Attention-Based Adaptive Sampling for Continuous EMG Data Streams

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***Abstract*— This paper presents an online attention-based adaptive sampling approach for EMG data streams. Our sampling strategy is based on dynamically tuning the duty cycle of an EMG monitoring and recognition system. A response model was developed to adjust the EMG system's sampling rate depending on the signal pattern. The response model was implemented by two sampling rate states. We report a case study of an eyeglasses diet monitoring system that implements the adaptive sampling strategy to monitor the Temporalis muscle activity. We show that the adaptive sampling approach can reduce energy consumption in a free-living study dataset with ten participants. Compared to a static uniform sampling, our approach yields an energy saving on 70%, while recognition performance remained above 80%.**

I. INTRODUCTION

Energy consumption for sensors and processing electronics often limits the runtime or sampling rate of wearable systems that are intended to continuously monitor behaviour. Simply increasing the battery capacity would imply increased device size, which is frequently contradicting continuous, unconstrained use in free-living. As a consequence, the application options of current wearable systems are limited.

An important observation which leads to our adaptive sampling approach is that events relevant for the analysis of everyday behaviour are typically sparse along time. Such 'interesting' events in physical or physiological data are distributed across relatively long phases of irrelevant data. An adaptive strategy, that estimates the relevance of future data samples, has thus the potential to balance information retrieval performance and resources use.

In an adaptive sampling scenario, two main challenges can be identified. First, a context measure mechanism is required to estimate relevance of future samples. Second, a response model is needed to control the system's duty cycle based on the context measure. The overall system behaviour policy must be implemented by the response model: Keep all energy-consuming components as long as possible in a low-power mode and only activate them if, according to the context model, relevant data events are expected.

This paper provides the following contributions:

1) We present an attention-based adaptive sampling approach for EMG data streams. As context measure, we use a basic representation of EMG signal energy. As response model, we employ a feed-forward state-based model that alternates between attentive and sleep states.

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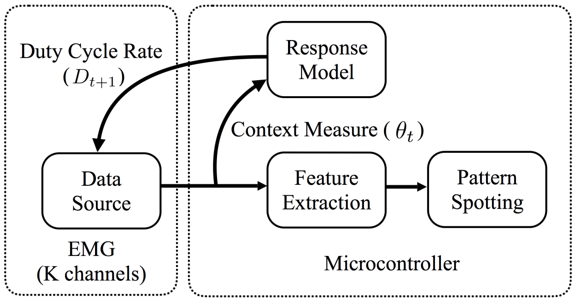

Fig. 1: Schematic of our attention-based dynamic sampling system for spotting EMG signal patterns. The context measure θ_t serves as input to a response model, which controls the duty cycle rate D_{t+1} for the next time period. D_{t+1} corresponds to the EMG sampling rate.

2) We analyse our adaptive sampling approach in a case study of smart eyeglasses to monitor the Temporalis muscle activation. We employ an algorithm to spot eating events based on captured muscle contractions. We estimated the energy consumption of sampling and processing stages by simulating the complete sensing and processing system. The tradeoff between information retrieval performance and energy consumption was evaluated for eating event spotting in continuous EMG data acquired in a free-living study with ten participants.

II. RELATED WORK

Adaptive sampling aims to balance energy consumption and information acquired by a wearable or mobile systems. An extensive analysis of techniques for energy consumption reduction on wearable sensors for healthcare applications was provided by Rault et al. [1]. Balouchestani et al. [2] introduced a method to compress the EMG signal during acquisition, before the analog to digital conversion. The authors adjusted the sparsity level of the signal using a dynamic thresholding approach to control the downsampling level. Mesin [5] proposed a proactive adaptive sampling based on sample prediction. A sample was required only when the uncertainty of the prediction exceeded a threshold. As context measure, a portion of the acquired signal was used. The data section length used for prediction was determined by embedding theory. As a response model, a multi-layer perceptron was employed, which required model training. The method was evaluated using EMG, ECG and EEG data streams. Our approach differs, as we employ a transparent state-based response model.

Rieger and Taylor [3] proposed a real-time adaptive approach to tune the sampling rate proportionally to the signal curvature. As a context measure, the second derivative of the signal was used. A response model was implemented by thresholding the sampling error. The method was evaluated using ECG, EEG, blood pressure, and gait pressure sensors. While signal-to-noise ratio and energy consumption of the adaptive approach improved compared to uniform sampling, a-priori knowledge was required. Average sample frequency and data rate were over 50%, and 38%, respectively, below uniform sampling. In contrast to Rieger and Taylor's low-power analog system, we consider a pattern spotting problem to analyse performance.

Feizi et al. [4] implemented a customisable sampling function, designed to select only innovative samples. Their sampling function had to be chosen depending on the application. The functions of context measure and response model were embedded in the sampling function. The sampling function's output depended on previous samples. The method was evaluated using ECG data streams.

Scarabottolo et. al. [6] presented a mechanism to adapt the sampling frequency to the spectral content of the signal. Specifically, a spectrum-based change detection test, designed to be executed on low-power embedded devices, was introduced. The context measure relied on energy features extracted from spectral sub-bands. The response model was designed to discriminate between changes and aliasing. Our work differs from the Scarabottolo et al., as our context measure relied on the energy of the taken samples in the time domain.

An analysis of an adaptive sampling procedure, which depends on a context measure, should not neglect context-related effects on the behaviour of the response mechanism. For example, behavioural differences between users reflect in different degrees of activity intensity, duration, and sparsity. In contrast to the aforementioned works, we evaluated the effects of the adaptive sampling procedure by analysing data recordings from ten participants in a free-living scenario. By estimating retrieval performance of an online spotting pipeline, we evaluated the capability of the adaptive sampling method to balance between energy consumption and information quality.

In [7] we analysed a novel method to save energy on a wrist-mounted inertial measurement unit (IMU). Our method was based on a motion-adaptive controller to tune the duty cycle of the wrist's orientation estimation using a Madgwick filter. As a context measure, we employed an estimation of motion based on the gyroscope signal. As response model, a proportional relation between the gyroscope signal and the sensor duty-cycle was defined. Performance was evaluated by deriving the quaternion estimation error and accuracy of a natural intake gesture recognition task.

In the present work, we analyse the energy consumption reduction method for an EMG monitoring and recognition system. We introduce our adaptive context measure and our switching response model, i.e., attention-based two-state response model. The switching response model served as mechanism to preserve spectral content when sampling potential target patterns. In contrast to our previous work, a paradigm of n-shots measurement was adopted. We evaluated the performance considering the retained spectral signal and regarding the retrieval performance of an event spotting task.

III. Attention-Based Adaptive Sampling

Our adaptive sampling mechanism is composed of two components. The context measure extracts information from the stream of data, and the response model computes a response signal to tune the sensor's and microcontroller's duty cycle.

Context Measure: We adopted a n-shots measurement paradigm, i.e., the sensor wakes up, captures n samples, and goes to sleep again. The adoption of the n-shots measure is justified by the nature of the EMG signal. A single sample may be insufficient to identify patterns in an EMG signal, as the pattern shape depends on muscle fibre firing rates. The context measure, derived by energy content from the n samples, was computed according to the following equations:

$$\epsilon_k = \frac{\sum_{i=1}^{n} s_{i,k}}{n}, \quad \theta_t = \max\Bigg(\epsilon_1, \ldots, \epsilon_k, \ldots, \epsilon_K\Bigg), \tag{1}$$

where ϵ_k is the signal energy for the k^{th} channel, $s_{i,k}$ is the i^{th} value sampled from the n-shots measurement, θ_t is the context measure, t corresponds to the current sampling period, K is the number of channels that connect to the same system.

Response Model: We employed a linear mapping function to convert θ_t to a candidate duty cycle rate D^*_{t+1} for the next period:

$$D^*_{t+1} = D_l + \left[\frac{D_h - D_l}{\theta_h - \theta_l} \cdot \theta_t - \theta_l\right], \tag{2}$$

where D_l is the minimum duty cycle rate set to θ_l, which was estimated from the EMG noise. The maximum duty cycle rate D_h was set to θ_h. We adjusted the model's sensitivity by tuning θ_h.

To determine the duty cycle rate of the next period, the candidate duty cycle rate D^*_{t+1} was compared to a threshold value D_{TH}. Eq. 3 shows the behaviour used. The attentive state was defined as monotonically increasing duty cycle rate. The response model switches to the attentive state each time that the candidate duty cycle rate surpasses D_{TH}. The response model switches back to the inattentive state if the candidate duty cycle rate is below D_{TH} and the attention time τ has elapsed. The duty cycle rate's decision rules for the two states were defined as follows:

1) Inattentive state

If $(D^*_{t+1} < D_{TH})$ and τ elapsed) :

$$D_{t+1} = D^*_{t+1}$$

2) Attentive state (3)

If $(D^*_{t+1} > D_{TH})$:

$$D_{t+1} = \begin{cases} D_t, & D^*_{t+1} \leq D_t \\ D^*_{t+1}, & D^*_{t+1} > D_t. \end{cases}$$

IV. Evaluation Methods

A. Simulation

We considered a wearable smart eyeglasses system to evaluate the energy savings of a real hardware case scenario. We adopted the finite-state machine simulation approach used by Buschhoff et al. [8], in order to reproduce dependencies among different components and between hardware and software.

B. Energy Consumption Model

The system elements, i.e., sensor and microcontroller, were modelled independently:

$$E^{\text{tot}} = E^{\text{emg}} + E^{\text{mcu}}, \tag{4}$$

where E_{emg} is the EMG electronics' energy consumption, E_{mcu} is the microcontroller's energy consumption.

1) Sensor Energy Consumption: In active state, the average current I_{act} for a duration t_{act} was considered. In standby state, the digital circuitry of the sensor consumed a current I_{stby} for a duration t_{stby}. We estimated the average instantaneous consumption of the EMG system in adaptive sampling mode by applying the following equations:

$$\begin{aligned} &I_t = I_{\text{act}} \times D_t + I_{\text{stby}} \times (1 - D_t), \\ &E^{\text{emg}}_t = I_t \times V \times t_r, \\ &E^{\text{emg}} = \sum_{t=1}^{T} E^{\text{emg}}_t, \end{aligned} \tag{5}$$

where E^{emg}_t and E^{emg} are the instantaneous and total energy consumption in Wh, T is the total simulation time, and t_r is the temporal resolution of the simulation expressed in hours, i.e., in our simulation $t_r = 1/(3600 * f) = 1.11 * 10^{-6}$ being equal to the inverse of the frequency f of our dataset.

2) Microcontroller Unit Energy Consumption: We estimated the energy consumption required by the microcontroller, as proportional to the function computational cost required for reading the sensors data, extracting features, detecting the target pattern and generating the response signal. In Tab. I, an overview for the implemented functions and their computational costs is presented. The average energy consumption E^{mcu} of the microcontroller was modelled as:

$$E^{\text{mcu}} = \sum_{i=1}^{I} \sum_{j=1}^{J_i} t^i_{\text{proc}} P_{\text{act}} + (T - \sum_{i=1}^{I} \sum_{j=1}^{J_i} t^i_{\text{proc}}) P_{\text{low}}, \tag{6}$$

where t^i_{proc} is the processing time, expressed in hours, proportional to the clock cycles, where J_i is the total number of function's executions during the simulation time, i refers to a specific function to execute, and E^{mcu} is expressed in Wh. We computed the processing time of a function's execution as follows:

$$t^i_{\text{proc}} = \frac{n^i_{\text{m}} + n^i_{\text{a}} + n^i_{\text{c}}}{f_{\text{mcu}}}, \tag{7}$$

where n^i_{a} is the number of cycles for additions, n^i_{m} is the number of cycles for multiplications, n^i_{c} is the number of cycles for comparisons, to execute the function i, and f_{mcu} is the clock frequency of the microcontroller, i.e., 3.69 MHz for the TI MSP430F1611. Tab. I reports also the number of cycles required by the microcontroller to execute the arithmetical operations.

C. Eating Event Spotting

Method: We applied the pattern spotting method introduced by Zhang and Amft [9] in order to identify eating moments by monitoring the Temporalis muscle contractions during chewing. Our system design was composed by an online spotting pipeline that continuously processed a stream of EMG data using an online non-overlapping sliding window segmentation. A feature extraction module computed features from K data stream channels and fed the pattern spotting module. A one-class support vector machine (ocSVM) provided prediction at a frame-based level. Details of the feature extraction and one-class classification can be found in [9].

Validation Method: We used leave-one-participant-out (LOPO) cross-validation strategy. Hyperparameter optimisation, i.e., γ and ν, was performed using grid search during LOPO training phases.

Retrieval Performance: The algorithm performances were evaluated using precision, recall and F1 score metrics calculated as follows: Recall $= \frac{TP}{GT}$, and Precision $= \frac{TP}{RET}$. In the formulas, GT is the total number of samples of all eating events according to ground truth labels, RET is the total number of samples of all retrieved eating events, and TP is the sum of time durations of correctly retrieved eating events segments.

D. Frequency Analysis

The signal was presegmented in eating events and non-eating data, i.e., the rest of the data. We computed the Power Spectral Density (PSD), by computing the Fast Fourier transformation of the EMG signal segments, for two conditions: eating events and non-eating data. For the purpose, Bartlett's method was employed. The average PSD with standard deviation for eating and non-eating data was computed by averaging the PSDs obtained from the presegmented data, i.e., both sides and all subjects. The mean and standard deviation of the mean PSD were calculated on 2 Hz frequency bins from 0 to 128 Hz, after normalising the amplitudes to their maximum value.

V. Free-Living Data Collection

Ten healthy volunteers (4 females, 6 males) aged between 20 and 30 years wore personalised 3D-printed monitoring eyeglasses with integrated EMG electrodes for one day [10]. The eyeglasses were used to monitor

Module	Function	Add	Mult	Div	Root	Comp	Exp
Feature extraction	Standard deviation	$3m-1$	m	2	1	-	-
	Fast Fourier trasform	$m\ log_2 m$	$\frac{m}{2}\ log_2 m$	-	-	-	-
	Maximum	-	-	-	-	$m-1$	-
	L2-norm	$d-1$	d	-	1	-	-
Spotting	Kernel SVM	v	$2v$	-	-	-	-
	+ Radial basis kernel	$v(2d-1)$	$v(d-1)$	-	-	-	v
Response Model	Context measure	$2n$	$-$	2	-	-	-
	Response output	4	1	1	-	-	-
	Attention time (τ)	-	-	-	-	2	-
Number of cycles for TI MSP430F1611		177-184	153-395	405	668-1008	37	334-2004

TABLE I: Computational cost overview for feature extraction, spotting, and adaptive sampling. The computational costs were used for the estimation of the energy consumption of the system, see Sec. IV for details. For feature extraction, the variable m denotes the length of the segmented time series. For spotting, the variable d denotes the dimensionality of the feature space, and the variable v is the number of support vectors. The variables m, d and v, correspond to algorithm hyperparameters.

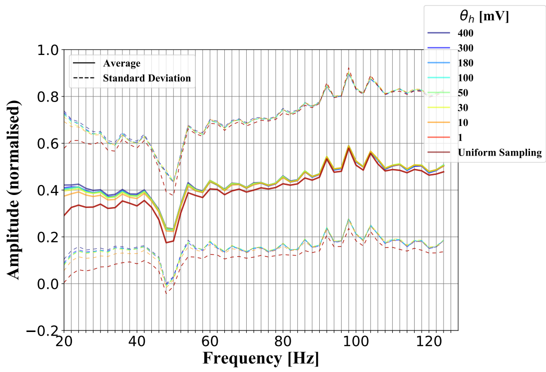

Fig. 2: Power spectrum density for eating events across participants. The used parameters are: $D_h = 1$, $D_l = 0.1$, $D_{TH} = 0.6$, $n = 4$, $\theta_l = 10\,mV$.

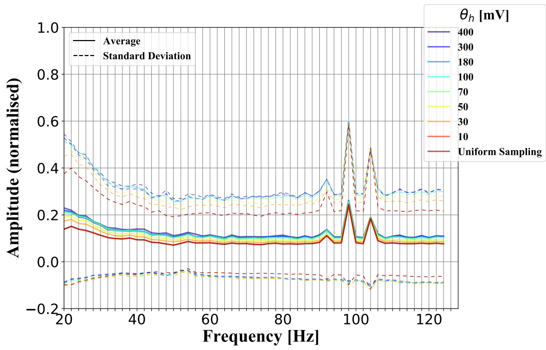

Fig. 3: Power spectrum density for the non-eating data across participants. The used parameters are: $D_h = 1$, $D_l = 0.1$, $D_{TH} = 0.6$, $n = 4$, $\theta_l = 10\,mV$.

chewing by measure muscle contraction forces in a bilateral EMG measurement. The eyeglasses were attached after getting up in the morning and kept on till bed time. When a risk of contamination with water existed, the participants were allowed to remove the eyeglasses. Participants manually logged the occurrence of eating events in a diet journal with a one minute resolution. A reference EMG channel was derived from the Temporalis measurement position according to the standard EMG electrode positions. The reference EMG and the diet journal were combined to derive eating event annotations used in the performance analysis.

The 2-channel EMG recorders (Actiwave, CamNtech) provided a differential voltage between channel and common electrodes. Temple end electrodes were wired together as common electrode, while temple ear bend electrodes served as left and right channels respectively. The sampling rate was set to 256 Hz per channel.

The EMG signals were passed through a notch filter of 50 Hz to remove power line's interferences, likely to occur in free-living. The signals were also de-trended by a digital high pass filter of 20 Hz and rectified.

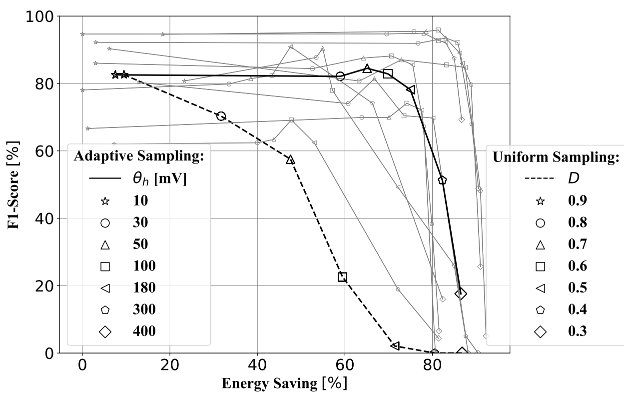

Fig. 4: Retrieval performance vs. energy saved across participants. Black lines indicate average performance for uniform sampling and adaptive sampling mode. Grey lines indicate participant-specific performances for adaptive sampling mode. In uniform sampling mode, D is varied. In adaptive sampling mode, θ_h is varied. The used parameters for the adaptive sampling mode are: $D_h = 1$, $D_l = 0.1$, $D_{TH} = 0.6$, $n = 4$, $\tau = 3\,s$, $\theta_l = 10\,mV$.

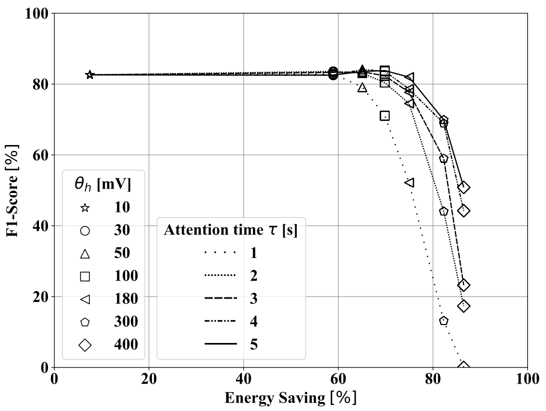

Fig. 5: Effect of the attention time τ on the energy saving trade-off when θ_h is varied. The used parameters are: $D_h = 1$, $D_l = 0.1$, $D_{TH} = 0.6$, $n = 4$, $\theta_l = 10\,mV$.

	Sensing (EMG) $[mWh]$	Processing (μC) $[mWh]$
Uniform sampling mode	162.10 (12.91)	2.71 (0.21)
Adaptive Sampling mode	35.79 (22.63)	1.24 (0.27)

TABLE II: Simulated energy consumption estimation for the EMG system and the microcontroller. The estimation is averaged across ten participants. The duty cycle rate for the uniform sampling mode is $D = 1$. The used parameters for the adaptive sampling mode are: $D_h = 1$, $D_l = 0.1$, $D_{TH} = 0.6$, $n = 4$, $\tau = 3\,s$, $\theta_h = 180\,mV$, $\theta_l = 10\,mV$.

VI. Results

In our analysis, we compared performances of uniform sampling mode, with a constant duty cycle rate D, and adaptive sampling mode. Tab. II shows the simulated energy consumption estimations reported for uniform sampling mode and adaptive sampling mode. Fig. 4 shows results related to the trade-off between the F1-score against the energy saving, when uniform sampling is applied and when adaptive sampling is applied. With uniform sampling the retrieval performance quickly degrades as the duty-cycle ratio decreases. In adaptive sampling mode, the retrieval performance remains over 80%, while reaching almost 70% of energy saving. The plot demonstrates the effectiveness of the adaptive sampling compared to uniform sampling. The effectiveness of the adaptive sampling stands in the capability to increase the sampling rate in case of potential target patterns. The assumption is that the higher the detected activity intensity, the higher the probability to detect a target pattern.

Fig. 4 furthermore shows results of adaptive sampling for individual study participants. The variance of the energy saving estimation is mostly due to the highly stochastic and variable nature of individual participant behavioural patterns. In fact, the temporal variance of behavioural patterns among participants strongly affects the adaptive sampling behaviour. With adaptive sampling, a proportional relation between activity intensity and duration with the energy saving can be assumed.

Considering retrieval performance F1-score was mostly affected by the attention time τ. Fig. 2 shows the influence of τ. For $\tau = 1$, a rapid decrease of F1-score when decreasing the sensitivity was observed. As the attention time increases, more samples are collected, causing a minor degradation of spotting performances.

The switching mechanism of our response model is designed to preserve spectral content of potential target patterns. Thus, we expect a minimal downsampling degradation effect on the spectral content across different sampling mode for eating events. Figs. 2 and 3 show frequency spectra for eating and non-eating events. The graphs illustrate downsampling effects in the power distribution across frequency components. As expected, the power spectrum standard deviation's amplitude shows that the effect of the downsampling on the eating events is minimised by the switching response model. In fact, the standard deviation of eating events is considerably lower than the standard deviation's amplitude of non-eating events. We attribute the minor spectral content degradation for eating event patterns to the attentive state of the response model. In contrast, larger spectral content degradation was observed for non-eating data patterns, which can be attributed to the more frequently used inattentive state of the response mode.

VII. Conclusion

In this work, an adaptive sampling approach for continuous EMG data stream was presented. We reported a case study of eyeglasses for eating event spotting in free-living. We demonstrated that our method can reduce energy consumption in resource-limited monitoring system. We analysed the behaviour of our attention-based response model in tuning the duty-cycle of the sensor. An energy consumption model was implemented to estimate the energy consumed by the EMG system. We tested our estimation procedure in free-living study data, analysing recordings from ten participants. Further studies are required to evaluate variables that may affect the energy consumption and retrieval performance, including limited resource requirements, e.g., execution time, battery size, energy budget, and user characteristics, e.g., eating habits, gender, BMI, and age.

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