Design optimization of flexible analog-to-feature converter for smart sensors

Mikhail Manokhin, Paul Chollet, Patricia Desgreys

C2S Team, ComElec Dept., *LTCI, Télécom Paris, Institut Polytechnique de Paris*, Palaiseau, France emails: {mikhail.manokhin; pachollet; patricia.desgreys}@telecom-paris.fr

Abstract—Analog-to-Feature (A2F) conversion is an attractive alternative for the significant reduction of energy consumed by wireless communication systems during data transfer from sensor to aggregator. This work illustrates the simulation results of anomaly detection in ECG signals via A2F conversion based on Non-Uniform Wavelet Sampling (NUWS). Moreover, another application is envisioned to show the genericity of the proposed converter and determine its parameters for a circuit design.

Index Terms—Analog-to-Feature conversion, smart sensors, Non-Uniform Wavelet Sampling, Machine Learning.

I. INTRODUCTION

Nowadays, the fast development of the Internet of Things (IoT) and Wireless Sensor Networks (WSN) leads to the need for new context-aware smart sensors. However, emerging applications impose certain constraints: such sensors should remain cheap, compact, reliable, with a lifetime of several years. Thereby, the reduction of total energy consumed by wireless communication systems is of primordial importance. Since the transmission of samples acquired at Nyquist rate from sensor to aggregator can represent up to 96% of the global consumption budget of sensors [1], it is, therefore, the main lever for saving energy and increasing their autonomy.

To achieve this, one needs either to improve the energy efficiency of the transmission system or to adopt a novel data acquisition technique, such as compressive sensing (CS) for Analog-to-Information (A2I) conversion [2]. Although CS reduces the number of acquired samples, it requires the reconstruction of the original signal usually with the help of complex algorithms and it also has a limited compression ratio [3]. An even greater reduction of energy consumption can be obtained by Analog-to-Feature (A2F) conversion, which extracts the useful features directly in the analog domain [4] and uses them as inputs for Machine Learning (ML) algorithms for further classification at sensor or aggregator level.

This work is a continuation of [5] aiming to design a generic A2F converter for different low-frequency signals (electrocardiogram (ECG), electroencephalogram (EEG), electromyography (EMG), voice, etc.). A2F based on Non-Uniform Wavelet Sampling (NUWS) [6] has been proposed in [5] mainly for anomaly detection in ECG signals, showing the benefit of this approach over A2I and conventional sampling in terms of energy consumption. In contrast to [5], herein the ML algorithms are reimplemented using Python and TensorFlow instead of MATLAB® tools, allowing for more complicated and efficient ML models, especially Neural Networks (NNs).

II. CURRENT RESULTS

a) Analog-to-Feature conversion: The proposed reconfigurable converter, given in Fig. 1, is based on the NUWS architecture, which mixes the analog signal with tunable wavelets prior to integration and digital conversion to extract features. NUWS provides several degrees of freedom and, thus, requires feature selection algorithms to determine a reduced set of features relevant for a given classification task.

b) Simulation results: Anomaly detection in ECG signals is performed using the MIT-BIH Arrhythmia database [7] (48 recordings of 30 min each, sampled at 360 Hz) for supervised learning with a 70/30% proportion between learning and test sets. In this work, NUWS exploits only Haar wavelets (square functions taking values ± 1 , 0), which reduce the digital wavelet generator's complexity and allow to use a simple mixer composed of 4 CMOS transmission gates [5]. According to [5], the best classification results are obtained with the Feedforward NN classifier, Information Gain (IG) method serving as a pre-selection stage to reduce the feature set before Sequential Forward Search (SFS). Fig. 2 shows the impact of the SFS algorithm on the ECG anomaly detection







Fig. 2. Impact of SFS algorithm on accuracy, sensitivity and specificity

performances obtained using NNs with one hidden layer of 10 neurons trained during 1500 epochs. The accuracy, sensitivity (recall) and specificity (selectivity) of binary classification are plotted against the number of selected features.

Each extractor is capable of extracting simultaneously only the sequence of features that do not superpose in the analysis window of a heartbeat (256 samples long). Therefore, an adapted SFS algorithm has been proposed, which limits the maximum number of parallel extractors to reduce the system's power consumption. Fig. 3(a) illustrates the performances of this algorithm for a different number of extractors with distinct markers indicating the extractor to which a selected feature is attributed. A2F converter's energy consumption is estimated considering the state-of-the-art amplification stage (Low Noise and Programmable Gain Amplifiers) and ADC (Analog-to-Digital Converter) from [8], G_m-C integrator from [9], as well as the digital wavelet generator [5] synthesized in XFAB CMOS 0.18 µm technology. An optimized SFS algorithm takes into account the energetic cost during feature selection in order to minimize the total energy consumption, while maximizing the classification accuracy, as shown in Fig. 3(b). The optimized SFS algorithm achieves 98.17% accuracy with 8 extracted features and 2.6 µJ energy consumption, while the adapted SFS algorithm requires 7 features and 8.5 µJ for slightly higher accuracy of 98.33%.

c) New applications: As the current work aims at the design of a generic A2F converter chip, applications other than ECG arrhythmia detection should be explored. This will allow



Fig. 3. Accuracy, sensitivity and energy consumption using adapted and optimized SFS algorithms

to define the relevant features for extraction and eventually the required system's parameters, such as the number of parallel extractors, their internal parameters (e.g., analysis window length, integrator's cut-off frequency, wavelet generator's operating frequency), classifier's structure and position in chain (in-sensor classification or transmission of features to aggregator). Although a preliminary study of the converter's reconfigurability has been conducted using EEG signals in [5], the trained NN showed poor seizure detection sensitivity due to a low occurrence of seizure events in database recordings. Thus, other applications are yet to be found, including voice activity [10], physical activity [11], or fall detection [12] using EMG, accelerometers, gyroscopes, or other signals.

III. CONCLUSION

We have presented a successful transition of earlier implemented A2F conversion based on the NUWS approach to more suitable and advanced software tools. However, so far only anomaly detection in ECG signals has been explored. In this regard, the search for another application is still in progress in order to show the genericity and reconfigurability of the proposed A2F converter and determine its parameters required for the complete circuit design and chip fabrication.

ACKNOWLEDGEMENT

This work was partly carried out in the context of Beyond5G, a project funded by the French government as part of the economic recovery plan, namely "France Relance", and the investments for the future program.

REFERENCES

- [1] N. Verma, A. Shoeb, J. Bohorquez, J. Dawson, J. Guttag, and A. P. Chandrakasan, "A micro-power EEG acquisition SoC with integrated feature extraction processor for a chronic seizure detection system," *IEEE Journal of Solid-State Circuits*, vol. 45, no. 4, pp. 804–816, 2010.
- [2] E. J. Candes and M. B. Wakin, "An introduction to compressive sampling," *IEEE Signal Processing Magazine*, vol. 25, no. 2, pp. 21–30, 2008.
- [3] E. Crespo Marques, N. Maciel, L. Naviner, H. Cai, and J. Yang, "A review of sparse recovery algorithms," *IEEE Access*, vol. 7, pp. 1300– 1322, 2019.
- [4] B. Rumberg, D. W. Graham, V. Kulathumani, and R. Fernandez, "Hibernets: energy-efficient sensor networks using analog signal processing," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 1, no. 3, pp. 321–334, 2011.
- [5] A. Back, "Conception et intégration d'un convertisseur analogiqueparamètres flexible pour les capteurs intelligents," Theses, Institut Polytechnique de Paris, Feb. 2022. [Online]. Available: https://tel.archives-ouvertes.fr/tel-03624373
- [6] M. Pelissier and C. Studer, "Non-uniform wavelet sampling for RF Analog-to-Information conversion," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 65, no. 2, pp. 471–484, 2018.
- [7] G. Moody and R. Mark, "The impact of the MIT-BIH arrhythmia database," *IEEE engineering in medicine and biology*, vol. 20, pp. 45– 50, 2001.
- [8] H. Bhamra, J. Lynch, M. Ward, and P. Irazoqui, "A noise-power-area optimized biosensing front end for wireless body sensor nodes and medical implantable devices," *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, vol. 25, no. 10, pp. 2917–2928, 2017.
- [9] J. Pérez-Bailón, B. Calvo, N. Medrano, and J. Ramírez-Angulo, "A 1.8 V Gm-C highly tunable low pass filter for sensing applications," in 2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), 2020, pp. 1–5.

- [10] K. M. H. Badami, S. Lauwereins, W. Meert, and M. Verhelst, "A 90 nm CMOS, 6 μW power-proportional acoustic sensing frontend for voice activity detection," *IEEE Journal of Solid-State Circuits*, vol. 51, no. 1, pp. 291–302, 2016.
- [11] S. Mekruksavanich and A. Jitpattanakul, "Exercise activity recognition with surface electromyography sensor using machine learning approach," in 2020 ECTI DAMT & NCON, 2020, pp. 75–78.
- [12] S. Abbate, M. Avvenuti, F. Bonatesta, G. Cola, P. Corsini, and A. Vecchio, "A smartphone-based fall detection system," *Pervasive and Mobile Computing*, vol. 8, no. 6, pp. 883–899, 2012.