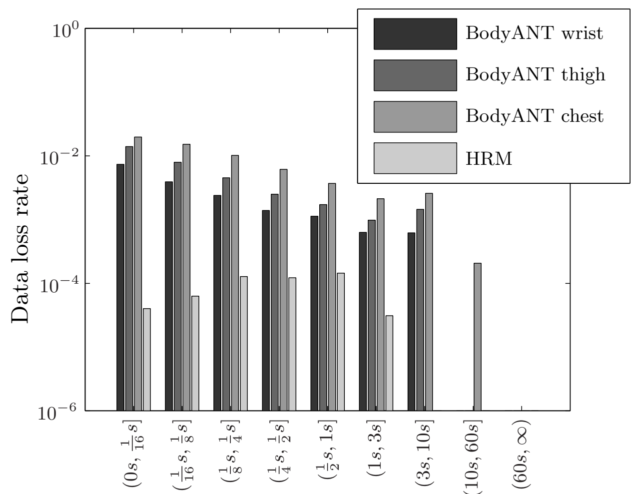

Figure 5: Sensor data loss rate in the daily activity study in different loss duration intervals $(a, b]$.

These results confirm a robust operation of our BSN. Although the network was exposed to very dynamic conditions in this experiment, none of the nodes failed completely. Table 1 shows the total data losses for individual users and sensor nodes.

Table 1: Sensor data loss rates for individual users and sensor nodes in our daily activity monitoring study, (BA=BodyANT).

User	**BA wrist**	**BA leg thigh**	**BA chest**	**HRM**	**Time in dataset**
Data rate	16 Hz	16 Hz	16 Hz	∼1 Hz	
User 1	3.7%	6.4%	14.2%	0.0%	40 h
User 2	0.5%	1.4%	0.5%	0.1%	41 h
Total	2.0%	3.9%	7.2%	0.1%	80 h

Data losses for the HRM sensor were lower than losses of BodyANTs because this device transmitted heart period data of ∼1 Hz at a message rate of 5 Hz. In comparison, BodyANTs had a data sampling rate of 16 Hz at a message

[b]See: http://www.suunto.com

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rate of 32 Hz. We observed a difference in data losses between the users, in particular for the chest-worn BodyANT sensor node. As user 1 and user 2 wore the same BodyANT node devices, we assume that user 1 exhibited different skin tissue properties, which may have perturbed RF propagation characteristics, in particular at the trunk. Similar issues had been reported before [17].

We analyzed the data loss for all nodes in the network, except the GPS device. Our recordings included long periods of indoor activities where no satellite signal was available. As the device detected such situations and would turn off during these phases, it did not transmit samples that could be analyzed and counted.

5.4 Activity recognition analysis

We applied a continuous activity recognition for each sensor data stream to derive basic activity, user state, and physiological information. This recognition was subsequently used to analyze the transmission performance during different activities in Section 5.5.

For all BodyANT sensor nodes, we trained feature models from mean and variance of each acceleration sensor axis. These feature models were obtained using a separate training dataset that was not part of the study set. The feature models were subsequently used to recognize activities in the study set. The training set was recorded from one user only and had a duration of 10 minutes. We annotated all activities in this set that were used for training the recognizer. Continuous recognition was performed by applying a nearest center classifier on sliding windows of 3 s and step-size of 0.5 s. On this result a majority vote of 3 s windows was applied to obtain a final result.

At the wrist sensor five arm postures, which are typical in daily activities, were investigated: adducted-normal, adducted-pronation, adducted-supination, elevated over head, and extended. All adducted postures were performed with an elbow flexion of 90°. At the leg thigh, we recognized four activity classes: sitting, walking, standing, and bicycling. Finally, for the chest-worn sensor we considered: walking, bend forward, lean back, and upright. For our training dataset we obtained recall and precision rates of above 90% for all recognizers and classes, confirming that the activities could be discriminated. We performed an evaluation on the unseen study dataset for the leg-based activities only, since it was not feasible to annotate all other categories in the large data set. The leg-based recognizer achieved a good recognition performance for all categories (R=Recall, P=Precision), with sitting: R=98%, P=99%, walking: R=90%, P=98%, standing: R=73%, P=97%, and bicycling: R=87%, P=93%.

Using the HRM data, we distinguished three heart rate levels with fixed thresholds to estimate physiological state as low ($<$ 70 bpm), normal (70 bpm $<$ x $<$90 bpm), and high ($>$ 90 bpm). A threshold was applied on GPS speed data to identify outdoor transitions, such as walking, riding bicycle and using public transport from indoor and stationary activities. For both HRM and GPS recognizers, we selected a sliding window size of 6 s. Subsequently, we utilized the recognized activities to analyze the BSN transmission performance.

5.5 Activity-specific transmission analysis

We further investigated the data losses in more detail to determine impact of individual activities and to derive first quantitative results for activities frequently observed in daily routine. For this analysis we considered both, our manual annotation of activities and the continuous activity recognition detailed in Section 5.4 above. This strategy allowed us to robustly analyze high-level daily routines from annotation, such as eating and social interaction. As particular low-level activities and states, including activity intensity, upper body postures etc., were not systematically reported by the users, no annotation was available in our study dataset. Consequently, we utilized activity recognition results for the loss analysis of these activities. Our good recognition results for selected low-level activities presented in Section 5.4, confirm that this strategy is a feasible approach.

Table 2 shows data loss rate comparisons between annotation and recognition for individual activities. For this category of activities, annotations were made by the users and refined after the recording. Nevertheless, these annotations were still not precise, e.g. short periods of walking may have been omitted. Hence, the recognition provides additional insight in the data loss distribution. Our results show that annotation and recognition are in good agreement.

Table 3 presents our transmission performance summary for recognized upper body and arm postures, physiological state (heart rate level), activity dynamics (rhythmic movement vs. sedentary), and GPS-based activity (stationary vs. moving).

These results were obtained by recognizing states and activities from the BSN data. Our analysis showed that transmission losses were depending on activity dynamics, especially for the chest-worn BodyANT node. While this node position worked well for sedentary activities and different torso postures, it incurred elevated losses for physical activities. We observed that physical activity seems more critical regarding data losses than a particular posture. Loss rates of the HRM and BodyANT nodes at wrist and leg thigh showed only minor variations across different activities. We surmised that the relative orientation of the sensor node to the receiver contributed to this observation. However, it should be noted that loss rates with respect to activity categories primarily serve as an indicator of the influence caused by different postures and activities. The data loss results in

Table 2: Comparison of annotation-based (A) and recognition-based (R) data loss rate w.r.t. activity duration, (BA=BodyANT).

Activity	A/R	BA wrist	BA leg thigh	BA chest	HRM	Time in dataset
Sitting	A	1.9%	3.5%	6.2%	0.0%	3413 min
	R	2.5%	3.1%	4.6%	0.1%	3414 min
Walking	A	2.0%	3.0%	6.8%	0.1%	377 min
	R	0.8%	4.7%	14.3%	0.0%	713 min
Standing	A	2.3%	4.5%	9.3%	0.1%	921 min
	R	1.2%	6.7%	13.6%	0.0%	686 min
Bicycle	A	0.1%	0.7%	0.8%	0.0%	23 min
	R	1.0%	8.1%	6.2%	0.2%	56 min

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Table 3: **Recognition-based sensor data loss rate in the daily activity monitoring experiment w.r.t. activity duration, (BA=BodyANT).**

Category	BA wrist	BA leg thigh	BA chest	HRM	Time in dataset
Heart rate state*					
Low	2.0%	2.7%	3.0%	0.1%	2973 min
Medium	2.4%	6.1%	13.9%	0.0%	1698 min
High	0.4%	3.7%	12.6%	0.0%	235 min
Activity dynamics					
Movements	0.9%	4.7%	12.8%	0.0%	900 min
Sedentary	2.3%	3.7%	6.0%	0.1%	3978 min
GPS-based activity					
Stationary	2.3%	4.3%	8.3%	0.0%	3712 min
Moving	1.1%	2.4%	3.6%	0.2%	1132 min
Torso posture					
Walking	0.7%	4.1%	11.3%	0.0%	874 min
Bend forward	2.8%	4.0%	6.9%	0.1%	2734 min
Lean back	3.9%	5.2%	5.4%	0.0%	130 min
Upright	1.2%	3.4%	5.4%	0.0%	1172 min
Arm posture**					
Adducted, normal	4.6%	4.1%	8.2%	0.1%	914 min
Adducted, pronation	1.6%	3.3%	5.1%	0.1%	2443 min
Adducted, supination	1.5%	4.1%	10.7%	0.1%	218 min
Elevated, above head	1.3%	3.7%	9.6%	0.0%	1011 min
Extended	1.1%	8.1%	11.6%	0.0%	295 min

*) Heart rate states: Low:<70bpm, Medium:70<x<90bpm, High:>90bpm.
**) Arm postures: adducted postures with 90° elbow flexion.

Table 4: Annotation-based data loss rate w.r.t duration of frequent daily activities, (BA=BodyANT).

Activity	BA wrist	BA leg thigh	BA chest	HRM	Time in dataset
Office	1.7%	4.0%	6.9%	0.1%	2389 min
Lecture	3.2%	3.5%	10.9%	0.0%	220 min
Conversation	4.2%	5.7%	14.0%	0.0%	538 min
Eating	1.7%	4.7%	7.0%	0.0%	329 min
Hygiene	2.4%	2.3%	9.4%	0.0%	33 min
Public transport	2.0%	1.9%	3.2%	0.1%	738 min

Table 3 cannot be compared between the different activity categories as these categories are not independent from each other.

Data loss analysis results for daily routines that were annotated by the users are summarized in Table 4. As this summary shows, our network performed very well for all daily routines. However, the chest-worn BodyANT node lost most of the data during conversations. We attributed this loss to motions of the upper body, arm gestures in particular, which may have perturbed the transmission to the receiver, located at the belt. Similar observations had been made earlier [7]. These results confirm our observations made for physical activities in Table 3 before.

Figure 6 shows the data loss rate of the BSN in different loss duration intervals for frequent daily routines. Predominantly, loss durations are shorter than 1 s. The probability of loss durations longer than 0.5 s is below 10^{-2}.

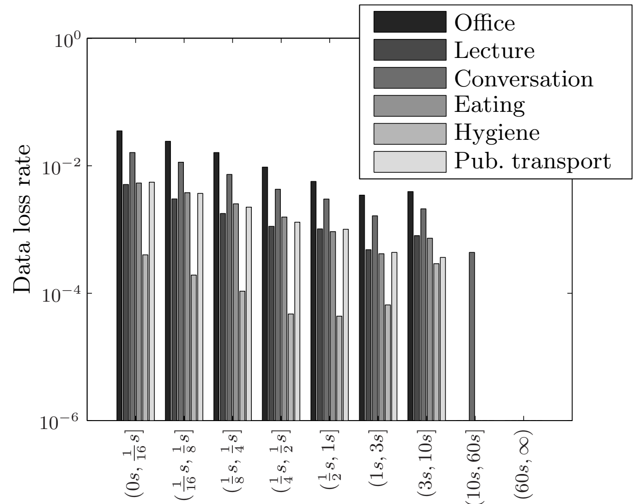

Figure 6: Data loss rate w.r.t. annotated daily activities in different loss duration intervals $(a, b]$.

6. CONCLUSION AND OUTLOOK

In this paper we introduced BodyANT, a novel on-body sensor node design for BSN-based monitoring of daily activities. Our design particularly addressed challenges for on-body use, including a small outline and low weight, as well as minimal energy requirements, while continuously sampling and transmitting sensor data. BodyANTs exhibit excellent properties with respect to these challenges. While our current BodyANT implementation focused on body motion, which provided vital information on daily activities, our design can accommodate various other sensing modalities as well. We analyzed BodyANTs in laboratory experiments and confirmed their applicability for daily activity monitoring. The nodes can continuously transmit at 32 Hz for almost 5 days, or at least 10 days, when used in a typical monitoring task for 12 h each day. Moreover, our design performed well for typical BSN setups of up to eight nodes. In a naturalistic study of daily activities, we evaluated BodyANT nodes in a BSN with two further devices, a HRM to monitor heart activity, and a GPS device to track speed and distance. We collected and annotated an extensive dataset of 81 h.

Overall data loss due to wireless transmissions was 3.3%, indicating an excellent performance of our network. Transmission performance of individual BodyANT nodes depended on node location at the body, but also on performed activities. A quantification of this performance can provide essential information on the feasible BSN configurations. We analyzed node performances for individual activities and daily routines using manual annotations as well as automatic recognition results. Our results show that body movements can alter antenna orientation and consequently perturb transmission of individual nodes, resulting in up to 15% data loss for individual activities.

Activity-specific data loss rates presented in this work had been derived by normalizing lost samples during a specific activity by the total activity duration. If a daily loss rate is considered, these results should be weighted by the contribution of the activity during the entire recording day. As a result, relatively short activities, such as personal hygiene

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have a reduced impact on the loss, whereas the contribution of long-lasting activities, such as office work, become very crucial. Hence, BSN data loss should be analyzed in the considered application scenario to confirm its proper operation. Data loss distributions in our study showed that losses were typically shorter than 10 s. Short-term data interpolation approaches could be applied to compensate such errors.

Given the excellent performance of our BodyANT design, our future work will address feature computation on the nodes and recognition of daily routines using this new sensing platform.

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