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Real-Time Acoustic Monitoring of Foraging Behavior of Grazing Cattle Using Low-Power Embedded Devices

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***Abstract*—Precision livestock farming allows farmers to optimize herd management while significantly reducing labor needs. Individualized monitoring of cattle feeding behavior offers valuable data to assess animal performance and provides valuable insights into animal welfare. Current acoustic foraging activity recognizers achieve high recognition rates operating on computers. However, their implementations on portable embedded systems (for use on farms) need to be further investigated. This work presents two embedded deployments of a state-of-the-art foraging activity recognizer on a low-power ARM Cortex-M0+ microcontroller. The parameters of the algorithm were optimized to reduce power consumption. The embedded algorithm processes masticatory sounds in real-time and uses machine-learning techniques to identify grazing, rumination and other activities. The overall classification performance of the two embedded deployments achieves an 84% and 89% balanced accuracy with a mean power consumption of 1.8 mW and 12.7 mW, respectively. These results allow this deployment to be integrated into a self-powered acoustic sensor with wireless communication to operate autonomously on cattle.**

***Index Terms*—embedded system, real-time acoustic processing, precision livestock farming, foraging behavior, low-power microcontroller**

I. Introduction

The new and diverse precision livestock farming tools and applications significantly reduce farm labor [1]. Precision livestock farming solutions allow individualized monitoring of animals to optimize herd management in most production systems [2]. Monitoring the feeding behavior of livestock can provide valuable insights into animal welfare, including their nutrition, health, and performance [3]. Changes in feeding patterns, periodicity and duration are used to improve pasture allocation management [4] and ruminant diets that signal anxiety [5] or stress [6], as well as an early indicator of diseases [7], rumen health [8], and the onset of parturition [9] and estrus [10].

Grazing and rumination are the most relevant foraging activities of free-ranging cattle, which together may account for 40-80% of their daily time allocation [11]. Grazing comprises the process of searching, apprehending, chewing and swallowing herbage. This process involves three distinct types of jaw movement (JM) events produced in a non-predefined sequence: chews, bites, and composite chew-bites [12]. Rumination involves cycles of chew events followed by a pause required to swallow and regurgitate the feed cud [13]. In both activities, approximately one JM-event per second is produced. Sequences and types of JM-events can be analyzed at higher temporal scales to determine foraging activity bouts [14].

Ruminant feeding activities have been monitored with wearable sensors [15]. Typical accelerometer-based applications are widely used to discriminate among various nutrition, position, and displacement behaviors [16]. However, this type of sensor has inherent operability and calibration challenges for application with free-range livestock, including difficulties in accurately classifying sensor data with grazing behavior variables associated with pasture dry matter intake. On the other hand, head-placed microphones in free-grazing cattle have been used to identify JM-events [17], discriminate both rumination and grazing bouts [18], distinguish plants and feedstuffs eaten, and estimate dry matter intake [13] using computer software. Despite progress, few autonomous acoustic sensors are available for real-time acoustic monitoring of

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grazing cattle for practical use on farms [19], [20]. Motivated by this need, this work describes two embedded implementations of a state-of-the-art foraging activity recognizer on a low-power ARM Cortex-M0+ microcontroller. The embedded algorithm allows the estimation of grazing and rumination bouts of cattle. It analyses segments of identified JM-events associated with grazing and rumination to delimit activity bouts in real-time. To the best of our knowledge, this is the first implementation in a low-power device of an acoustic algorithm to recognize grazing and rumination behaviors suitable for pasture environments.

II. Materials and Methods

A. Foraging Activity recognizer

The approach presented in this work is the *Noise-Robust Foraging Activity Recognizer* (NRFAR) acoustic method. It outperformed previous acoustic-activity recognizers reported in the literature [18], [21] in quiet and noisy environments. NRFAR is a pattern recognition system that uses masticatory sounds to identify foraging activities [22]. The audio signal is processed sample-by-sample with the *Chew-Bite Energy Based Algorithm* (CBEBA) to recognize JM-events [17]. CBEBA is a real-time pattern recognition algorithm that distinguishes four JM-event classes (*rumination-chews*, *grazing-chews*, *bites*, and *chew-bites*) in adverse conditions. It is implemented through four sequential stages (Fig. 1):

- **Signal preprocessing** - a second-order Butterworth band-pass filter is applied to the audio signal to constrain the signal bandwidth. The filtered signal is squared to compute the instantaneous power signal. The former is used to compute two down-sampled signals that are used by the following stages: a decimated envelope signal and an energy signal calculated by frames. These signals have a lower frequency (150 Hz) than the input audio signal, thus decreasing the computation of the next stages.
- **JM detection** - the presence of peaks in the envelope signal, above a time-varying threshold, indicates the detection of a candidate JM-event. Then, the JM is bound in time by comparing the energy signal with an adaptive threshold.
- **JM feature extraction** - the delimited signals are employed to compute five heuristic JM features: zero-cross derivative of the envelope, accumulated absolute value of the derivative of the envelope, duration, symmetry and total energy. These features are related to the waveform shape and duration of the JM-events and the sound intensity and variation.
- **JM classification** - the values of the JM features are used to decide if the candidate JM-event should be discarded or classified by a multilayer perceptron (MLP) [23]. The MLP network is formed by an input layer (5 neurons corresponding to the JM features), a hidden layer (5 neurons) and an output layer (4 neurons corresponding to the JM-event classes). Then, the thresholds of the JM detection stage are updated according to the signal-to-noise ratio estimated over the energy and envelope signals.

The final stage of the NRFAR buffers the recognized JM-events during 5 min to generate a set of statistical activity features (the JM rate and the percentage of the total JM-events of each class: rumination-chew -%rc-, grazing-chew -%gc-, bite -%b- and chew-bite -%cb-). The five features feed the input of an MLP activity classifier to generate one of the three possible activity labels (Fig. 1). The MLP classifier has one hidden layer with nine neurons and uses the hyperbolic tangent sigmoid and softmax activation functions in the hidden and output layers, respectively. The resulting output labels are smoothed with a third-order median filter to reduce the fragmentation of recognized activity bouts. A detailed description of CBEBA and NRFAR is provided in [17], [22], respectively.

B. Model deployment

This section describes different approaches employed to reduce the computational requirements of NRFAR without significantly affecting the performance for later deployment in an embedded system.

The NRFAR algorithm analyses JM-events from audio signals sampled at 44.1 kHz to determine foraging activities. JM-events are recognized using the CBEBA algorithm. However, CBEBA has reported that its performance does not change with a sampling frequency higher than 2 kHz, although the computation load does. Thus, a variation of the NRFAR algorithm is proposed using audio signals sampled at 2,450 Hz (18 times less than the original), hereafter called NRFAR-MLP. The down-sampling frequency was chosen to match the requirement for the other approaches. The acronym MLP refers to the machine learning classifier used to recognize foraging activities. An MLP is a feed-forward artificial neural network capable of generating non-linear decision boundaries of data classes [23]. An artificial neural network involves the computation of non-linear activation functions. These mathematical operations are not computationally efficient for implementation in constrained low-power microcontrollers. To address this issue, machine learning classifiers with simpler mathematical operations can be used to recognize foraging activities. The proposed NRFAR-DT algorithm uses a decision tree (DT) classifier. A DT generates linear decision boundaries to make predictions based on a sequence of hierarchical binary *if-else* statements. A DT consists of nodes and edges, with the nodes representing decision points and the edges representing the paths taken based on the input values. The root node is split into child nodes based on the value of a chosen input. The leaf nodes represent the final decision or prediction of the algorithm [24].

The implementation of both NRFAR-MLP and NRFAR-DT algorithm into an embedded system requires further optimization. The original implementations use a double-precision floating-point numerical representation. It provides high resolution but poses challenges for computation on typical low-power microcontrollers [25]. To address this issue, two deployments in a low-power microcontroller are proposed. The

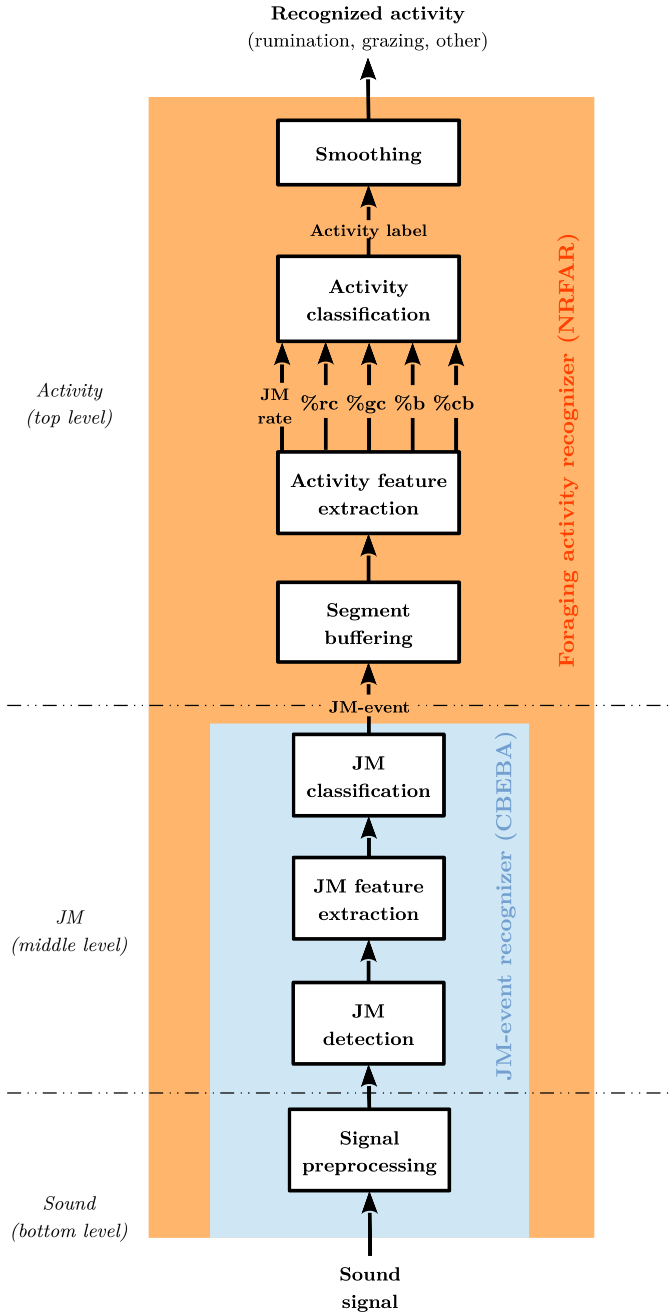

Fig. 1. Block diagram of the different stages of the NRFAR algorithm.

first deployment embeds the NRFAR-MLP algorithm using single-precision floating-point data representation. We refer to it as single-NRFAR-MLP. This deployment focuses on optimizing the foraging activity recognition performance. The second deployment focuses on reducing the microcontroller energy consumption by using a fixed-point data representation (FP-NRFAR-DT). FP-NRFAR-DT uses the state-of-the-art fixed-point representation of the CBEBA algorithm (FP-CBEBA) [26]. Table I summarizes the distinctive characteristics of the different NRFAR algorithm approaches.

TABLE I
MAIN PARAMETERS OF THE DIFFERENT NRFAR ALGORITHM APPROACHES.

Algorithm approaches	Activity classifier	Data format representation	Input sampling frequency [Hz]
NRFAR*	MLP	Double-precision	44,100
NRFAR-MLP	MLP	Double-precision	2,450
NRFAR-DT	DT	Double-precision	2,450
single-NRFAR-MLP	MLP	Single-precision	2,450
FP-NRFAR-DT	DT	Fixed-point	2,450

*State-of-the-art algorithm used for reference.

C. Dataset

The fieldwork to collect acoustic signals took place at the Michigan State University's Pasture Dairy Research Center at the W.K. Kellogg Biological Station, Hickory Corners, MI, USA in August of 2014. The procedures for animal handling and use were revised and approved by the Institutional Animal Care and Use Committee of Michigan State University. The experimental cows were part of a herd that was housed and managed on a pasture-based robotic milking system with voluntary cow traffic as described by [27]. Twenty-four hours of continuous acoustic recordings were obtained on 6 non-consecutive days. Every day, the foraging behavior of 5 lactating high-production multiparous Holstein cows was recorded by 5 independent equipment devices that were rotated daily across the 5 cows, according to a 5 x 5 Latin-Square design. Each device included two directional electret microphones connected to a digital recorder (Sony Digital ICD-PX312, Sony, San Diego, CA, USA). The recorder was enclosed in a weatherproof case (1015 Micron Case Series, Pelican Products, Torrance, CA, USA) for protection, which was attached to a halter located on the neck of the animal. The microphones were placed at the forehead of the cow in a non-invasive way and held and protected by an elastic band to prevent microphone movement, reduce noise caused by wind, and protect microphones from friction and scratches [28]. One microphone was positioned facing outwards to collect masticatory sounds. The other microphone faced inwards to capture the vibrations transmitted through the animal's bones. Each recorder generated four audio recordings of 6 h duration daily. The recordings were saved in stereo with a 16-bit resolution using a sampling rate of 44.1 kHz. The channel of the audio recordings corresponding to the microphone faced inwards was only used in this study because they present better sound quality. More relevant information on the conditions of this experiment is given in [22]. The ground truth identification of foraging activities was carried out by two experts with extensive experience in foraging behavior scouting and digital analysis of acoustic signals. Both experts listened to the recordings to identify, delimit and label activities. Activity blocks were labeled into one of three classes: *grazing*, *rumination* or *other*.

D. Experimental Setup

The experiments were carried out in Matlab R2022b (MathWorks, Natick, MA, USA), except for specific cases mentioned in the following. This study used 92 audio recordings, totaling 349.4 h of outdoor activities. The sampling frequency was decreased from 44,100 Hz to 2,450 Hz using the decimate function of Matlab. This function applies an 8th-order infinite impulse response Chebyshev Type I low-pass filter to the original signal to avoid aliasing. The filter is applied forward and reverse to avoid phase distortion. Classes distribution corresponds to 50.5% *grazing*, 34.9% *rumination* and 14.6% of *other* activities, which reflects typical cattle behaviors [11]. A 5-fold cross-validation scheme was conducted to train and test the models. In each fold, 80% and 20% of the audio recordings were used for training and testing, respectively. The training data were balanced using synthetically oversampled with random undersampled algorithms [29].

To assess the algorithm's performance, the roster of labeled blocks, accompanied by their corresponding activity types and bouts for each audio signal was partitioned into 1-second frame sequences. This division allows for a direct one-on-one comparison between the algorithm output predictions and the ground-truth labels, producing a high-resolution activity recognition analysis of 1,257,759 frames. Furthermore, this approach eliminates the need to handle time offsets, block fragmentation, and merging in the time series activity classification [30]. The balanced accuracy metric was computed for each audio recording to determine model performance. This metric is a reliable performance indicator for imbalanced multi-class problems [31].

The MLP activity classifier of NRFAR-MLP has the same architecture and was trained in the same way as the MLP classifier of NRFAR. A grid-search method was used to determine the optimal values for the two hyperparameters: learning rate and the number of neurons in the hidden layer. The number of neurons was evaluated within a range of 4 to 10 and the learning rate was evaluated at values of 0.1, 0.01, 0.001, and 0.0001. The network weights and biases were optimized using the scaled conjugate gradient backpropagation algorithm. The DT classifier of the NRFAR-DT was built using the classification and regression tree algorithm [24]. To limit the growth of the tree, the maximum number of splits was limited to 20, and the minimum number of samples required to be considered a leaf node was optimized during model training.

The Fixed-Point Designer tool of Matlab was used to manually adjust the bit-accurate fixed-point representation of the variables of FP-NRFAR-DT. No modification over the FP-CBEBA used internally in the FP-NRFAR was conducted. The original 16-bit input audios were requantized to 9-bit resolution to match the requirements of the FP-CBEBA. Unlike the NRFAR approaches using double-precision floating-point representation, the foraging activity recognition performance of FP-NRFAR-DT and single-NRFAR-MLP was evaluated using the compiled C code. The C code was compiled with arm-none-eabi-g++ and deployed in an RP2040 microcontroller mounted on a Raspberry Pi Pico board, using the default peripheral and clock configurations. The RP2040 microcontroller is a 32-bit dual-core ARM Cortex-M0+ based processor able

TABLE II
ACTIVITY RECOGNITION PERFORMANCE OF THE NRFAR ALGORITHM USING DIFFERENT INPUT AUDIO FREQUENCIES.

Algorithm approach	**Input sampling frequency [Hz]**	**Balanced Accuracy (median ± SD)**
NRFAR*	44,100	88.7 ± 10.8
NRFAR-MLP	2,450	89.0 ± 9.6

*State-of-the-art algorithm used for reference.

TABLE III
PERFORMANCE RATE FOR THE PROPOSED ALGORITHM USING DIFFERENT FORAGING ACTIVITIES CLASSIFIERS. THE INPUT AUDIO FREQUENCY IN ALL CASES IS 2,450 HZ.

Algorithm approach	**Activity classifier**	**Balanced accuracy (median ± SD)**
NRFAR-MLP	MLP	89.0 ± 9.6
NRFAR-DT	DT	87.4 ± 11.4
single-NRFAR-MLP	MLP	88.8 ± 9.9
FP-NRFAR-DT	DT	83.8 ± 12.9

to operate up to 133 MHz with 264 kB of embedded static random-access memory, 30 general purpose input/output pins and two main power-saving modes. The *dormant* sleep mode uses a real-time clock to wake up the microcontroller, which is suitable for our implementations [32]. In our deployments, the current consumptions were 29 mA and 0.18 mA for the active and sleep mode, respectively, using a power supply of 3.3 V and a clock frequency of 125 MHz.

III. RESULTS

The effect of decreasing the sampling frequency of the audio signal from 44,100 Hz to 2,450 Hz is shown in Table II. The balanced accuracy averaged over the audio signals presented a small improvement of 0.3% in favor of NRFAR-MLP (p = 0.81; Wilcoxon signed-rank test [33]). Table III shows that NRFAR-DT exhibited a lower performance of 87.4% than NRFAR-MLP (p=0.01). The embedded implementation of single-NRFAR-MLP achieved an 88.8% balanced accuracy, which is comparable to the 89.0% reported by the double-precision NRFAR-MLP (p = 0.78). Moreover, the fixed-point implementation of FP-NRFAR-DT decreases the performance by 3.6% in comparison to the double-precision NRFAR-DT (p=0.01).

The energy consumption to periodically classify the segments of 5 min ($t_{segment}$) in the RP2040 microcontroller depends on the inference time ($t_{inference}$) and the power consumption in active (P_{active}) and sleep (P_{sleep}) modes. The energy consumption in active (E_{active}) and sleep (P_{sleep}) modes and the mean power consumption $\overline{P}$ are given by:

$$E_{active} = P_{active} * t_{inference} \tag{1}$$

$$E_{sleep} = P_{sleep} * (t_{segment} - t_{inference}) \tag{2}$$

$$\overline{P} = \frac{E_{active} + E_{sleep}}{t_{segment}} \tag{3}$$

The inference time and energy/power consumption for both algorithm deployments are presented in Table IV. Table IV also gives the time required to recognize the JM-events (bottom and middle levels in Fig. 1) and to classify the performed activity (top level in Fig. 1). The entire computation for classifying a 5 min segment depends almost entirely on the processing time associated with recognizing JM-events, as over 99% of the total inference time is dedicated to this task. These findings agree with the results of the NRFAR [22]. The single-NRFAR-MLP algorithm consumes 3.66 J to compute the identification of a segment during 38.23 s. During the idle state, it consumes 0.16 J over 261.77 s. Therefore, on average, it consumes 12.71 mW. Similarly, FP-NRFAR-DT consumes 0.35 J in active mode during 3.70 s and 0.16 J in sleep mode during 296.30 s, resulting in an average power consumption of 1.77 mW.

IV. Discussion

Acoustic monitoring is a reliable method for continuous monitoring of ruminants' foraging behavior. It provides insight into animal welfare and pasture management practices. In recent years, algorithms for monitoring the foraging behavior of cattle have been developed. However, its real application on autonomous sensors designed to work in field conditions still needs to be researched. In this work, an acoustic-based foraging activity recognizer has been deployed in an embedded system for real-time application. The motivation of this work is to provide farmers with a reliable tool to enhance productivity through the individualized monitoring of animals. To the best of our knowledge, it is the first embedded implementation able to accurately classify rumination and grazing activities using masticatory sounds. The NRFAR algorithm was chosen as the target for this embedded implementation due to its high performance even in noisy environments commonly found in pastures. NRFAR is based on the statistical analysis of different JM-events classes. Their proper operation depends, therefore, on the correct recognition of the JM-event classes. To achieve the computational and power requirements for the embedded implementation, the NRFAR algorithm has been modified using different approaches. The effect of reducing the sampling frequency of the audio from 44,100 Hz to 2,450 Hz presented a slight increase in performance of 0.3%, although this is not statistically significant (Table II), which is consistent with the requirement to properly recognize JM-events established in a previous work [17]. We hypothesize that the increase in performance is due to the anti-aliasing filter removing high-frequency noise. Therefore, the algorithm approaches described in the following operate with an audio sampling frequency of 2,450 Hz. Machine learning classifiers based on logic operations present good results in several problems and are feasible to implement in most microcontrollers. The original MLP neural network activity classifier in NRFAR-MLP was replaced with a DT (NRFAR-DT), resulting in a slight decrease in performance by 1.3%. This level of performance drop is deemed acceptable for a classifier that requires a maximum of 20 comparison operations. NRFAR-MLP using single-precision data representation (single-NRFAR-MLP) and NRFAR-DT using fixed-point data representation (FP-NRFAR-DT) were deployed on an RP2040 microcontroller.

The single-NRFAR-MLP algorithm has a higher recognition performance metric than FP-NRFAR-DT (88.8% vs. 83.8%) (Table III). However, the inference time of single-NRFAR-MLP is 10 times longer (38.2 s vs. 3.7 s) which increases its power consumption by more than 7 times (12.7 mW vs. 1.8 mW) (Table IV). This is related to the optimized fixed-point data representation and mathematical operation used by the FP-NRFAR-DT. In both deployments, the total inference time has a remarkable dependency on the inference time for the recognition of JM-events (bottom and middle levels with blue background color in Fig. 1). While the JM-events recognizer processes all input signal samples, the last stage of the algorithm for classifying the foraging activity performs only once per segment (top level of Fig. 1). These results support the basis for the deployment of a fixed-point data representation of NRFAR using an ensemble tree classifier to improve the recognition performance of FP-NRFAR-DT in a future study. Remarkable is that the energy consumed in sleep mode for the FP-NRFAR-DT represents 33% of the total energy consumption (active mode plus sleep mode). The energy profile of FP-NRFAR-DT of this deployment could be improved using an ultra-low-power microcontroller with lower power consumption in sleep mode. However, due to its higher computational requirements, embedding single-NRFAR-MLP on ultra-low-power microcontrollers could be ineffective. Using the RP2040 microcontroller allows us to implement a complex algorithm, able to provide high recognition rates, in a portable device for developing a practical device to be used in farms. Moreover, the microcontroller has an ARM Cortex-M0+ processor. This processor presents a simpler architecture than other Cortex-M family and is commonly used in low-cost, low-power embedded applications [34].

V. Conclusion

This study presented the real-time implementation in a low-power embedded system of an algorithm for the recognition of grazing and rumination activities in cattle. As far as we know, this is the first time masticatory sound signals are used to recognize foraging activities in an electronic device. The state-of-the-art NRFAR algorithm was selected as the reference for deployment on an energy- and resource-constrained microcontroller. Various parameters, such as input audio frequency, data bit resolution, and the machine learning activity classifier, were fine-tuned to reduce computational requirements without compromising algorithm accuracy. Two optimized algorithm approaches were embedded in an ARM Cortex-M0+ microcontroller, achieving a balanced accuracy metric of 83.8% and 88.8%, while consuming 1.8 mW and 12.7 mW, respectively. These promising results lay the groundwork for creating a completely autonomous acoustic sensor with wireless communication and energy harvesting capabilities in future work.

TABLE IV

INFERENCE TIME AND ENERGY CONSUMPTION OF THE EMBEDDED ALGORITHMS TO CLASSIFY A SEGMENT OF 5 MIN.

Algorithm deployment	single-NRFAR-MLP	FP-NRFAR-DT
Inference time to recognize JM-events (median $\pm$ SD) [s]	38.23 ± 0.05	3.70 ± 0.00
Inference time to classify foraging activities (median $\pm$ SD) [μs]	964.60 ± 8.14	59.70 ± 0.90
Total inference time (median $\pm$ SD) [s]	38.23 ± 0.05	3.70 ± 0.00
Energy consumption in active mode (Eq. 1) [mJ]	3658.61	354.09
Energy consumption in sleep mode (Eq. 2) [mJ]	155.49	176.00
Average power consumption (Eq. 3) [mW]	12.71	1.77

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