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Antidictionary-Based Cardiac Arrhythmia Classification For Smart ECG sensors

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***Abstract*— Cardiovascular diseases can be detected early by analyzing the electrocardiogram of a patient using wearable systems. In the context of smart sensors, detecting arrhythmias with good accuracy and ultra-low power consumption is required for long-term monitoring. This paper presents a novel cardiac arrhythmia classification method based on antidictionaries. The features are sequences of consecutive slopes generated from the input signal's event-driven processing. The proposed system shows an average detection accuracy of 98% while offering an ultra-low complexity. This antidictionary-based method is also particularly suited to imbalanced datasets since the antidictionaries are created exclusively from heartbeats classified as normal beats.**

Keywords—Cardiac Arrhythmia Classification, Electrocardiogram, Event-driven, Antidictionary

I. Introduction

Cardiovascular diseases (CVD) are the leading cause of death globally [1]. Electrocardiogram (ECG) is used for early CVD diagnosis and wearable at-home monitoring systems can avoid patient examinations at the hospital. To enable wearable health monitoring systems with long battery life, their power consumption must be extremely low. Smart ECG sensors rely on the near-sensor computing paradigm, in which the ECG signal is directly processed in the sensor, by extracting features and determining if arrhythmias have occurred. This reduces the volume of data to send to a data center for further analysis, and thus the power consumption of the embedded device.

Besides, ECG signals do not hold uniformly distributed information in time. They show rapid changes in short periods, around the QRS complex, and small changes over longer periods. Event-driven sampling, which relies on generating a sample when a threshold is crossed, is beneficial for sparse signals compared to Nyquist sampling. It is demonstrated in [2] that level-crossing ADCs (LC-ADCs) offer two main advantages, compared to traditional uniform sampling, for low-to-medium resolution applications (< 8 bits). Fewer samples are generated, which leads to energy-frugal processing, and the majority of these samples are located around the R-peaks, which can be leveraged with efficient processing [3].

Many solutions exist in the literature to classify ECG signals. In particular, [4] introduces an ultra-low-power event-driven feature extraction and classification based on an Artificial Neural Network (ANN) and shows accuracy results exceeding 99%. In [5], the morphology of the ECG signal is extracted from a wavelet transform and then used as a classification method.

Classes within labeled ECG records are inherently imbalanced. For example, in the MIT-BIH database, arrhythmia-related classes represent on average 15 percent of the total number of heartbeats in records considered as symptomatic. To compensate for the imbalanced dataset and be able to use them with conventional ANNs, [4] proposed a biased training procedure, in which the abnormal beats are duplicated before training. This method boosts the classification accuracy and creates a bias in the reported accuracy.

In [6], antidictionaries (AD) are introduced for cardiac arrhythmia classification (CAC). This method uses only normal beats to create the antidictionary. However, the proposed method is software-based while the classification accuracy is up to 97%.

In this work, we investigate a novel classification method based on ADs that exploits the imbalanced nature of the dataset. An AD represents a set of non-appearing patterns from an original dataset. If the AD is created from normal beats, it can be used to detect arrhythmias without training on arrhythmic beats, thus avoiding the insertion of a bias.

Additionally, performing the inference with an offline-learned antidictionary has the potential to be extremely low power, thus compatible with a wearable solution. It has been demonstrated in [7] that the event-driven extraction of a sequence of slopes from an ECG signal is a relevant feature for CAC. A finite sequence of slopes is therefore suitable for the creation of ADs. The present work exploits the combination of event-driven quantized slopes and antidictionary-based classification to provide an ultra-low complexity solution for CAC with decent accuracies.

This paper is organized as follows. In section II, the process of creation of ADs is described and inference for the validation and testing phase. This section also details the required reduction of the size of the AD. The classification

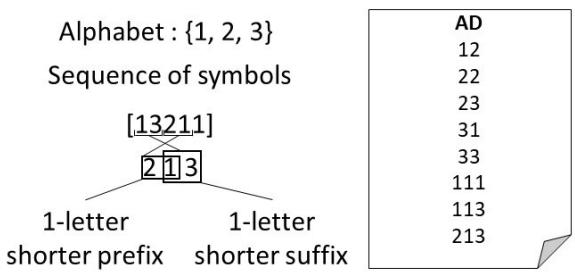

Fig. 1. Antidictionary generated from the sequence of symbols [13211] with the alphabet {1, 2, 3}

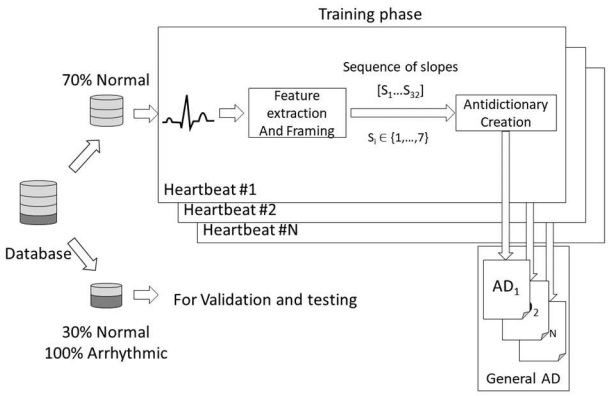

Fig. 2. Process to create a general antidictionary from a single record

results are presented in section III and the efficiency and interest of the proposed classification method are discussed.

II. Classification using Antidictionaries

A. Definition and creation of antidictionaries

An AD is a list of forbidden words (FBW) produced from negative information of a sequence of symbols, each symbol being part of a predefined alphabet [7]. The FBWs are formed following three rules: 1) the FBW is not a subpart of the sequence of symbols; 2) the 1-letter shorter prefix of the FBW is a subpart of the sequence of symbols; 3) the 1-letter shorter suffix is a subpart of the sequence of symbols. In the example given in Fig. 1, the AD lists all the FBWs generated from the given sequence of symbols [13211] with the alphabet{1, 2, 3}. The sub-sequence 213 is an FBW of the sequence [13211] since 213 does not appear in the sequence but the 1-letter shorter prefix 21 does appear, as well as the 1-letter shorter suffix 13.

To create ADs from normal beats of ECG signals, the symbols must be selected to represent a characteristic feature. Coarse-quantized slopes between two consecutive event-driven samples have been proven to be effective features for CAC with a state-of-the-art classifier and constitute a limited set of distinct values [8]. The process to create ADs is represented in Fig. 2. 70% of the normal beats of the dataset are used for AD creation. The rest of the database is later used for validation and test. Each normal heartbeat is converted to a finite-length sequence of slopes with a limited alphabet (the quantization levels of the slopes). From [8], 7 quantization levels offer the best trade-off between classification accuracy and system complexity, and the sequence of slopes is limited to 32 consecutive slopes centered around the R-peak. Each FBW in the AD represents an impossible pattern for this specific heartbeat. All ADs are then combined to build the antidictionary of the whole record. Although there can be many ways of combining ADs, the most common is to aggregate all impossible patterns into a general AD. It is to note that the number of FBWs stored in the general AD is large (767 on average overall records). This requires a lot of memory and computation power for on-chip implementation. Further reduction techniques are studied later in the paper.

B. Inference with antidictionaries

The extracted sequence of slopes is analyzed regarding the general AD to classify an incoming heartbeat as arrhythmic or not. Using a simple identification process, with *e.g.* a content-addressable memory (CAM), a flag is generated for each subset of the sequence that is present in the AD. Each heartbeat will then generate several flags that determine the number of times FBWs have appeared in the sequence. This process is applied on the validation dataset, composed of 15% of the normal beats and 85% of the arrhythmic beats, randomly selected.

For this validation set, Fig. 3 gives an example of the scores obtained for record 105 and record 114 in the case of normal and arrhythmic beats, in the form of a box plot. It can be observed that the number of flags differs for normal and arrhythmic beats in record 114. A threshold can then be set to classify the heartbeat type. If the number of times the FBWs flag is higher than the threshold, then the beat is considered arrhythmic, otherwise, it is considered normal.

However, this is not the case for all records. As shown in Fig. 3, when using the general AD created as the union of all the ADs, no clear separation can be envisioned for record 105, as an example. This is because few FBWs in the AD are too specific to a particular normal beat and flags are detected even for other normal beats. This constitutes another reason why the number of FBWs in the general AD must be reduced to enable a clear delimitation between arrhythmic and normal beats.

C. Antidictionary Reduction

The size of the general antidictionary is reduced in two steps. The first step is to ignore all FBWs with a length greater

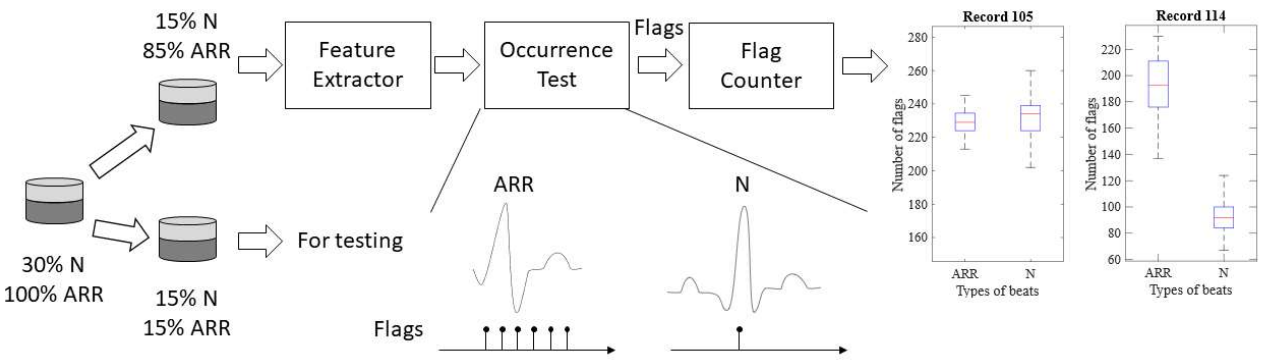

Fig. 3. Arrhythmia detection process used in validation, exemples on records 105 and 114 of MIT-BIH database while using the general AD. The central line is the mean number of flag appearing, the quare represent the number of flag for 50% of the beats and the top and bottom line represent statistical extremum, calculated from the difference between the mean and the quartile values, values outside of the extremum are statistical outliers representing 0,7% of normally distributed datas and are not represented. A separation in the number of flags for arrhythmic (ARR) and normal (N) beats can be seen for the record 114 but not the record 105.

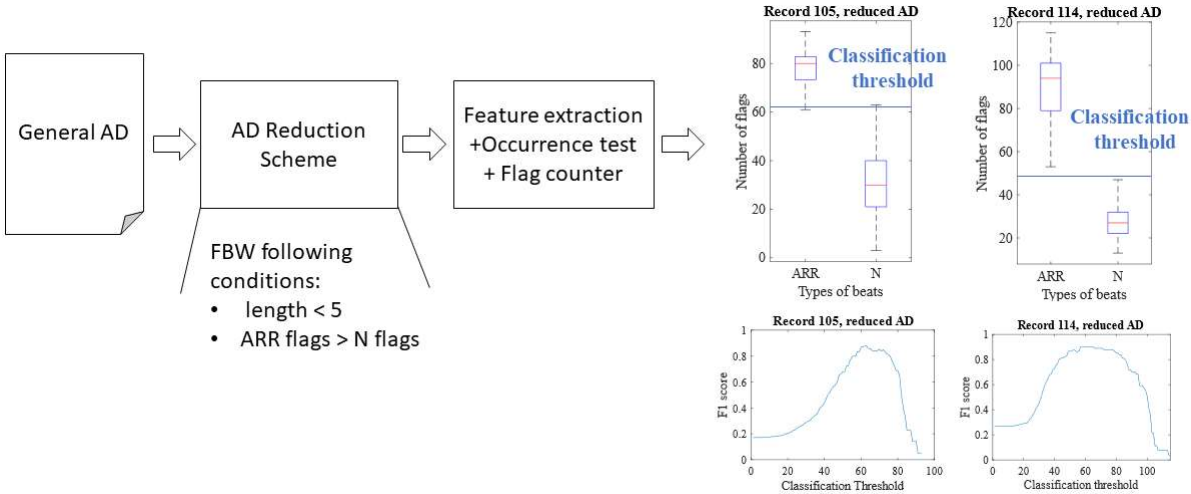

Fig. 4. Proposed process for AD reduction. The box plots show the number of FBW appearing in normal and arrhythmic beats of the validation dataset, for records 105 and 114. Indicative classification thresholds are represented by the blue lines. At the bottom, the F1-scores are plotted versus the classification thresholds when the reduced AD is used on the validation dataset.

than 5 symbols. The longer the FBW, the more heartbeat-specific it tends to be. If the FBW is too specific, it is likely to generate flags even for normal beats, as shown previously for record 105.

The second step is to reduce the antidictionaries depending on how FBWs react to the validation beats. Only FBWs flagging more in arrhythmic beats than in normal beats are aggregated in the general antidictionary. This reduction process is illustrated in Fig. 4 and applied to records 105 and 114. For these two records, the proposed AD reduction technique decreases the number of FBWs from 1767 to 34, and from 1273 to 50, respectively. Using the validation dataset, for record 105, the number of flags on each normal heartbeat is in the range from 2 and 68, while for arrhythmic beats, it ranges from 60 to 95 times. A classification threshold can then provide decent discrimination of the class of each heartbeat. For record 114, we can also observe that the classification process is still effective after the reduction of the AD.

More globally, using these two reduction steps over all the records, the average size of the general ADs is reduced to 32 while the accuracy results are always higher than with the complete AD. It is thus very beneficial for a low-complexity embedded implementation.

For imbalanced datasets, the F1-score is a relevant metric. It is the mean between the recall and the precision. The recall, or sensitivity, represents how well the arrhythmic beats are classified. The precision, or positive predictive value, represents what proportion of beats classified as arrhythmic are from the arrhythmic class. As opposed to the accuracy, the value will not be influenced by an imbalanced dataset composed of a majority of normal beats.

In Fig. 4, the evolution of the F1-score is shown depending on the classification threshold value. For record 105, the highest F1-score is 89.74%, obtained for a threshold at 98. For record 114, the highest F1-score is 88.89%, for a threshold of 75.

To reduce even further the number of FBWs in the AD during the validation phase, FBWs can be ordered using the ratio between the number of times they appear in the arrhythmic beats and the number of times they appear in normal beats. The most relevant FBWs (i.e. with the highest ratio) are then used to create the reduced AD. The resulting ADs and the optimal classification thresholds can then be used during the testing phase.

III. Classification Results

A. *Antidictionary classification with the test dataset*

The proposed AD-based classification is tested on records from the MIT-BIH database containing mainly Premature Ventricular Complex (PVC) arrhythmias: 105, 109, 114, 119, 205, 210, 215, 219, 221, 228, and 233. The testing subset is composed of the remaining 15% normal beats and 15% arrhythmic beats. The accuracies and F1 scores are calculated using reduced ADs and associated classification thresholds. The classification was simulated using Matlab.

Fig. 5 represents the evolution of the accuracy obtained with reduced ADs of different sizes, for all the records. For each AD size, a new optimal classification threshold is set as presented in Fig. 4. The accuracy varies from 72% to 100% depending on the record and number of FBWs used. However, an area of interest appears for all records when using between 2 and 8 FBWs in the AD. In this region, the classification accuracy is always higher than 92%.

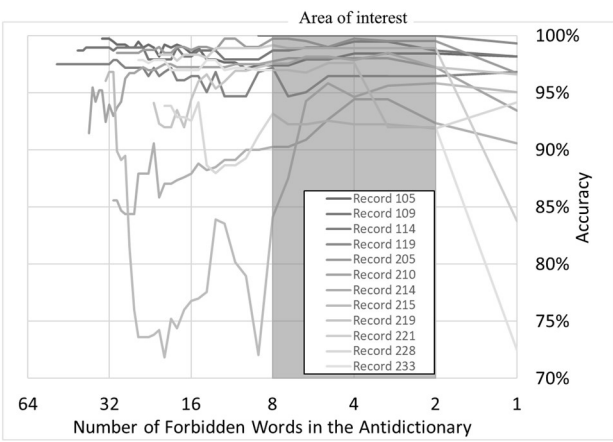

Fig. 5. Evolution of the accuracy as a function of the number of FBWs in the AD.

TABLE I. Maximum accuracy and F1-score for each tested record

Record	Accuracy (%)	F1-score (%)	# of FBW	Classification threshold
105	99.74	92.31	32	61
109	99.47	83.33	3	1
114	97.86	70.00	30	38
119	100	100	2	3
205	99.75	96.30	4	3
210	97.98	87.10	3	1
214	94.40	94.40	4	1
215	96.83	69.23	31	26
219	98.45	73.68	3	1
221	99.17	97.44	8	6
228	94.16	81.63	1	2
233	97.83	96.15	21	7
Average	**97.97**	**86.80**	-	-

Additionally, for all records, the maximum accuracy is always found with a maximum of 32 FBWs in the AD. Table I reports, for each record, the maximum accuracy, the F1-score, the associated number of FBWs, and the optimal classification threshold. The maximum accuracy for each record varies between 94.40% and 100% with an average of 97.97% and the F1 scores vary from 69.23% and 100% with an average of 86.80%.

B. Comparison with the state of the art in CAC

Table II gives a comparison of the proposed approach with recent works. The arrhythmia classification in [5] relies on wavelet transforms and a deep convolutional neural network (CNN). Although it shows high accuracy, the method requires uses a lot of computational resources, not compatible with an ultra-low-power on-chip solution system.

The work in [4] displays the best accuracy with a very high F1-score for CAC. The features are reduced to a 96-bit vector. However, the RR-intervals still need to be measured and quantized into 11 bits, which requires a precise clock in the system, even though it is event-driven. The dataset is also biased during training to balance the number of arrhythmic and normal beats used to train a shallow fully-connected feed-forward artificial neural network (ANN).

In [8], the timing feature from the RR-intervals is not used to enable a fully event-driven system. This allows for a very small fully-connected feed-forward ANN. The training still requires a bias to obtain good accuracies. The F1 score is not reported. Additionally, even though the number of multiply-and-accumulate (MAC) operations needed is smaller than in [4], the weights of the ANN must be stored and accessed. For 8-bit weights and 296 MAC operations, a total of 2,368 bits is necessary for the classification.

The system presented in this paper can reach an accuracy similar to the state of the art (1% lower than the best-reported accuracy), with no timing information on the RR-intervals and no arrhythmic data augmentation for the biased training. The inference method is also less complex than the other works, with a maximum of 32 FBWs, composed of a maximum of 5 3-bit letters (480 bits total), that can be easily

TABLE II. COMPARISON WITH EVENT-DRIVEN PVCS CLASSIFICATION SYSTEM

	[5] Entropy 2021	[4] TBioCAS 2020	[8] BioCAS 2021	*This work*
Classification Accuracy	98%	99%	98%	98%
Classification F1-Score	68%	95%*	-	87%
Extracted features	Wavelet transfrom + RR interval	74-bit event-driven direction + 2×11-bit RR interval	32×3-bit event-driven slopes	32×3-bit event-driven slopes
Inference method	18-layer CNN	32x16x5 ANN	8x4x2 ANN	4 to 32 FBW AD

*calculated from the given sensitivity and positive predictive value

addressed and identified through a simple CAM. The classification threshold used in the counter can be coded on 6 bits since the highest classification threshold needed is 61. With all the information needed for the classification stored on 486 bits and a completely clockless event-driven system, ultra-low energy consumption can be envisioned for a future wearable health monitoring system.

IV. CONCLUSION

In this paper, a novel classification method based on ADs is presented. The ADs are created using extracted features from normal heartbeats, in the form of quantized event-driven slopes. The proposed classification method allows a system with low complexity for inference, while the training (creation of the ADs) benefits from the imbalanced nature of the datasets. This solution shows promising results with an average 97.97% accuracy for PVC CAC. This system offers an accuracy similar to the state of the art while being extremely simple and easily adaptable from patient to patient.

ACKNOWLEDGMENT

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REFERENCES

[1] "Cardiovascular diseases (CVDs)." https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds) (accessed Apr. 22, 2021).

[2] J. Van Assche and G. Gielen, "Power Efficiency Comparison of Event-Driven and Fixed-Rate Signal Conversion and Compression for Biomedical Applications," *IEEE Trans. Biomed. Circuits Syst.*, vol. 14, no. 4, pp. 746–756, Aug. 2020, DOI: 10.1109/TBCAS.2020.3009027.

[3] M. Saeed *et al.*, "Event-Driven ECG Classification Using an Open-Source, LC-ADC Based Non-Uniformly Sampled Dataset," in *2021 IEEE International Symposium on Circuits and Systems (ISCAS)*, May 2021, pp. 1–5. DOI: 10.1109/ISCAS51556.2021.9401333.

[4] Y. Zhao, Z. Shang, and Y. Lian, "A 13.34μW Event-driven Patient-specific ANN Cardiac Arrhythmia Classifier for Wearable ECG Sensors," *IEEE Trans. Biomed. Circuits Syst.*, pp. 1–1, 2019, DOI: 10.1109/TBCAS.2019.2954479.

[5] T. Wang, C. Lu, Y. Sun, M. Yang, C. Liu, and C. Ou, "Automatic ECG Classification Using Continuous Wavelet Transform and Convolutional Neural Network," *Entropy*, vol. 23, no. 1, Art. no. 1, Jan. 2021, DOI: 10.3390/e23010119.

[6] G. Frias, H. Morita, and T. Ota, "Arrhythmia Detection with Antidictionary Coding and Its Application on Mobile Platforms," in *Body Area Networks: Smart IoT and Big Data for Intelligent Health Management*, Cham, 2019, pp. 50–67. DOI: 10.1007/978-3-030-34833-5_5.

[7] Maxime Crochemore, Filippo Mignosi, Antonio Restivo, Sergio Salemi. Text Compression Using Antidictionaries. *International Conference on Automata, Languages, and Programming* (Prague, 1999), 1999, France

[8] J. Duforest, B. Larras, D. John, O. Märtens, and A. Frappé, "Slope-Based Event-Driven Feature Extraction For Cardiac Arrhythmia Classification," *IEEE Biomedical Circuits and Systems Conference 2021*, Berlin, 6-9 October 2021.