Integration of Distributed Event Detection in Wireless Motion-Based Training Devices

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***Abstract*—Athletes can improve their skills by using supervising training devices with integrated digital feedback. For example, martial art techniques are often complex in detail and need to be perfectly adopted from the teacher. Distributed event detection systems for digital devices enhance the individual training, resulting in a higher precision of the technique repetition. Distributed event detection, as employed in Wireless Sensor Networks, enables cooperative evaluation and detection of spatialy or temporaly distributed events like fire or earthquakes.**

We evaluate the feasibility of integrating a distributed event detection approach into a wireless motion-based training device, to support fight stick training. We present an ubiquitous computing device for in-network event detection, which enables users to obtain direct feedback from the device itself. Multiple sensors help to improve the reliability of the device, while the wireless technology ensures flexibility in a multi-part device. After a brief introduction to distributed event detection, we evaluate event detection accuracy and how link quality effects different scenarios.

I. INTRODUCTION & RELATED WORK

In the area of consumer products, multiple sensor nodes can be integrated into training devices or rehabilitation devices. Sensor nodes are miniaturized computers that need to cover embedded requirements without hindering the user or the environment. Sensor nodes are typically based on low-power microcontroller-units, integrated memory, a radio transceiver, energy source and one or more sensors to gather data. The radio transceiver is the main cause of energy consumption, which motivates the reduction of any unnecessary communication e.g. by local data processing, data compression and aggregation in a Wireless Sensor Network (WSN) [1].

Our approach is beneficial for precise learning and evaluation of complex movements with a training device. We implement this approach by using in-network data processing to extend network lifetime and to avoid the requirement of a base station during event detection. As a result, this architecture achieves the aims and principles of typical WSNs. We adopt distributed event detection [2] for in-network data processing that enables event monitoring from different perspectives or locations. Each sensor of our multi-sensor device captures one of those perspectives, and in conclusion gathers only parts of the event to detect. A perspective is represented by typical features as employed in the field of pattern recognition [3]. The features are calculated by the sensor nodes that register an event, followed by feature distribution and in-network feature fusion. This autarkic in-network processing performs event evaluation without a base station. Our sensor-based training device is thus generally applicable which is very desirable for a training device.

Martial art students need to get corrections from their teacher to improve their skills. During the absence of the teacher, a student can be taught and motivated through assistance that indicates whether the performed techniques and their order are correct. To give a visual feedback to the user, light-emitting diodes (LEDs) are attached to the sensor nodes. Compared to other approaches, we are able to give an immediate user feedback by using in-network feature fusion of different sensor nodes equipped with distributed event detection. For instance, in contrast to the Nintendo Wii [4], our system does not need any centralized base station for regular operation. Since the user should not be handicapped by wires or technical extensions [5], the usage of wireless communication is fundamental prerequisite.

In related work, Ghasemzadeh et al. [6] decompose movements of a body area network into segments of movements. Their approach is based on a string matching algorithm. In contrast to our approach, they neither implemented nor evaluated the distributed algorithm on a real sensor node. Prior approaches to integrate event detection in WSNs typically make use of threshold detection, like the fence surveillance system introduced by Kim et al. in [7]. Li et al. [8] investigate event detection by the example of a coal mine surveillance that takes benefit of the raw data evaluation on a base station with an a priori in-network validity check. Heinz et. al [5] analyse motions of Wing Chun techniques with industrial sensors with the goal of extracting features to roughly discriminate between amateurs and experts performing martial art techniques. They use a wired scenario that limits the mobility of the user during training.

Our system for distributed event detection has previously been applied for construction site surveillance in order to detect different kinds of intrusions. In [2], we examined the event detection and its dependencies on resource requirements. In [9], a sensor and software platform is presented that is tailored to the specific needs of distributed event detection. In this paper, we now present a personal training device with the

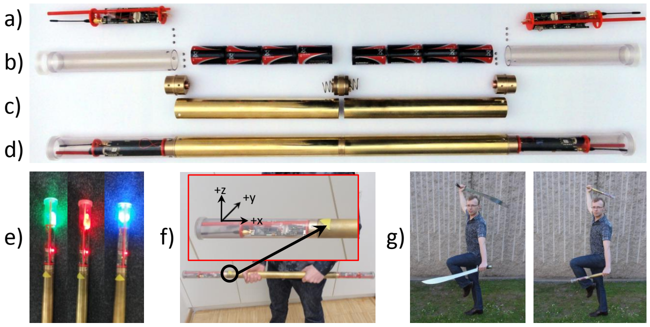


Fig. 1. a) sensor nodes & socket, b) batteries, c) brass housing & coupling, d) assembled device, e) feedback-LEDs, f) orientation marker, g) future work

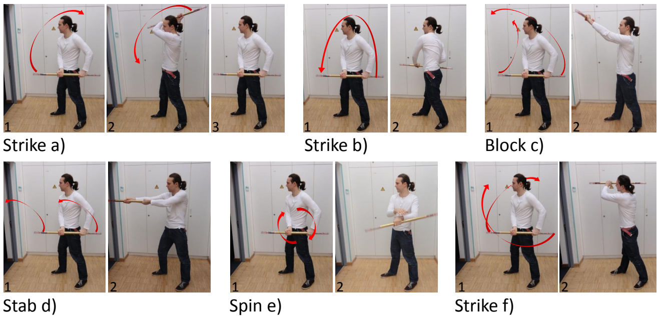


Fig. 2. Performing six predefined techniques with our training device.

look and feel of a real fighting stick, built upon our system for distributed event detection. We employ six exemplary martial art fighting stick techniques for evaluation. The training device consists of two sensor nodes that give visual feedback. The feedback illustrates whether the correct technique has been performed. The training device can be trained freely for further techniques and therefore remains flexible to the user.

We extend the work in [2] with the pattern recognition features *strength* and *orientation*. Further, we extended the hardware and housing [9] and present our threefold contribution:

- A new embedded training device that has the look and feel of a real fighting stick
- Integration of distributed event detection in a new feedback-based ubiquitous computing device
- Evaluation of event detection accuracy and link quality in different scenarios

II. INTEGRATION OF EVENT DETECTION

In the following paragraphs we present our system for distributed event detection which adapts two kinds of features to enhance the training device for martial arts.

A. System Adjustment

The distributed event detection system is divided into two main components: first, a supervised a priori training with an integrated feature selection [10], and second, a distributed event detection with integrated event notification and rejection [9]. For the supervised a priori training process all extracted features are sent to the base station. The system calculates an optimal feature set based on leave-one-out cross-validation [11], that supports the Euclidean-distance-based Nearest Prototype Classifier [2]. The prototypes are calculated by averaging the features of the gathered supervised a priori training data for each class. These prototypes contain features that represent characteristics of both sensor nodes. Finally, the prototype vectors are transferred from the base station to the integrated sensor nodes of the training device to finalize the supervised a priori training. For the subsequent actions (technique performance) the base station is not needed any more.

During event detection, each node calculates the selected features and sends the features to node 1 (right hand). The combined feature vector will be classified as introduced in [2] with the Euclidean-distance-based Nearest Prototype Classifier.

We take advantage of several preconditions in our scenario to reduce the complexity by using a fixed but extendible number of sensor nodes and a predefined orientation at the beginning of the event, see 1f). This enables us to reduce the communication effort to an unidirectional data flow between the sensor nodes. We attached exactly two sensor nodes, each of them with a 3D acceleration sensor, to detect and analyse rotations and translational movements on all axis.

In contrast to our previous work on fence monitoring [9] we use all three degrees of freedom due to the expected movements. A maximum of two axis are involved to collect enough information for a typical fence monitoring scenario. Our training device is not limited in its freedom of movement compared to linked fence elements in [2]. Thus, we expect a positive influence of our distributed event detection by gathering data from all three degrees of freedom.

B. Feature Set

In contrast to Wittenburg et al. [2], given *histogram* and *intensity* features did not perform as expected. Hence, we add two new features to our feature pool, which are assessed as most suitable by the integrated feature selection during the supervised a priori training.

$$\vec{v}_{int} = \vec{v}_1 + \vec{v}_2 + .. + \vec{v}_k \tag{1}$$

$$\vec{o}_{int} = \frac{1}{||\vec{v}_{int}||} * \vec{v}_{int} \tag{2}$$

$$||\vec{v}_{int}|| = \sqrt{\langle \vec{v}_{int}, \vec{v}_{int} \rangle} = \sqrt{x^2 + y^2 + z^2} \tag{3}$$

For the scenario of movement detection with different orientations and intensities we introduce two additional features that are used by the distributed event detection system. Both features are generated for n intervals with k samples of the event to describe the event in its progress. Each interval represents a chronological part of the event, where the interval size is freely configurable. The acceleration values of sample i are combined as vector $\vec{v}_i$ in the Euclidean space $\mathbb{R}^3$ using all axis namely (x, y, z). To calculate the features, all $\vec{v}_i$ of a certain interval are summed to the interval vector $\vec{v}_{int}$, see formula (1). The first feature is called *orientation feature*. The orientation feature is defined by an orientation vector $\vec{o}_{int}$ describing the physical direction of all three acceleration axis within a certain interval. We need to process a typical vector normalization to delete inherent strength data, see formula (2).

The second feature is called *stength feature*. The strength feature directly allows us to know how much strength the performing person induces into the training device. The strength feature is calculated by separating the length of the interval vector $\vec{v}_{int}$ during its normalization, as depicted in formula (2). So both information are preserved but in different parameters. In detail, the strength feature is calculated as the square root of the scalar product over all degrees of freedom in formula (3).

By separating these features, we are able to regulate the difficulty for the students' performance. Both features represent a characteristic part of the movement. While the orientation feature represents the movement by its sequence, the strength feature is able to detect whether the movement is performed with correct intensities in distinct intervals of the movements. By varying the interval size and by focusing on selected intervals we are able to manipulate the training focus in a minor degree for the student.

III. PLATFORM

The training device as presented in Fig. 1d) is a combination of multiple devices and structural components. As the splash-proof housing is initially inspired by the demands of the use case of distributed event detection on construction site surveillance, only rugged materials were chosen to prevent vandalism. Similar demands can be found in the domain of martial art: Even if it is not the aim to harm other persons, it is a training device for both professional and novice students, so accidents can not be excluded. The main body is a combination of two identical brass housings, depicted in Fig. 1c), coupled at their lower ends. Fig. 1a-c) exhibit the completely unassembled device. The power supply (6 V) is placed inside the brass housing of the stick using four standard D-cells that can be seen in the center of Fig. 1b). Two wireless sensor nodes shown in Fig. 1a) are plugged to the opposing sides and sheltered with Makrolon® tubes for highest solidity, as depicted in Fig. 1b). To ensure that the test persons knows whether the stick is oriented properly, markings provide advice for the correct handhold, see Fig.1 f).

The wireless sensor nodes are inspired by the concept of a MSB-A2 [12] that has been extended to the aims of motion-based applications and localization, called *AVS-EXTREM sensor node*. It is further based on an ARM7 NXP LPC2387 MCU with 96KB RAM and 512KB ROM, 868MHz transceiver CC1101 from Texas Instruments. For acquiring movement data, the applied sensor is a triaxial acceleration sensor, a *SMB380* with a range of up to 8g and 10-bit resolution. Sensor data is forwarded by an interrupt-driven architecture to an internal buffer in system memory. This enables time-delayed concurrent access to the data, e.g. from different processes using distinct algorithms for analysis. By using buffered data, important tasks like radio communication and routing can already be preferred prior analysing acceleration data.

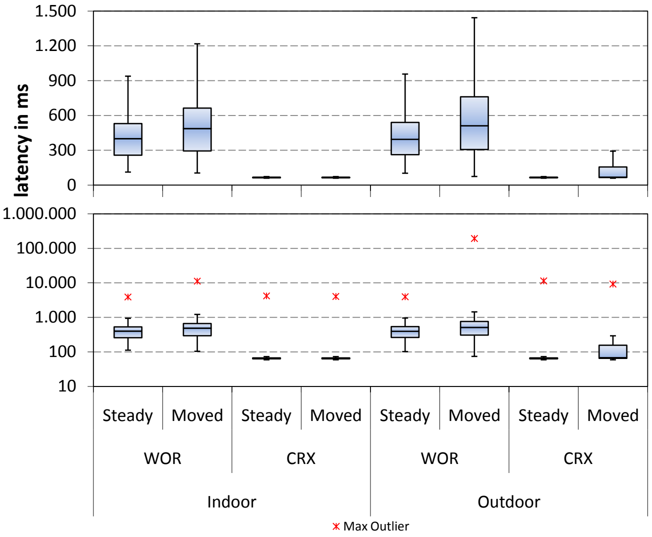


Fig. 3. Latency in standard (upper) and logarithmic visualization (lower)

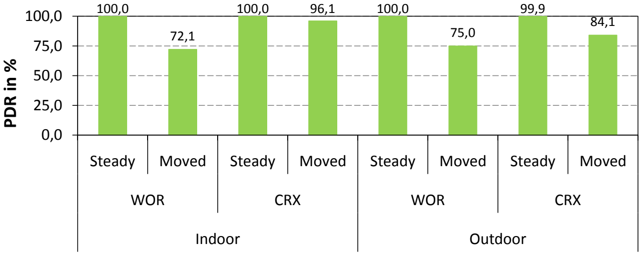


Fig. 4. Packet Delivery Ratio

Furthermore, the FireKernel [13] low-power operating system was chosen to support our concepts to evaluate concurrent algorithms on a sensor platform.

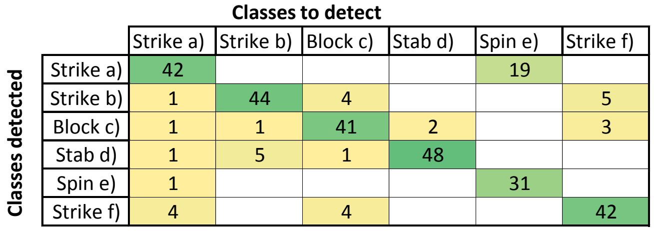
The expected runtime based on a continuous training is about 400 hours with the prior mentioned energy source while the pure stand-by time is about 250 days by benefiting of the all energy saving optimizations in FireKernel. As a conclusion, for one day training sessions, standard AAA-cells are also sufficiently dimensioned and can be inserted with a standard adapter as alternative energy source. As a side effect the device weight will be lowered and can optionally be optimized further by changing the brass made housing to light-weighted synthetic materials.

IV. EXPERIMENTS

We perform two experiments to evaluate accuracy of the distributed event detection and link quality.

A. Link Quality

Since the sensor nodes are aligned horizontally to one another, both antennas have a suboptimal orientation for direct



Classes to detect

Classes detected	Strike a)	Strike b)	Block c)	Stab d)	Spin e)	Strike f)
Strike a)	42				19	
Strike b)	1	44	4			5
Block c)	1	1	41	2		3
Stab d)	1	5	1	48		
Spin e)	1				31	
Strike f)	4		4			42

Fig. 5. Confusion matrix: principal diagonal is well-marked

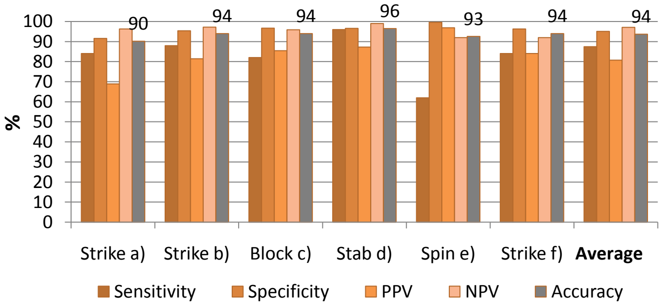


Fig. 6. Accuracy of distributed event detection with training device

communication. For ideal communication, a line of sight path between antennas is highly recommended [14]. In contrast to typical needs, we have to deal with opposing orientations of antennas (see Fig. 1d)) and have to evaluate the expected drawbacks in communication reliability.

The resulting communication characteristics are evaluated in section V-A. We investigate Packet Delivery Ratio (PDR) and latency. Inevitably, PDR needs to be high enough and latency needs to be low enough to give a continuous user experience without inappropriate pauses while performing the techniques. We evaluate the link quality based on the given techniques in different scenarios: indoor vs. outdoor and *steady* vs. *in motion*. We compare PDR and latency during the energy-saving mode Wake-On-Radio (WOR) of the CC1101 Transceiver introduced in [15] to the standard transceiver mode (CRX). Even if the communication in our scenario is unidirectional, we simplify our experimental setup by measuring the round-trip time (RTT) of 800 packets in each test to avoid focusing on clock drift between both nodes, and in conclusion, avoiding a mandatory time synchronization between them. Packets are transmitted once a second, comparing the RTT and PDR in *steady* state while repeating techniques with the device.

B. Distributed Event Detection

In martial arts, a typical training part consists out of a series of techniques and is called a *form*. In our scenario, we distinguish six martial art techniques (three different strikes, one block, one pad, one spin), which are generally called *classes*. All techniques start at the same position, but end in different ones, see Fig. 2. During operation, each technique is classified by the distributed event detection system. This evaluation is done by the training device after performing the technique without the need for a base station. An LED feedback signalizes the evaluation result. As depicted in Fig.1 e), we currently support three kind of LEDs. The green LED will light up, if the user performs the technique correctly. The red LED will light up, if the user did not perform the technique correctly or the user performs the wrong technique. The blue LED is reserved for future work. It is for example conceivable that after performing a complete series of techniques in the correct order, blue LED will light up finally.

For event detection evaluation the following configuration is chosen as a well balanced setting: To acquire the wide range of occurring acceleration forces, we set the sensitivity of the accelerometer to $8\,\mathrm{g}$ and the sampling frequency to $100\,\mathrm{Hz}$. Each class is trained 20 times by a teaching person using the training device, in order to generate reference data. Furthermore, *WOR* is activated to evaluate a real world scenario and to extend the lifetime.

V. EVALUATION

A. Link Quality

In order to guarantee a higher reliability than standard UDP we used a stateless TCP derivative, by supporting a retransmission function in case of packet loss. Latencies of indoor and outdoor scenarios indicate only a slight increase on average outdoor latencies, while at the same time maximum latencies increase up to 20 seconds in rare cases. We conclude that while movement in CRX mode, indoor radio wave reflection helps to maximize PDR on antipodal omnidirectional antennas, which are practically out of sight otherwise. The energy savings achieved by WOR consistently result in approximately $400\,\mathrm{ms}$ to $500\,\mathrm{ms}$ higher latencies compared to CRX mode. Furthermore, movements result in an additional latency of approximately $130\,\mathrm{ms}$ to $230\,\mathrm{ms}$ in WOR mode. Movements have only a slight effect in CRX mode in both scenarios resulting in a median of $89\,\mathrm{ms}$. As a conclusion, both, *steady* and *in motion* deliver acceptable PDR and latency values for our scenario. Only in very rare cases, the communication failed for a certain time and the user received no feedback for up to 74 seconds. Due to the fact that a user is not interested in waiting for an indefinite period of time, all packets with a higher latency than 15 seconds will be marked as lost in our tests. This rule affects about 1% of all transmitted packets. In complex surroundings PDR and latency can be optimized by choosing CRX, but this was not necessary in our experiments. As long as the latencies do not interfere the process of data collection and distribution, the resulting data aggregation will proceed successfully.

B. Event Detection Accuracy

During the supervised a priori training, the strength and orientation features are extracted from raw data. The best features are selected by performing cross-validation, as described in [2]. For both nodes five strength and five orientation features are selected. For node 1 (right hand) two orientation features for the X-Axis and three for the Z-Axis are selected. For node 2 (left hand) two orientation features for the X-Axis, two for the Y-Axis and one for the Z-Axis are selected. The strength features always involve all axis.

We decided to evaluate the event detection by choosing a learning person that is not involved in the previous training. The learning person attempts to imitate the training of the teacher by performing each motion class 50 times. It should be mentioned that both the teacher and the student are familiar with some kind of martial art.

We evaluate the training using the strength and orientation features in Fig. 6, by applying the metric of specificity, sensitivity, positive predictive value (PPV), negative predictive value (NPV) and accuracy defined in [2]. Furthermore, we present the confusion matrix in Fig. 5 of our experiments. All techniques have been detected with an accuracy of at least 90%. The confusion matrix clearly indicates a well-marked principal diagonal. Thus, we conclude that the distributed event detection classifies the techniques very good, except of slight interferences between some classes.

Strike a) has very good characteristics, but classifies itself once as each of all other classes, except for *Strike f)* which is mistakenly classified four times. *Spin e)* reaches an accuracy of 93%, but interferes with *Strike a)* that reaches an accuracy of 90%. In general, sensitivity is below specificity which leads to some lacking insensitivity especially in the cases of *Spin e)*. In general, *Strike b), Block c), Stab d), Strike f)* deliver a very high accuracy of at least 94%. By the usage of strength and orientation features, we are able to reach an overall classification accuracy of 94%. The learning person was able to learn from the feedback given by the training device, and improves his own technical skills during technique performance. The training motivation is increased by the direct feedback through the LED. The absence of the teacher could compensate in the way that rough mistakes can be easily detected by the training device.

VI. CONCLUSION

Distributed event detection enhances training devices to supervising devices that operate independently from a base station. Activating WOR or performing techniques outdoor increases latency and decreases PDR. Nevertheless, communications are very stable and make a continuous user experience possible. Overall, the device is adequate for users improving the their abilities. The detection accuracy reaches an average of 94%, but some techniques interfere with each other, especially *Spin e)* often is interpreted as strike *Strike a)*. The functionality is reached, which can be seen by the fact that the motivation and the technical skills of the student is raised during the training. Nevertheless, the given results show that our system is well balanced, as prior stick fight experiments with histogram features and intensity features as used in Wittenburg et al. [2] were unsuitable for the training device application.

VII. FUTURE WORK

In future work, we want to reduce the self-calibration time of three seconds that is necessary after each technique. Analysis of optimized features will help to improve our event detection accuracy. Further, we plan to optimize the brass housing and its weight for a better handling in the future. As depicted in Fig. 1g), we aim to have a fully flexible device that will be used in manifold application like training of double weapons and probably also in a miniaturized version that can be attached as a body sensor network to expand the quality of our distributed event detection system.

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