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Next Generation Cooperative Wearables: Generalized Activity Assessment Computed Fully Distributed Within a Wireless Body Area Network

MARTIN SEIFFERT[1], (Member, IEEE), FLAVIO HOLSTEIN[2], RAINER SCHLOSSER[3], AND JOCHEN SCHILLER[1], (Member, IEEE)

[1]Department of Mathematics and Computer Science, Freie Universität Berlin, 14195 Berlin, Germany
[2]Department of Computer Science, Technical University of Berlin, 10623 Berlin, Germany
[3]Hasso Plattner Institute, University of Potsdam, 14482 Potsdam, Germany

Corresponding author: Martin Seiffert (seiffert@inf.fu-berlin.de)

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ABSTRACT Currently available wearables are usually based on a single sensor node with integrated capabilities for classifying different activities. The next generation of cooperative wearables could be able to identify not only activities, but also to evaluate them qualitatively using the data of several sensor nodes attached to the body, to provide detailed feedback for the improvement of the execution. Especially within the application domains of sports and health-care, such immediate feedback to the execution of body movements is crucial for (re-)learning and improving motor skills. To enable such systems for a broad range of activities, generalized approaches for human motion assessment within sensor networks are required. In this paper, we present a generalized trainable activity assessment chain (AAC) for the online assessment of periodic human activity within a wireless body area network. AAC evaluates the execution of separate movements of a prior trained activity on a fine-grained quality scale. We connect qualitative assessment with human knowledge by projecting the AAC on the hierarchical decomposition of motion performed by the human body as well as establishing the assessment on a kinematic evaluation of biomechanically distinct motion fragments. We evaluate AAC in a real-world setting and show that AAC successfully delimits the movements of correctly performed activity from faulty executions and provides detailed reasons for the activity assessment.

INDEX TERMS Body sensor networks, distributed computing, motion analysis, physical activity assessment, biomechanics, multilevel systems.

I. INTRODUCTION

Body-worn sensor systems, so-called wearables, in the form of fitness bracelets and smart watches become part of everyday life. These systems already allow to classify various activities of the user (walking, running, swimming, etc.) and determining the intensity of particular activities (e.g., by counting). Most current available systems are based on a single wearable sensor node, e.g., [1]–[3], but wireless systems based on multiple sensor nodes equipped with appropriate wireless communication devices (WBAN) are already emerging, e.g., [4]. Underlying technology is mainly driven by advances in the field of micro-electro-mechanical systems (MEMS) and research in activity recognition (AR) [5]–[8] over the past decades.

Beyond the classification of activities, a WBAN equipped with inertial sensors contains great potential for qualitative activity analysis [9]. Especially the use of multiple nodes attached to the particular limbs of the human body enables the analysis of the human motion in its entirety. While AR investigates "which" activity was performed at a specific point in time and thus groups together different instances of a movement and generalizes them into an activity, activity assessment (AA) investigates "how well" a known specific activity is performed and thus aims at distinguishing the different instances of one particular activity in quality. If the quality of an activity can be determined, a feedback to the quality becomes possible. Feedback relating to the quality of execution of an activity is a very interesting field, especially within the application domains of sports and healthcare. In sports training and physical rehabilitation, feedback regarding wrong body movements is crucial for learning and improvement of motor skills and physical fitness [10]–[12]. In this context, it is advantageous that the feedback is close to the execution of corresponding movements of the activity. Real-time feedback, e.g., in the form of haptic feedback [13], which is made available to the quality of an activity performed by the user, not only allows immediate improvement in performance [14]–[16], but also warning of movements that could possibly lead to injuries [17], [18].

Since parts of an activity to be assessed must first be recognized, research in AA is closely linked to the current research in AR. Bulling *et al.* [6] give a tutorial to the typically used general-purpose framework called activity recognition chain (ARC). The ARC comprises raw data acquisition of multiple sensor nodes, preprocessing of the data to remove noise and interfering artifacts, data segmentation, feature extraction and selection, and finally activity classification and decision fusion. Many of the current AR approaches are focused on improving the basic processes of the ARC. Khan *et al.* [19] investigate optimal sampling rates for accelerometry based AR to reduce system requirements related to energy consumption or memory whilst retaining recognition accuracy. Banos *et al.* [20] investigate signal segmentation and present a study that analyzes the effects of the windowing process on AR system performance. Ghasemzadeh *et al.* [21] present a feature selection approach that considers classification accuracy as well as the energy consumption required for feature computation. Alternatively, Ghasemzadeh *et al.* [22] investigate the energy consumption of the ARC by distributing the classification problem on several weak classifiers with different energy consumption. Thus, the energy consumption of the ARC can be optimized for a desired accuracy by a suitable set of weak classifiers. Saez *et al.* [23] compare various state-of-the-art classification techniques for cross-person activity recognition. For collaborative decision-making based on the data of multiple sensor nodes, data fusion algorithms are of fundamental importance. Gravina *et al.* [5] provides a comprehensive survey on multi-sensor fusion in the area of WBANs. Furthermore, Fortino *et al.* [24] present the open-source signal processing framework SPINE [25] for the rapid prototyping of WBAN applications. The framework supports the basic processes of the ARC at programming level and is specifically designed to support distributed online processing in WBANs.

More complex approaches in AR focus on generic activity recognition and use the concept of hierarchical decomposition of activities in time series sub-patterns. These approaches in general utilize processes of the ARC to classify low-level sub-patterns of activities first, to identify higher-level activities as sequential or concurrent combinations of sub-patterns. These approaches contribute to real-world problems, for example: AR on streaming data to identify activities of interest among other activities [26], [27], recognition of concurrent and interleaved activities [28], [29], training of AR systems based on limited training data [30], or sharing AR systems across platforms [31]. Galzarano *et al.* [32] extend the SPINE framework with a task-oriented paradigm so that distributed and collaborative in-network applications can be programmed as a set of tasks that are to be instantiated on the sensor nodes of the WBAN. Thus, the authors consider the requirements for the realization of more complex activity recognition systems by supporting the modular implementation of higher-level process chains distributed on multiple sensor nodes.

While a lot of work regarding generalized systems for AR already exists, research on generalized AA is very scarce. In our work, we propose a trainable process chain as a generalized concept for the distributed assessment of activities within a WBAN. In this context, it is worthwhile to distinguish between different types of activities in relation to their temporal nature. Bulling *et al.* [6] categorize activities such as *periodic*, *static*, and *sporadic*. Periodic or cyclic activities are characterized by a series of recurring similar movements such as walking, running, rowing, cycling or many other physical rehabilitation exercises. Static activities are characterized by a lack of movement and are mainly determined by the posture of the human body, such as standing, sitting or driving a car while sporadic or non-cyclical activities consist of different types of movements, such as cooking or tidying up. For the qualitative assessment of activities, cyclical activities are of particular interest, since a correct or incorrect execution of the repetitive movement has a cumulative effect on the final result of the activity. Therefore, in this work, we focus on the assessment of cyclic activities. Our main contributions are threefold:

- We summarized the state of the art of AA in WBANs and derive functional and semantic requirements for generalized activity assessment.
- We present the generalized process chain AAC for the detailed assessment of cyclic activity, which is designed to work in a fully distributed fashion within a WBAN and thus enables immediate feedback to particular faults of the execution of an activity.
- We implement AAC and evaluate the applicability and the practical value in a real-world case-study of indoor rowing.

The remainder of this paper is organized as follows. In Section II, we investigate methods of quality quantization used in current work of AA followed by the resulting requirements for our work in Section III. In Section IV and V, we present the multi-layered concept of AAC as well as details of the implementation. We evaluate the AAC in a small case study based on indoor rowing activity in Section VI and present the results in Section VII. In Section VIII, we discuss the results regarding the requirements in Section III as well as open issues. We close with our conclusion in Section IX.

II. RELATED WORK

Velloso *et al.* [33] refer to a general term of quality defined by the International Organization for Standardization (ISO), which define quality "as the degree to which a set of inherent characteristic fulfills requirements" [34]. Furthermore, the authors define a qualitative activity recognition system "as a software artifact that observes the user's execution of an activity and compares it to a specification". Therefore, a reference is necessary that describes the requirements of which the quality is to be measured. While most of the related work follows a similar concept of quality, they can be divided by the way the reference is created and how a deviation from it is measured.

A. MODEL DRIVEN

Most of the existing approaches are driven by expert knowledge of the specific application domain they have been designed for. These model-driven or knowledge-driven approaches are powerful because they rely on a deep understanding of the modeled activity and can benefit from scientifically-based relationships. They start with an abstract model of application dependent knowledge and then implement and apply the model through sensed data. Manually modeling each domain-specific feature based on expert knowledge leads to a semantically clear term of quality in the context of the modeled activity.

Thompson *et al.* [35] present a wireless sensor network, consisting of four sensor nodes, attached to the legs of horses. Acceleration and angular data are streamed via bluetooth to a smart phone in the riders pocket. From these data, they derive measurements of key performance attributes that are of relevance for describing the characteristics of dressage movements. Based on these attributes, the system provides a quality feedback in the form of spider plots for the rider, which is related to international dressage guidelines.

Ladah *et al.* [36] utilize two wrist-worn accelerometers to capture a climber's movements in natural settings. The approach filters out climbing moves from background activity and provides climbing skill assessment by utilizing a domain-specific quality model based on features which are relevant for rock climbing.

The aforementioned approaches have the advantage that, based on the semantic expert knowledge included in the implemented domain-specific assessment model, feedback concerning the assessment of the activity can be easily connected to the knowledge of the application domain. In addition, after implementation, these approaches do not necessarily need an inertial training, neither of correctly nor of incorrectly conducted samples of the activity. Hence, no inertial configuration effort is necessary. However, domain-specific modeling does not generalize well, as the implemented domain-specific logic cannot be easily applied to other application domains.

B. DATA DRIVEN

Enabled by machine learning, data-driven approaches use generalization algorithms to learn a quality model from motion data. Depending on which data is used to learn the quality model, this work can be further distinguished in explicit and implicit machine learning approaches.

1) EXPLICIT MACHINE LEARNING (EML)

EML approaches learn a model for each quality class to be distinguished by using a supervised training of a classifier on appropriately performed activity samples. Thus, AA is translated into a classification task, as is the case with AR. Subsequent new samples of the activity are assigned to one of the previously trained quality classes.

Yurtman and Barshan [37] use the sensor data of five sensor nodes attached to the limbs of the human body to learn a quality model for physical therapy exercises. Within the data, they distinguish between eight exercises and three different quality classes. For classification, they propose a multi-template multi-match dynamic time warping algorithm to detect multiple occurrences of more than one exercise type in the recording of a physical therapy session. Velloso *et al.* [33] extract statistical features from the inertial data of four sensor nodes attached to the upper human body and a dumbbell to distinguish five qualities of the execution of a weight-lifting exercise. To reduce the amount of the resulting features, they use an automatic feature selection algorithm, followed by a Random Forest approach for classification. Ghasemzadeh *et al.* [38] utilize five sensor nodes, two nodes on a golf club and three on the upper human body, to measure acceleration and angular velocities of golf swings. Based on this data, they distinguish between nine different quality classes related to the wrist rotation of the golfer to provide feedback on quality of movements for the purpose of golf training. Adelsberger and Tröster [39] investigate the assessment of weight-lifting activity. For this purpose, they use the acceleration data of two sensor nodes, which are attached to the wrist and hip of the human body. The authors use a support vector machine algorithm to determine whether completed weight-lifting movements are assigned to a beginner or experienced athlete.

As a result of the supervised training of a quality class which should be detected, the domain-specific meaning of the different quality classes is known. Thus, an appropriate semantic feedback to the assessment of an activity is possible. Systems using this approach can be transferred more easily to other application domains where an appropriate training of correctly as well as incorrectly conducted activity samples is possible. Depending on the intended granularity of the assessment of an activity, the inertial training of the quality classes can be expensive. Nevertheless, the training of all intended quality classes is not always possible. Especially in motor learning or physiotherapy applications, the accomplishment of the purposefully incorrectly performed activity is not recommended. In this case, the approach is restricted to applications where historical data on incorrectly performed samples of the activity is available. Another drawback of the EML approach is that the resolution of the assessment is limited to the amount of explicit trained quality classes. Khan *et al.* [40], address this by assigning relative quality labels through pairwise comparison of explicit trained activity samples by a domain expert and thus providing a quality scale. New activity samples are assessed by ranking them within the prior trained quality scale.

EML approaches successfully demonstrate that AR can be used to detect erroneous activity executions, but the inherent requirement to train defective activity samples limits these approaches to applications where this is possible and affordable.

2) IMPLICIT MACHINE LEARNING (IML)

IML approaches learning their quality model from ground truth data representing activity samples at the best affordable quality only. Upcoming activity samples are assessed by delimitation of the previously modeled ideal quality class against motion data which do not correspond to the trained activity. Hence, this approach makes use of algorithms known from the *null class* problem [6], also known as the problem of the *"other class"* [26] respectively. This can be seen as a form of implicit learning, in other words, learning about faulty conduction of the activity without knowing the faults in particular.

For example, in [12] and [41], the data from several inertial sensors is merged centrally into a kinematic body model representing the pose of the user. Based on the angular data of this model, a Hidden Markov Model is used to detect movements of a particular fitness activity. In a second step manual selected feature values, which were extracted from the raw data of a recognized movement, are checked for predetermined thresholds. If a feature value exceeds the corresponding threshold, the movement is reported as faulty. Velloso *et al.* [33] describe a similar approach, with the difference that the body model is calculated from the data of a Microsoft Kinect sensor. Alternatively, in [42], sub parts of movements of an activity are recognized separately. Further execution of movements of a prior trained activity are assessed by the amount of correct classified sub-patterns of the movements.

As for the EML approach, a supervised training is needed for generalization across application domains. But the training is limited to the correct conduction of samples of the intended activity only, which results in a reduced inertial configuration effort. As the supervised training did not comprise any faulty activity samples, this method did not include semantic knowledge corresponding to faulty conductions by default.

III. REQUIREMENTS

Model-driven approaches cannot be reused across application domains and are expensive to develop. EML approaches can be reused, but require a relatively complex training of all quality levels that is not possible in any application domain. The IML approach requires the least training and generalizes best, but while model-driven approaches and EML approaches are semantically clear, IML approaches are not, by default.

We focus on the sustainable development of a generalized process chain for the evaluation of activities. Because the IML method generalizes across multiple application domains best, we use this method.

A. SEMANTIC PROPERTIES

Semantic properties connect algorithms of activity recognition and assessment with human knowledge [43]. Especially when it comes to using the result of a system for the assessment of activities by humans, this connection is of crucial importance. As a drawback, the IML approach lacks in semantic knowledge, included by design (e.g., how is the assessment composed and what can I do to improve my performance). We address this gap by adding biomechanically modeled aspects to the processes chain. As in [42], we establish the assessment of an activity on biomechanically distinct motion fragments (see Fig. 1b) and aggregate the motion assessments on different abstraction layers concerning the hierarchical decomposition of a motion performed by the human body (see Fig. 1a). Thus, we add temporal and spatial context to the assessment. In contrast to [42], we realize the fragment assessment by detailed evaluation of the feature values which characterize a motion fragment. Therefore, we implement a descriptive set of kinematic features that give intuitive reason to the assessment of a motion fragment (see Fig. 1c).

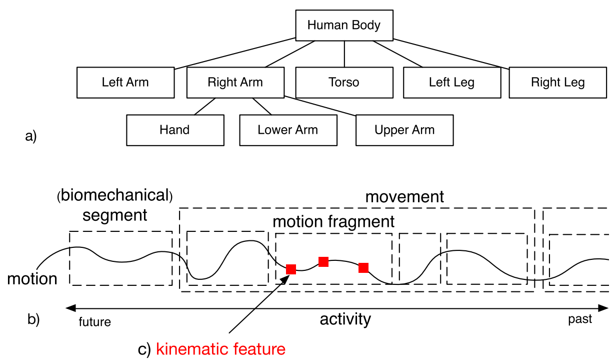

FIGURE 1. **(a) and (b) Spatial and temporal decomposition of an activity conducted by the human body as well as (c) the role of kinematic features.**

B. DISTRIBUTED COMPUTING

Almost all of the above mentioned related work for AA require the centralized computation of the data of the particular sensor nodes [33], [35]–[37], [39], [41]. Centralized systems are tied to communicate with the central base station. This typically results in a lack of mobility or in a temporal separation of data collection and their evaluation. We propose the distributed computation of the sensor data within the

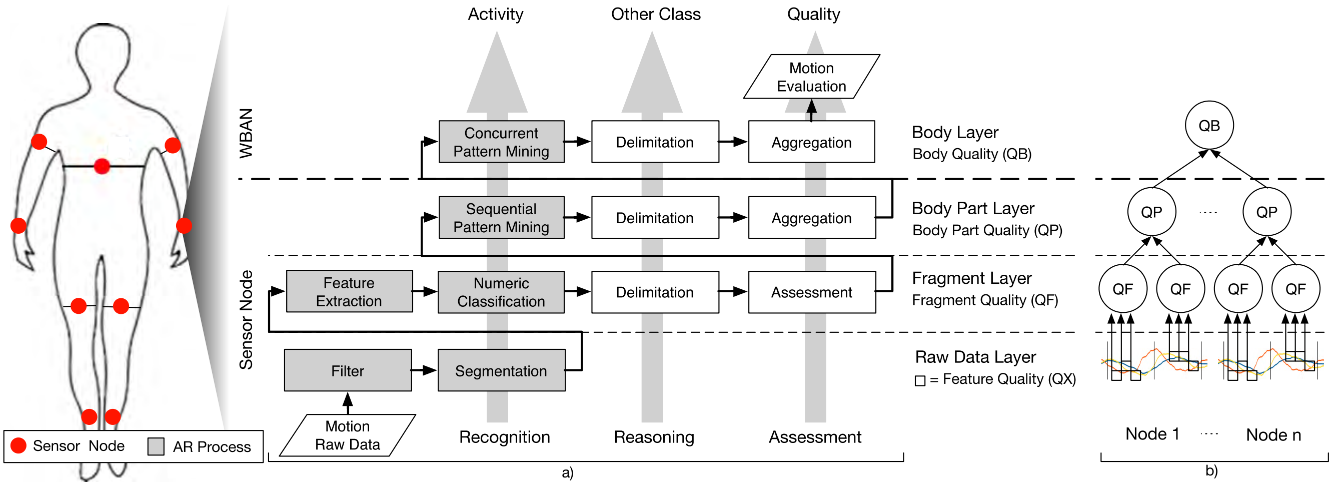

FIGURE 2. **(a) Processes of the AAC and their assignment to various abstraction layers (Fragment, Body Part, Body) as well as to different data flows (Recognition, Reasoning, Assessment). (b) Quality aggregation model.**

network, as a more promising approach to support human motion directly [42], [44]. If the sensor nodes of the WBAN are independently able to decide on the quality of a part of a movement of an activity, they can provide a direct feedback to a particular motion, independent of any infrastructure and while the activity is carried out, so as to allow use in daily activities outside a laboratory.

IV. ACTIVITY ASSESSMENT CHAIN

For the implementation of the IML method, taking into account the above-mentioned semantic demands, we propose the concept of AAC for generalized AA within body area networks, as depicted in Fig. 2a. The AAC consists of a sequential flow of processes which are assigned to abstraction layers related to the hierarchical decomposition of motion performed by the human body, namely: *raw data layer*, *fragment layer*, *body part layer*, and *body layer*. The AAC contains processes known from AR which are marked with a grey background. We distribute the work load within the WBAN by processing the motion data of a certain body part concerning the first three layers directly on a node which is attached to the respective limb. On the last layer, the data computed on the sensor nodes attached to multiple body parts are exchanged and fused to achieve the whole picture of the body movement. Each abstraction layer contains processes of three data flows which accomplish different functions within the AAC: *recognition*, *reasoning*, and *assessment*.

A. RECOGNITION

The recognition flow involves processes aiming for the basic identification of the trained activity and implements a typical ARC. On the raw data layer, the *segmentation* process recognizes biomechanically distinct motion segments within the processed raw data stream that contain information about a potential activity. Typically, before segmentation, the raw data passes a *filter* process to reduce noise and interfering information on the raw data signal. On the fragment layer, recognized segments are identified and labeled by the *fragment classification* process based on features extracted by a *feature extraction* process. On the body part layer, in the resulting temporal sequence of classified motion fragments, a *sequential pattern mining* process identifies accomplished body part movements of the conducted activity. On the body layer, several concurrently identified body part movements are collected and combined by the *concurrent pattern mining* process to obtain the body movement in its entirety.

B. REASONING

In a real-world setting not all parts of a continuous data stream are relevant for the trained activity, e.g., when disrupting the trained activity with other activities. To avoid diffusing assessments, the reasoning flow discards motion data which do not correspond to the trained activity and thus handles the problem of the "other class" on multiple layers. On each abstraction layer, a *delimitation* process verifies the decision of the preceding recognition process and thus determines which motion data will be handled by the subsequent *assessment* process and which motion data will be discarded. Depending on the algorithm utilized for recognition, the delimitation process can be included in the preceding recognition process.

C. ASSESSMENT

The assessment of biomechanically distinct motion fragments that pass through the delimitation process on the fragment layer ensures that the assessment can be intuitively linked to natural parts of movements of an activity (see Fig. 2b). The fragment quality (QF) can be derived on the detailed evaluations (QX) of the features extracted by the feature extraction process. The quality of recognized body part movements (QP) as well as the body quality (QB) can be aggregated from the assessments of the respective previous abstraction layer. Assessments on the fragment layer contain temporal semantic as they are connected to successive motion fragments. Assessments on the body part layer contain spatial semantic by their assignment to body parts.

D. WBAN

The AAC is designed to run online and completely distributed within a WBAN. Hence, we respect the limited resources of wearable wireless sensor nodes: computational power, memory, and energy. With the abstraction of the raw data by feature extraction and numerical classification early at the fragment layer, memory needed for the expensive raw data buffering is bounded to the size of a single motion fragment. Additionally, the complexity of the data processing at higher abstraction layers is reduced to save computational power at subsequent processes of the AAC. Up to the body part layer, no data has to be exchanged between the sensor nodes. For the body layer, only a few data characterizing body part movements are exchanged between sensor nodes to support recognition, reasoning, and assessment (e.g., time stamp, duration, and quality). Thus, we respect the energy consumption needed for costly wireless communication.

V. IMPLEMENTATION

The implementation considers a *training phase* and a *feedback phase*. While the training phase allows the customization of the system to a particular activity conducted by a determined person, within the feedback phase the system provides the assessment related to the conduction of the activity. During both phases the WBAN is attached to the body of the user. Once a motion is carried out by the user, sensor data are gathered and analyzed for a plurality of sensor nodes of the WBAN. As almost all movements of the human body are made possible by the joints and are mainly rotational [45], [46], we focus on angular motion data gathered from a three-axis gyroscope. We apply a Butterworth low-pass filter of second order with a cutoff frequency of 3 Hz for the reduction of noise and interfering information within the angular motion signal.

A. SEGMENTATION

The segmentation process within the AAC aims to divide the raw data measured by a sensor node for a particular limb of the human body into biomechanically distinct motion segments, e.g., flexion or extension of a body part. Therefore, we implemented the zero velocity crossing (ZVC) based segmentation algorithm presented in [42], as related results demonstrate that this approach reliably produces segments of angular raw data based on kinematics of human motion.

Typically, ZVC approaches identify segmentation points (SP), where the velocity value changes in sign, indicating that a joint has changed the direction of movement. Due to their simplicity, ZVC approaches are very fast and can operate online on sensor nodes with limited resources [47] but they tend to over-segment with noise or as the number of degrees of freedom (DoF) increases [48].

To overcome these drawbacks, the approach we implemented provides, in a first step, segmentation candidates (SC) for each of the axes, x, y, and z of the gyroscope (see Fig. 3). To respect noisy data, the approach detects an SC by monitoring whether the angular signal enters or leaves a corridor around zero. This corridor is defined by a threshold vector $\theta = (\theta_x, \theta_y, \theta_z)$ for each axis separately. The first SP is detected as soon as the angular signal of one of the axes leaves the corridor. In order to determine the principal DoF with respect to the current angular movement performed, the covered angles α_x, α_y and α_z between the preceding SP and the current SC are calculated separately for each axis and compared with each other. An SP is detected if the SC meets the following requirements:

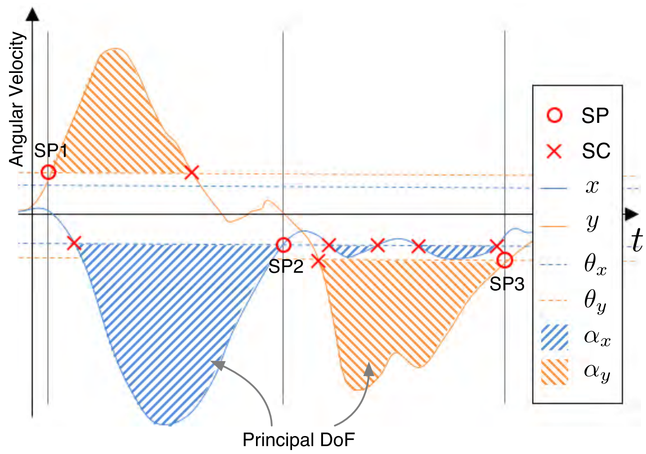

FIGURE 3. Biomechanical segmentation of angular data with two DoF (x, y): Segmentation begins by leaving the corridor at SP1 by y. The first segment is terminated by SP2, which is justified by the angle α_x covered by x at that time ($\alpha_x > \alpha_y$). The second segment is terminated by SP2, which is justified by the angle α_y currently covered by y ($\alpha_y > \alpha_x$).

- First, the covered angle of the corresponding axis has to be above the covered angles of the other axes, so that the SP can be regarded as caused by the principal motion axis, which determines the motion segment decisively.
- Secondly, the covered angle has to be above a minimum angle β such that the SC under consideration delineates a segment with a significant rotation for the trained activity.

A successfully detected SP indicates the end of a current motion segment and the start of a new motion segment. While α_x, α_y and α_z are determined online during the segmentation process, β and θ are previously determined as segmentation parameters by an automated validation process during the training phase as presented in [42]. Thus, the segmentation algorithm adapts to the individually performed activity of the user with regard to noise, relevant DoFs and intensity of angular motion.

B. FRAGMENT LAYER

As soon as biomechanical motion segments are separated, features are extracted from the raw data to identify motion fragments and label them as potential parts of the trained activity as well as for activity assessment.

Within the feature extraction process on the fragment layer, we use four kinematic feature-types [10] applied separately to the three axis of the angular motion data obtained from the gyroscope. We measure *displacement* (DP), *maximum velocity* (MV), *average velocity* (AV), and *time-to-peak* (TTP). We compute DP straightforwardly by computing the integral from the angular velocity signal. It is worth mentioning that motion segments built by the utilized biomechanical segmentation algorithm in general comprise small data sequences of a few seconds. Thus, the error generated during integration is tolerable. By TTP, we measure the time from the beginning of the motion fragment until the maximum of the velocity signal is reached and divide the value by the length of the motion fragment. In total, we compute a feature vector $x = (x_1, x_2, \ldots, x_n)$ composed of $n = 12$ feature values from the raw data of any motion segment.

As in [42], during the training phase, we derive a set of classes representing the motion fragments of the trained activity. We utilize k-means cluster analysis of the feature vectors extracted from motion fragments of movements that where performed during the training of the activity. The number of partitions k is provided by the number of motion fragments expected for a movement of the trained activity. Each class $c \in \{1, \ldots, k\}$ is represented by a prototypical feature vector $w \in \mathbb{R}^n$.

Within the feedback phase, for the classification of motion segments, we implement a classical nearest prototype classifier [49] utilizing the set W of prototypes $w \in \mathbb{R}^n$, known from training. The class of an unclassified feature vector x of a new segment is defined by Eq. 1.

$$c(x) := c(arg \min_{w \in W}\{d(w, x)\}) \tag{1}$$

We normalize x before classification and utilize the Euclidean distance measure as distance measure d. For delimitation, we consider the minimum bounding hyper rectangle R_c^T covering the set V_c^T of feature vectors v, which represents all motion fragments observed during the training (T) for class c, see Eq. 2.

$$R_c^T := \prod_{i=1}^{n} [v_{i\wedge}^{T,c}, v_{i\vee}^{T,c}] \; with \; \begin{cases} v_{i\wedge}^{T,c} := \min\limits_{v \in V_c^T} v_i \\ v_{i\vee}^{T,c} := \max\limits_{v \in V_c^T} v_i \end{cases} \tag{2}$$

The training contains only examples of the correctly performed activity. Hence, we add a margin to the intervals of R_c^T so that motion fragments can pass through the delimitation process even if they contain a limited error in their execution. This results in an extended (E) hyper rectangle R_c^E, see Eq. 3, $\delta > 0$.

$$R_c^E := \prod_{i=1}^{n} [v_{i\wedge}^{E,c}, v_{i\vee}^{E,c}] \; with$$
$$\begin{cases} v_{i\wedge}^{E,c} := v_{i\wedge}^{T,c} - \delta \cdot (\overline{v}_i^{T,c} - v_{i\wedge}^{T,c}) \\ v_{i\vee}^{E,c} := v_{i\vee}^{T,c} + \delta \cdot (v_{i\vee}^{T,c} - \overline{v}_i^{T,c}) \\ \overline{v}_i^{T,c} = \operatorname{mean}\limits_{v \in V_c^T} v_i \end{cases} \tag{3}$$

We define that any feature vector x outside of R_c^E did not represent the classified motion fragment of the trained activity. Hence, we relax the classification and reject x and the motion segment respectively, i.e., x belongs to the "other class". Each motion segment that passes through the delimitation process is regarded as a fragment of a movement of the trained activity and is evaluated by focusing on the position of x in the decision space in detail. Depending on its class $c(x)$, we compute the quality $q^X = q_i^{X,c}$ for each feature x_i, $i = 1, \ldots, n$, $v_{i\wedge}^{E,c} \leq x_i \leq v_{i\vee}^{E,c}$, by quantizing the error with a linear function that crosses the range of values between R_c^T and R_c^E, as defined in Eq. 4 and shown in Fig. 4.

$$q_i^{X,c}(x_i) = \begin{cases} 1 - (v_{i\wedge}^{T,c} - x_i)/(v_{i\wedge}^{T,c} - v_{i\wedge}^{E,c}) & \text{if } x_i < v_{i\wedge}^{T,c} \\ 1 - (x_i - v_{i\vee}^{T,c})/(v_{i\vee}^{E,c} - v_{i\vee}^{T,c}) & \text{if } x_i > v_{i\vee}^{T,c} \\ 1 & \text{otherwise} \end{cases} \tag{4}$$

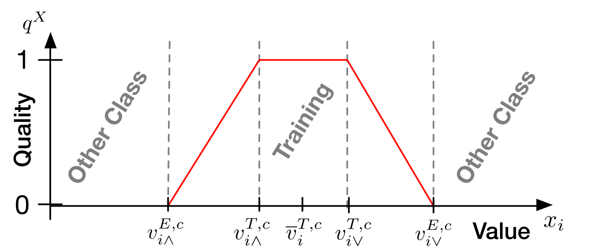

FIGURE 4. Quality Assessment Model: The quality of each feature is determined with respect to the position of its value within the boundaries calculated from training data.

We determine the fragment quality q^F as the mean of the single feature qualities of x, i.e., $q^F = q_c^F(x) = \operatorname{mean}\limits_{i=1,\ldots,n} q_i^{X,c}(x_i)$. The scaling parameter δ defines the tolerance of error accepted for the motion fragment layer as well as the value range for quality quantization.

After classification, delimitation, and assessment, a recognized motion fragment is represented by a tuple $f = f(x) = (c, t_s^F, t_e^F, q^F)$ where c represents the class label, t_s^F the start time, t_e^F the end-time, and q^F the assigned fragment quality.

C. BODY PART LAYER

On the body part layer, we consider sequences of recognized motion fragments f. The associated sequence of classes c is compared to a reference sequence of classes which represents the sequence of classifications determined for the trained activity at the dedicated body part out of the training data, as in [42]. As distance measure for the comparison, we use the Levenshtein distance, which is a well-known metric in AR [28], [29], [42]. If the measure is below a predefined threshold γ, a sequence of motion fragments is recognized as a certain body part motion. Assume a body part motion is characterized by a sequence of J motion fragments $S = \{f_1, f_2, \ldots, f_J\}$ then we define the quality of the body part motion q^P by the mean of the qualities of the motion fragments which the body part motion consists of, i.e., $q^P = \underset{f \in S}{\text{mean}}\, q^F(f)$.

Motion fragments which do not belong to any match are considered as motion of the "other class" and thus rejected.

After sequential pattern mining, delimitation, and aggregation of fragment qualities, a recognized body part movement is represented by a tuple $m = (id, t_s^P, t_e^P, q^P)$ where id is the node id, t_s^P the start time, and t_e^P the end time of the body part movement, and q^P the quality of the body part motion.

D. BODY LAYER

On the body layer, we consider in parallel recognized body part movements m of several sensor nodes. Incoming body part movements are stored in a buffer M of size r, where r is determined by the number of sensor nodes attached to the body. For recognition of the overall body movement, we consider the difference between the latest start and the earliest end of a body part motion m in M. The relative temporal coverage $u(M)$ of buffered body part movements is determined by Eq. 5.

$$u(M) = (\min_{m \in M} t_e^P - \max_{m \in M} t_s^P)/(\max_{m \in M} t_e^P - \min_{m \in M} t_s^P) \qquad (5)$$

Given a minimum coverage threshold p^T, a body movement is recognized if $u(M) \geq p^T$. The threshold p^T is defined by the minimum coverage determined for a movement of the training data: $p^T := u^T_{min} \cdot \varepsilon,\ 0 < \varepsilon \leq 1$. Incoming body part movements supersede the body part movement $m \in M$ which ends first. Body part motions, which are not part of a recognized body movement, are rejected and assumed as motion of the "other class". Finally, the body quality q^B for a recognized body movement is computed by the mean of the qualities of the respective body part movements, i.e., $q^B = \underset{m \in M}{\text{mean}}\, q^P(m)$.

The triple δ, γ, and ε controls the sensitivity of the reasoning flow of the AAC. A small δ, small γ, and big ε induce a sensitive delimitation on the abstractions layers closely to the trained activity. A bigger δ, bigger γ, and smaller ε induce more tolerance for error within the evaluated activity.

VI. USE CASE: INDOOR ROWING

For evaluation, we choose the assessment of rowing activity on an indoor rowing machine. A rowing machine is typically used to improve the rowing performance outside the water (e.g., when it is not possible to row on the water in winter) or to improve general fitness (e.g., in a health club). While performing the rowing activity with the right technique is beneficial for improving performance, improper rowing can lead to injuries [50], [51]. Thus, a precise and subtle technique of the rower is required to row efficiently and to avoid injuries. It is therefore essential to assist the user of a rowing machine with a feedback on the correct execution of the rowing activity.

A. HARDWARE SETUP

Driven by the needs of the application domain for distributed activity assessment within WBANs, we make use of the sensor board F4VI2 [52] (see Fig. 5, bottom). The sensor board provides a compact form factor of $35.5mm \cdot 24.3mm$ and resources that allow us to cache longer chunks of data and process the data within short time slots. We are implementing this on the F4VI2 by utilizing the Cortex-M4 microcontroller STM32F415RGT with a maximum of 168 MHz, 1 Mbyte Flash, 192 Kbyte SRAM, as well as DSP support and FPU unit. For the experiment, we use the data of the three-axis gyroscope of the integrated nine degrees of freedom motion tracking device MPU9150 at a sampling frequency of 100Hz. For the attachment of the sensor board to the human body, we integrated the F4VI2 (k) together with a miniaturized Bluetooth module (j) and a very small 110 mAh battery (l) into a reference housing. The translucent cover of the housing contains a small curved part (m) over the LED (n) to enable the clear perception of the LED light for interaction with user. With the aid of Velcro tape, the housing can be easily attached to the extremities of the human body.

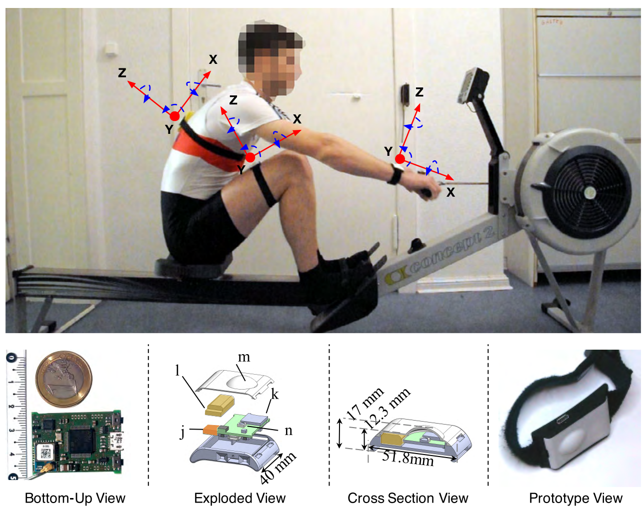

FIGURE 5. Hardware setup. (top) Placement. (bottom) Node configuration.

For characterization of the rowing activity, we use three F4VI2 sensor nodes attached to the human body (see Fig. 5, top). We add one node to the right wrist (RW), one node to the upper back (UB), and one node to the upper right leg (RL). The rowing activity was performed on a Concept 2 indoor rowing machine of type D. The sensor nodes are synchronized in time by broadcast at the start-up sequence.

B. MOTION MODEL

Rowing is a continuous motion comprising a sequence of strokes. The rowing cycle at an indoor rowing machine comprises two major phases: *drive* and *recovery*. Regarding this, two positions are relevant: *catch* and *finish*. The drive phase starts with the catch of the handle and is initiated with a push from the legs. After the legs are almost extended, the rower first begins to lean back and then the arms begin to draw the handle toward the body until the finish position is reached. The recovery phase begins at the finish and is initiated with the arms straightening followed by the trunk rising. If the arms are almost straight and the trunk reaches the upright position, the legs begin to flex until the shins are vertical and the catch position is reached again.

The rowing activity mainly causes motion along the sagittal plane of the human body. With respect to the experimental setup and the assembly of the sensor nodes, we expect angular motion to be measured primarily on the y-axis of UB and RL. During the rowing activity the hands are fixed by grasping the handle of the rowing machine. Thus, we expect motion to be measured at the y-axis as well as at the z-axis of RW but less angular motion is measured on the x-axis of RW during rowing.

For the evaluation, we consider five technical faults based on descriptions of an established indoor rowing training guide [53].

1) Leaning back too less: At the finish the rower does not lean back far enough. The stroke does not reach the maximum speed and the full potential of the back is not used. This error affects mainly the angular displacement and speed of movement of the back during the recovery and the drive.
2) Leaning back too much: The rower leans back too far. The energy costs for leaning back too far are greater than the gain from rowing a longer stroke. As with the first error, this error affects the movement of the back during recovery and drive, but in the opposite way.
3) Jerky finish: While ending the drive, the rower accelerates the handle too much. The jerky movement of the handle is powered by the legs and the arms. Instead of pulling the handle toward the body, he pulls himself forward towards the handle. This error affects the speed of the movement of the arms, legs and upper body during the drive. The movement during recovery is less affected by this error.
4) Unfinished stroke: The rower does not complete the pull of the handle toward the body and wastes a few centimeters of the stroke. The stroke does not reach the maximum speed and the full potential of the arm muscles is not used. This error mainly affects the angular displacement and speed of movement of the arms within the drive and the recovery.
5) Rushing the slide: The rower rushes down the slide during the recovery. He accelerates and moves his body too fast so that he wastes energy to stop the movement before he reaches the catch position. This error is characterized by a faulty speed of the movements of the legs and the upper body during the recovery. The movement within the drive is not affected.

In the following, we refer to correctly accomplished rowing strokes with quality C and to faulty accomplished rowing strokes with quality $E1$ to $E5$, based on the above list of technical faults.

C. EXPERIMENTAL SETUP

We record rowing activity of two rowing athletes $RA1$ and $RA2$ with several years of rowing experience. The rowing activity was supervised by an expert with more than ten years of rowing experience and documented by a video camera. All subjects are instructed by the expert to perform a continuous sequence of rowing activity in the six different qualities: C and $E1$-$E5$. Every subject starts the rowing session with two sequences of 22 correctly performed strokes. Thereafter the subject performs five sequences of 22 technically incorrect strokes according to the quality classes $E1$-$E5$. In total, every subject performs 154 strokes. The recorded motion data contain periods of resting between rowing sequences as well as the period of attaching the sensor nodes at the beginning of the session. The length of the period of attaching the sensor nodes at the beginning of the session differs for $RA1$ and $RA2$ by about 4 minutes. In total, the rowing session of RA1 resulted in a data set of about 16 minutes for $RA1$ and 19 minutes for $RA2$.

We apply the AAC to the respective data of each subject separately. We train the AAC on the first sequence of 22 correctly performed strokes. We skip the first and the last stroke, as these are influenced by taking and putting back the handle respectively, and train the AAC on the remaining 20 strokes. Taking the phases of a rowing stroke into account, a movement of the rowing activity is made by a sequence of two motion fragments: drive and recovery. Thus, for the clustering of motion fragments on the fragment layer, we set the number of clusters to $k = 2$.

For activity recognition and assessment, the rest of the session including 22 strokes of quality C and 110 strokes of quality $E1 - E5$ is processed by the trained AAC. We provide $\delta = 50$, $\gamma = 0$, and $\varepsilon = 0.6$, as this tolerance configuration recognizes correctly conducted as well as faulty strokes of the rowing activity, while other motion is rejected very well. The configuration of the delimitation process on the fragment layer with $\delta = 50$ means, that motion fragments can pass through the delimitation process on this layer, even if they contain a 50-fold higher deviation of a feature from the prototype than the maximum deviation measured in the training data. Thus, motion fragments can contain a large error before they are rejected. The tolerance configuration on the body part layer is due to the very short sequence of two motion fragments, that makes a movement of the rowing activity. The configuration of $\gamma = 0$ on the body part layer means that a rowing movement passes through the respective delimitation process only if the corresponding motion sequence contains no error at all. The configuration of ε affects the threshold for the minimal coverage required for body part movements to form a body movement. The value $\varepsilon = 0.6$ causes that body part movements of a recognized body movement must overlap at least 0.6 times of the smallest coverage value measure within the training data to pass through the delimitation process on the body layer.

VII. RESULTS

The ability to divide the raw data stream into biomechanically distinct motion segments reliably, is critical to the subsequent recognition, delimitation, and assessment processes. Thus, we first validate whether the segments separated on the raw data layer match the fragments of the motion model described in Section VI-B. We then evaluate the results of the recognition and the reasoning flow followed by focusing on the assessment of the rowing activity.

A. SEGMENTATION

The segmentation is done by all nodes of the body area network separately. For RA1 and RA2 together, the number of segmentation candidates (SC) and recognized segmentation points (SP) are depicted in Table 1. The numbers are shown for the individual sensor nodes (UB, RL, RW), for the angular axes (SP X, SP Y, SP Z), and for each in total.

TABLE 1. Number of considered segmentation candidates (SC) and recognized segmentation points (SP).

	SC	SP	SP X	SP Y	SP Z
UB	5402	731	75	633	23
RL	5526	582	18	557	7
RW	6552	818	145	618	55
Total	17480	2131	238	1808	85

For all nodes, the large majority of SCs are rejected by the segmentation algorithm with a similar rate between 86% and 89%. A number of 2131 SPs meets the requirements of the segmentation algorithm, to have been caused by the principal motion axis and to delineate a segment with a significant rotation for the trained rowing activity. Only a small number of SPs is caused by motion on the z-axis or the y-axis. With 85%, most SPs are caused by motion on the y-axis, which is what we expected for the rowing model with respect to the experimental setup.

Fig. 6 exemplary depicts the segmented angular data of the rowing activity measured at the various sensor nodes. The two alternating phases, drive and recovery, which make up the rowing activity, are well separated from each other at the characteristic catch position as well as at the finish position respectively. The implemented segmentation algorithm is able to handle the problem of over-segmentation, determines the most significant motion axis automatically, and reliably delineates the phases of the rowing activity within a continuous angular data stream.

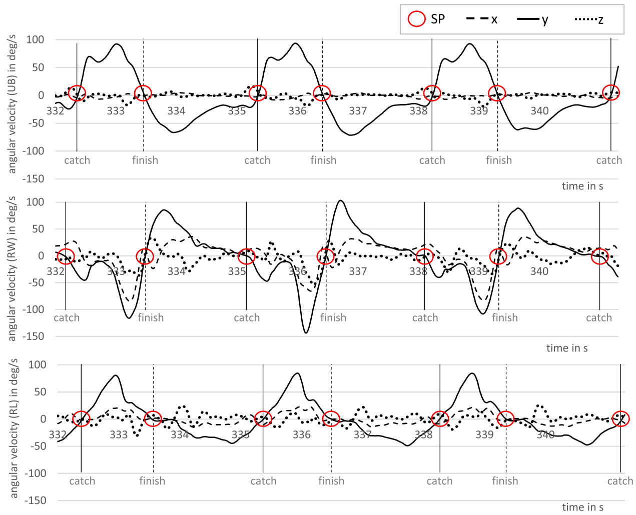

FIGURE 6. Filtered and segmented angular data of the three sensor nodes (top) UB, (middle) RW, and (bottom) RL for three rowing strokes of quality C conducted by RA1.

B. RECOGNITION & REASONING

The delineated motion segments separated at the raw data layer are processed by the remaining abstraction layers of the proposed AAC. At the body layer the AAC recognized 92.4% of the 264 accomplished rowing strokes. 120 strokes are recognized for RA1 and 124 strokes for RA2. Every detected stroke belongs to a stroke sequence. The AAC missed 20 accomplished strokes. Almost all belong to the start or the end of a stroke sequence. In addition, one stroke of RA2 within the stroke sequence E5 could not be detected on the body layer.

As previously mentioned, the first and the last stroke of a stroke sequence are influenced by taking and putting back the handle of the rowing machine. Thus, it could be expected that these strokes contain motion data which did not represent the stroke and therefore these strokes are not recognized correctly.

Since the additional missed stroke of RA2 is within a sequence of rowing strokes, we evaluate the processing of this stroke throughout the ACC in detail. The rowing stroke was correctly recognized upon the body part layer for the sensor nodes RW and RL, but not recognized by UB. On the body part layer of UB, the sequence of the classified motion fragments of the respective stroke did not match the trained reference sequence. The reason for this is that, at the fragment layer, the recovery-fragment of the stroke was falsely classified by UB as a drive-fragment. The raw data of the corresponding stroke as well as the preceding and the succeeding stroke are shown in Fig. 7. It can be seen that the segmentation of the raw data of the stroke sequence matches with the motion model, but the angular data of the respective recovery phase differ significantly from the raw data of the recovery phases of the preceding and the subsequent stroke, which have been classified correctly by UB.

The number of motion fragments recognized on the fragment layer (In) and the number of motion fragments

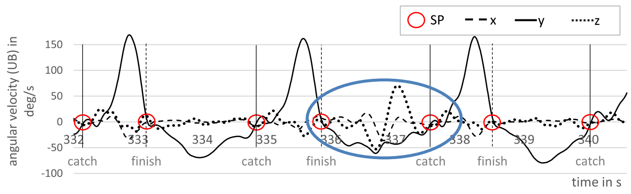

FIGURE 7. Filtered and segmented angular data of sensor node UB with respect to the missed stroke of RA2 within rowing sequence E5.

remaining after running through the AAC (Out), as well as the number of motion fragments separately rejected on the respective abstraction layers, are shown in Table 2. On the fragment layer, motion fragments are rejected due to large deviations of at least one value of the kinematic feature vector of the respective motion fragment from the trained prototype. On the body part layer, motion fragments are rejected if they do not arrive in the chronological sequence as they did during the training. On the body layer, body movements and thus the motion fragments associated therewith are rejected if the respective body part movements are not recognized in a suitable time interval or if at least one of the sensor nodes did not recognize a movement at all on the body part layer.

TABLE 2. Number of motion fragments discarded by the delimitation process on the respective abstraction layers: for the rowing athletes RA1 and RA2, various sensor nodes, as well as in total.

	RA1	RA2	UB	RW	RL	Total
Out	720	744	488	488	488	1464
Body	70	158	68	148	12	228
Body Part	88	192	95	152	33	280
Fragment	80	85	82	32	51	165
In	958	1179	733	820	584	2137

In detail, for RA1 and RA2 and all sensor nodes together, 2137 segments are recognized on the fragment layer. For RA2, more segments were identified than for RA1, which is due to the longer attachment period. Through cooperation of the sensor nodes, 31.5% of the recognized segments are rejected on all certain abstraction layers. Of the rejected segments at all, 24.5% were rejected at the fragment layer, 41.6% on the body part layer and 33.9% on the body layer. The smallest number of motion fragments was rejected on the fragment layer, followed by rejections on the body layer. Most of the rejections are due to an inappropriate chronological sequence of recognized motion fragments on the body part layer.

All sensor nodes and all abstraction layers contribute to the delimitation of the "other class". The rejection rates on the respective abstraction layers match the configuration of the feedback phase as set out in Section VI-C. It can be seen that the AAC is able of recognizing correctly conducted strokes as well as faulty ones, while rejecting any motion that belongs to the "other class". These results represent a very good recognition and delimitation accuracy and provide a strong basis for the following assessment of the activity.

C. ASSESSMENT

For the evaluation of the assessment capability of the AAC, we skip both the first and the last two strokes of each stroke sequence to ensure that the recognized strokes are not affected by the starting or by the ending of the stroke sequence.

The assessment of a rowing stroke is made up of the ratings of the three sensor nodes. These, in turn, are based on the assessment of two motion fragments each. For each motion fragment of a rowing stroke, 12 kinematic features are available for evaluation. In total, the quality assessment of a recognized rowing stroke on the body layer is based upon the values of 72 features. Each feature of the recognized rowing stroke is evaluated by the quality assessment model with respect to its position within the decision space, as shown in Fig. 4.

The final assessment of the 216 rowing strokes recognized on the body layer is shown in Fig. 8. Caused by the respective rowing error, an average of 25% of the 72 available features exceed the boundary defined by R_c^T during the training. The particular remaining part of the features is within the respective boundary and rated with 100%. Thus, all ratings on the body layer are in a small range above 98%.

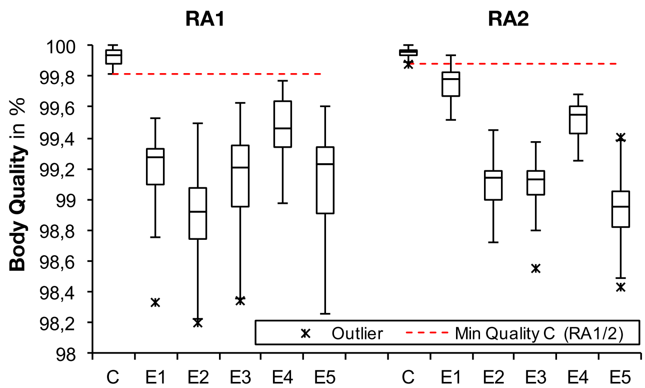

FIGURE 8. Body layer assessment of 216 rowing strokes, which were executed in different qualities (C, E1-E5) by RA1 and RA2.

The depicted assessments show a similar pattern of the ratings of the different quality classes of RA1 and RA2. As expected, the correctly performed strokes are rated with the highest quality and clearly stand out from the incorrectly performed strokes. 97.8% of the incorrectly performed strokes are rated with a lower quality than the minimum quality reached by the respective correctly performed strokes.

Four strokes of E4 executed by RA2 are rated with a quality above or equal to the minimum quality of respective correctly performed strokes. The box plots for E1-E5 are comparatively tall, meaning a larger distribution of the assessments than for the correctly performed strokes.

The review of the video data, recorded while the rowing motion was carried out, states the distribution for E1-E5. Correct strokes are trained as usual for RA1 and RA2. Thus, rowing strokes at quality C at constant level is easier than the

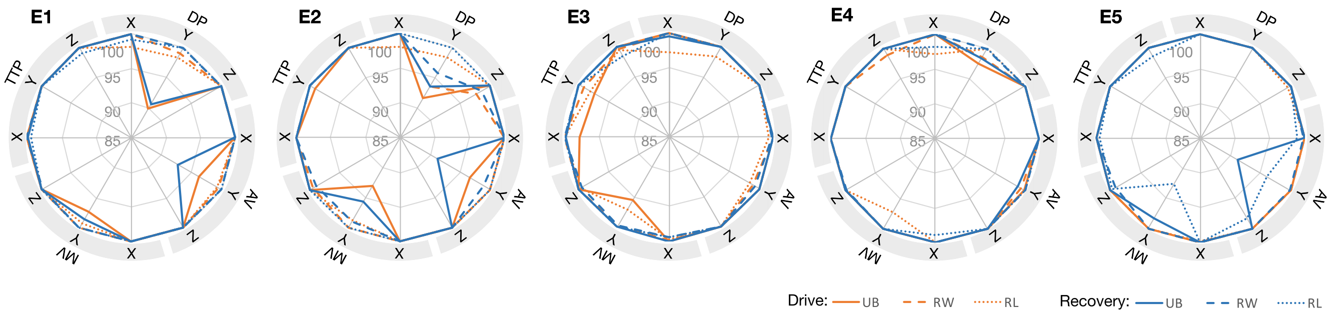

FIGURE 9. Detailed fragment layer assessment of the rowing activity performed in various qualities (E1-E5) by RA1.

simulation of a particular technical error. In addition, the error in strokes of E1 and E4 includes only small deviations to strokes of respective quality C. The error of the back in E1 is estimated by the expert for RA2 in average to 6° and for RA1 in average to 14° compared to the back in the respective quality C. The error of the handle for RA1 in E4 amounts to 4*cm* in average to the respective quality C and thus causes only minimal deviations of the angular motion.

Furthermore, we evaluate the temporal and spatial semantic in terms of which features of which motion fragment and which body part give reasons for the assessment. By reference to the aggregation model shown in Fig. 2b, we build 12-D spider plots for the visualization of the feature assessments. To focus on the most characteristic assessment pattern, we calculate the median for the quality classes E1-E5 from the feature assessments of all evaluated strokes. The resulting spider plots for E1 to E5 of RA1 are depicted in Fig. 9. It can be seen, that for all qualities and for all sensor nodes the y-axis implies the most relevant data. Furthermore, the motion fragments, the body parts, as well as the kinematic feature values which influence the evaluation most, can be determined from the spider graph. These findings, compared to the error descriptions in Section VI-B, provide information on whether the evaluations can be linked with the respective error descriptions. E.g., the assessment pattern of E1 is dominated by an error of DP-Y as well as AV-Y of UB within the drive and the recovery respectively. As E1 is defined by an angular error of the back at the finish and the rotation on the y-axis of UB correlates to the rotation of the back on the sagittal plane of the human body, the assessment of E1 conducted by RA1 can be easily connected to the error description of E1. Similar observations can be made for E2, E3 and E5.

For E4, a correlation between the error description and the assessments pattern is less evident. The assessment is influenced by features assigned to the drive as well as to the recovery. The worst rated features for E4 are MV-Y (97.2%) of RL followed by DP-X (97.2%) of RL at the drive and DP-Y (97.5%) of UB at the drive. We expected to measure the worst error on RW because E4 is defined by an unfinished arm movement. The worst feature quality of RW is measured with DP-Y at the drive (98.6%).

D. CONTRIBUTION OF SENSOR NODES

To evaluate the contribution of different combinations of sensor nodes to the assessment of the rowing activity, we apply the AAC with the above mentioned configuration to the possible seven combinations of the three sensor nodes. Based on the resulting assessments on the body layer, we determine the absolute separation value (ASV) to compare the ability of different configurations to distinguish between correctly and incorrectly accomplished rowing activity. With m_{Q-}^{Err} as the number of faulty accomplished rowing strokes evaluated with a lower quality than any correctly accomplished stroke and m_{all}^{Err} as the number of all faulty accomplished rowing strokes, ASV is defined as in Eq. 6. Furthermore, we determine the true positive rate (TPR) as well as the positive prediction value (PPV) to evaluate the capability of the configurations to identify the stroke from the continuous motion. With TP as the number of executed strokes which were recognized correctly, FN as the number of executed strokes which were not recognized, and FP as the number of falsely recognized strokes not belonging to an executed stroke, TPR and PPV are calculated as in Eq. 7 and Eq. 8.

$$ASV := m_{Q-}^{Err}/m_{all}^{Err} \tag{6}$$
$$TPR := TP/(TP+FN) \tag{7}$$
$$PPV := TP/(TP+FP) \tag{8}$$

While TPR states the extent to which the performed movements of the rowing activity have been recognized, PPV makes a statement about the extent to which the AAC can distinguish untrained activity from the trained rowing activity. ASV, PPV, and TPR are shown in Fig. 10 for each configuration. The AAC, when based on a single sensor node, can detect more than 95% of the movements of the rowing activity. However, the ability to distinguish untrained activities and erroneous movements differs depending on where a sensor node has been attached. Based on a single sensor node attached to the upper body, ASV, PPV and TPR achieve results of at least 90%, whereas for the single node on the right wrist, ASV and PPV are much lower. Configurations with two sensor nodes contain a higher potential to separate faulty strokes from correct ones than single node configurations, while the configuration containing all three sensor nodes has

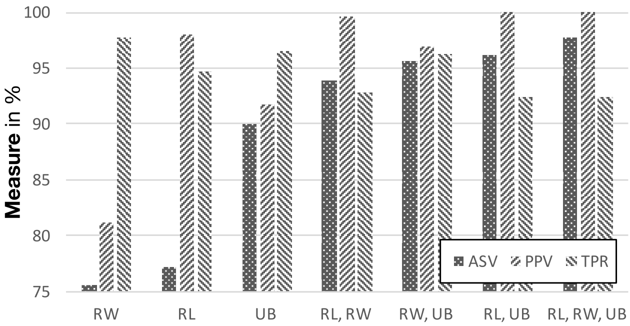

FIGURE 10. Comparison of the recognition and assessment capability of various combinations of sensor nodes.

the greatest potential. The sensor node, which is attached to the wrist, has the least influence on assessment of the stroke activity, while the node attached to the upper body contributes most to the separation of faulty executed strokes from correct executed strokes. The configuration based on the sensor nodes RL and UB achieves almost the same results as the configuration based on all three sensor nodes. For both configurations, 92.4% of all conducted strokes are recognized and every recognized stroke belongs to a stroke sequence. However, the additional use of RW results in a 1.7% improved ASV value.

VIII. DISCUSSION

The results of our case study demonstrate the practical value of the AAC as almost all strokes of the rowing activity are recognized, all motion of the "other class" is rejected and clear differentiation between rowing strokes in different qualities is possible. Therefore, no further application-related expert knowledge was implemented in the system. The configuration of the AAC is limited to the specification of the number of expected motion fragments for the training phase and the specification of the tolerance parameters δ, γ, and ε for the feedback phase. Nevertheless, due to the biomechanically modeled aspects integrated in the abstraction layers of the process chain, the AAC gives detailed insights concerning the reason of the activity assessment. For enough significant deviations of the conducted rowing activity from the trained activity, the AAC can provide a reasonable feedback, which can be used to identify the cause of the error and improve the performance.

With the case study, we have shown the practical applicability of the AAC on indoor rowing motion. The movements of indoor rowing are in large parts restricted by the system of the rowing ergometer. This largely results in motion conducted along one DoF of the respective evaluated body parts. While we show in [42] that the results for segmentation and recognition of more flexible motion models are promising, it is necessary to investigate in further studies how the full system behaves with different motion models and how far the results are comparable.

We show that multi-layered recognition and reasoning flows contribute to the successful delimitation of untrained motion to trained motion. In this context, our experimental data contain periods of resting between rowing sequences as well as periods of attaching the sensor nodes to the body. In further experiments, the proportion of untrained movements should be increased to further evaluate the delimiting ability of the system.

Due to the multi-layered assessment flow, the AAC can provide detailed reasons for the biomechanical aspects from which an assessment is made, e.g., which features of which motion fragment and which body part defer from the correct execution of the activity. Based on this information, feedback can be given to the user. A possible feedback which can be generated for quality class E1 of the case study is "Adjust the angular displacement of the first motion fragment of the current conducted movement". As the IML approach did not include any knowledge concerning the application depended technical terms, for formulation of the feedback within the application depended language an additional semantic layer is needed. Such layer could be used to map from the biomechanical based information provided by the ACC to an application depended feedback formulation. E.g., for E5 the feedback could be "Do more lean back during the drive".

The AAC is designed to run distributed on the sensor nodes of the WBAN. Each sensor node recognizes and evaluates a part of the motion independently. Depending on the body part to which a sensor node is attached and to which extent the corresponding body part is relevant for the execution of the activity, each sensor node contributes differently to the overall body evaluation. Based on the exchange of less data between the sensor nodes, a reliable assessment with respect to ASV, PPV and TPR of the entire body movement of an activity is generated, whereupon immediate feedback to the user is possible when the movement has ended. As the sensor nodes evaluate parts of the movements independently, feedback to motion fragments is even possible before the end of a movement, e.g., directly on the body part by vibration. In this case, dependent on the particular body part, a less reliable recognition with respect to PPV and TPR must be tolerated.

Due to the individual training of the AAC and especially of the biomechanical segmentation algorithm on a particular activity, segments of the trained activity can be accurately separated. In return, the AAC is restricted to a single trained activity at a time. Nevertheless, one way to support multiple activities is to combine this approach with existing activity recognition approaches, based on a sliding window segmentation, to first predict the current performed activity. In a second step, the parameter for the biomechanical segmentation for the activity can be loaded to support the activity assessment based on a precise segmentation of the activity.

Based on an IML approach, the concept of the AAC enables the generalized assessment of cyclical activities across application domains. In Section V, we present a definite implementation of the AAC. However, different algorithms can be used for the respective processes of the process chain. For further development and evaluation of the AAC, the integration into the open source framework SPINE is conceivable since SPINE already supports the basic processes of the ARC. In particular, the task-oriented approach presented in [32] can be beneficial to the development and the evaluation of different algorithms for particular processes and help to manage the complexity of the process chain.

IX. CONCLUSION

We summarize the current solution space for quality quantification in AR. While for AR a lot of work towards generalized systems exist, this is not the case for AA. Moreover, most of the available work require the centralized computation of the data of the sensor nodes. Hence, we introduced and analyzed the concept of AAC, which is a generalized trainable activity assessment chain for distributed online evaluation of periodic activity within WBANs. The AAC leverages the position of a characteristic set of kinematic features in the decision space to reject untrained motion and to achieve a fine-grained evaluation of biomechanically distinct motion fragments. To include spatial and temporal semantics, AAC first decomposes the human motion and then aggregates multiple levels of the resulting hierarchical structure. Our case study shows that AAC can be applied with minor configuration effort to indoor rowing activity and is not only able to clearly distinguish rowing activity from other motion but also to provide a detailed reasonable assessment of rowing strokes in different qualities. Thus, an immediate informational feedback to the user concerning the cause of the error, which is calculated fully distributed within the WBAN, becomes possible. Since each sensor node can recognize and evaluate a part of the motion of an activity independently, immediate feedback to motion parts is possible even during the execution of the motion. The results of our study are promising. In future work, we will compare AAC to additional motion scenarios as well as evaluate the configuration parameters of AAC in detail. In addition, we will investigate an additional application-dependent semantic layer, which is able to map from the biomechanically based assessment of an activity to a domain-specific formulated error description.

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MARTIN SEIFFERT received the Diploma degree in computer science from Freie Universität Berlin, Berlin, Germany, in 2012. He is currently pursuing the Ph.D. degree with a focus on semantically clear segmentation, classification, and the assessment of motion data within wireless body area networks to enable detailed online motion analysis and immediate feedback to the user. Since then, he has been a Research Assistant with the faculty of Mathematics and Computer Science, Freie Universität Berlin and with the faculty of Computer Science, University of Applied Science Darmstadt. He has been involved in several research projects concerning distributed pattern recognition and machine learning in wireless sensor networks.

FLAVIO HOLSTEIN received the bachelor's degree in computer engineering from the Technical University of Berlin in 2016. He is a Professional Rower and has been part of the German Rowing Team for three years. He is the founder of the AUGLETICS Company, Berlin, which aims to develop smart indoor rowing machines for rowing clubs and fitness studios. His research interests include usability engineering and activity recognition.

RAINER SCHLOSSER received the Ph.D. degree in operations research from the Humboldt University of Berlin in 2014. He is currently a Research Assistant with the Department of Enterprise Platform and Integration Concepts, Hasso Plattner Institute for IT Systems Engineering, University of Potsdam, Germany. His primary research interests include data analysis and the optimal control of dynamic systems.

JOCHEN SCHILLER received the Ph.D. (*summa cum laude*) degree from the University of Karlsruhe in 1996. He is the Head of the Group Computer Systems and Telematics, Institute of Computer Science, Freie Universität Berlin, Germany. Since 2001, he has been a Full Professor with Freie Universitat Berlin. His research focus is on wireless, mobile, and embedded devices, communication protocols, operating systems for devices with small footprint, and the quality of service and security in communication systems.