An Approximate Binary Classifier for Data Integrity Assessment in IoT Sensors

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***Abstract*—This paper presents a machine learning-based technique for quality assessment of electrocardiogram (ECG) signals in wearable Internet of Things (IoT) sensors. Quality assessment at the network edge aids in the elimination of corrupted data prior to storage or transmission. In this work, we used a *k*-nearest neighbor (*k*-NN) binary classifier for identifying whether the acquired sensor data is of acceptable quality for further processing and transmission. Feature vectors used for classification were derived from the raw signal using skewness and kurtosis based signal quality indicators (SQIs), and these SQIs do not require any prior processing or knowledge of fiducial points in the ECG signal. The proposed approach achieved a classification accuracy of 97.18% with an estimated complexity that corresponds to 12.72 fJs Energy-Delay-product (EDP) in terms of multiplications used. To further reduce computational complexity and power consumption, an approximate multiplier was used, and this method exhibited an accuracy of 96.48%. The EDP, while using an approximate multiplier for classifying a single record was found to be 34.5% lower at 8.333 fJs, and is within the power budget of a typical IoT device.**

***Index Terms*—Signal Quality Assessment, IoT Sensors, Electrocardiography, Approximate Multiplier**

I. Introduction

Long term monitoring of physiological signals like electrocardiogram (ECG), acquired using Internet of Things (IoT) sensors and analyzed in the cloud, can facilitate early detection of Cardio Vascular Diseases (CVDs). Various types of noise, such as electrode contact noise, muscle artifacts, and motion artifacts, often contaminate ambulatory recordings of physiological signals. Moreover, the transmission of large amounts of data from an IoT sensor to the cloud can pose a challenge. Hence, the quality of the acquired signals must be assessed in the IoT sensor prior to transmission to the cloud, enabling the use of these signals in subsequent analyses. Therefore, energy-efficient and time conservative algorithms for data integrity assessment need to be implemented in the IoT sensors. Assessment of signal quality at the network edge helps to 1) reduce data redundancies, 2) avoid transmission of corrupted data, and 3) optimize storage and battery resources in IoT devices [1].

In this article, we address the issue of signal integrity assessment at the edge for a single channel IoT wearable ECG system. This is achieved by using a *k*-nearest neighbor (*k*-NN) binary classifier to separate signals into either class of acceptable or unacceptable diagnostic/monitoring quality using signal features for training and prediction. The use of the proposed sensors in the medical domain calls for easily understandable systems. Studies have shown that case-based reasoning with the potential to use retrieved cases to explain predictions, where similarity is the basis of explanation, have higher user approval ratings when compared to rule-based reasoning [2], [3]. *k*-NN classifiers, which use distances for similarity assessment for classification, are shown to be suitable for case-based reasoning models, along with the ability to adapt to changes over time through the retention stage [4]. Furthermore, in *k*-NNs, no assumptions are made on the dataset, which is a salient requirement in healthcare devices. Therefore, in this study, a *k*-NN classifier was chosen for ECG signal acceptability assessment.

Various works on energy-efficient ECG analysis for feature extraction, data classification, etc., are available in the literature. However, most of these works assume that the input signals are of acceptable quality. Further processing of signals of poor quality can lead to incorrect inferences or false alarms, which can lead to alarm fatigue [5]. In wearable devices, signal integrity is ensured by just performing a simple lead-off detection check. Through this article, we address this gap by extending the simple lead-off detection technique to a more comprehensive acceptability detection check. The proposed method needs to be energy-efficient, area-efficient, and fast for real-time assessment. To achieve this, the *k*-NN classifier is used in conjunction with approximate multipliers for energy and area optimization. Here, we have considered only the single-channel signal quality assessment scenario, as IoT wearable devices usually have only a single information channel. Methods for indicating signal quality as multiple classes or continuous values that specify acceptability of ECG signals of diagnostic quality has been discussed in literature for the multi-channel case, with varying levels of accuracy [6]–[8]. All these studies dealt with multi-channel recordings using multiple features from a recording. In [7], it was concluded that the multi-channel signal quality is easier to be classified, for the CinC 2011 challenge dataset. In most of the works discussed in literature, QRS detection based signal quality indicator (SQIs)/ fiducial-feature based SQIs (F-SQIs) are commonly used along with a large number of SQIs for signal quality assessment. However, to achieve accurate QRS detection, the acquired signal has to be of acceptable quality. Therefore, QRS detection based SQIs are not ideal for

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determining the acceptability of the signal. In this article, we propose to use two non-fiducial feature-based SQIs (NF-SQIs) [9] for signal acceptability testing of single-channel ECG data.

II. Methodology

A. Method Outline

The methodology proposed outlines the calculation of SQI feature vectors and a k-NN classifier for signal acceptability testing. The flow diagram is as depicted in Fig. 1 with the details on SQI feature extraction discussed in Section III.

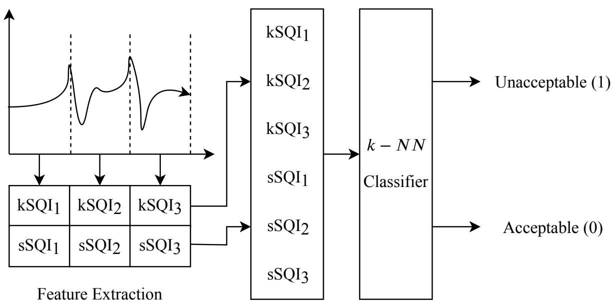

Fig. 1. Flow diagram of the proposed methodology with the details of the SQI features extracted (kSQI and sSQI) discussed in Section III.

B. Dataset

The Physionet CinC 2017 challenge training dataset with single-lead ECG acquired using an AliveCor mobile measurement device was used to evaluate the performance of the proposed algorithm [10]. This dataset was chosen as the records in the dataset are a good representation of the data that would be obtained from a typical wearable IoT device. The dataset for this experiment constitutes all the 284 noisy recordings in the Physionet CinC 2017 training dataset (as per references v2 of the labels) and 284 groups of normal recordings. The recordings were sampled at 300 Hz and were of length 30 s or 60 s. For this experiment, the signals were downsampled by 4 to reduce the number of computations.

III. Feature Extraction

SQIs provide an estimate of the quality of data obtained from wearable devices that are prone to a wide variety of noises. The feature vectors used in this work can be derived directly from the raw data and do not require any prior processing or prior knowledge of fiducial points in the ECG signal [11]. The SQIs were empirically chosen for this application after multiple trials with various SQIs discussed in literature. The study found that the separability between the two classes was greater with the combination of these two SQIs.

A. Skewness SQI (sSQI)

Skewness is defined as the third standardized moment of a random variable, an estimate of which is as per (1).

$$sSQI = \frac{\frac{1}{N}\sum_i (s_i - \hat{\mu})^3}{\hat{\sigma}^3}, \tag{1}$$

where $\widehat{\mu}$ and $\widehat{\sigma}$ are estimates of the mean and standard deviation of the set of samples s_i of size N. Skewness measures the symmetry of the distribution. A distribution with no outliers will be more symmetric, and consequently, have low values of skewness [11].

B. Kurtosis SQI (kSQI)

Kurtosis is defined as the fourth standardized moment of a random variable. Kurtosis is a measure of how sharp the peak of the distribution is. A distribution with many outliers is expected to have a low value of kurtosis since its probability distribution will be flatter and will approach zero slower [11]. kSQI index has been used to assign the quality of signal segments in [6]. kSQI is computed based on (2) [12]:

$$kSQI = \frac{\frac{1}{N}\sum_i (s_i - \widehat{\mu})^4}{\widehat{\sigma}^4} \tag{2}$$

In this work, we divide the n^{th} record into 3 equal windows and compute the $kSQI_i^{(n)}$ and $sSQI_i^{(n)}$ for each window indexed by $i = 1, 2, 3$, resulting in a feature vector for the n^{th} record, $x^{(n)} = [kSQI_1^{(n)}\ kSQI_2^{(n)}\ kSQI_3^{(n)}\ sSQI_1^{(n)}\ sSQI_2^{(n)}\ sSQI_3^{(n)}]$. A single SQI value will not be able to provide a good representation of the signal quality for the entire record, and therefore this method is chosen. Once all the feature vectors in the training set are computed, the features are normalized and arranged into a matrix $\mathbf{Z}$:

$$Z_k^{(n)} = \frac{x_k^{(n)} - \overline{x_k}}{\sigma_{x_k}} \tag{3}$$

where in (3), $\overline{x_k}$ and σ_{x_k} indicate the mean and standard deviation of each column, with k indicating each feature in the training set.

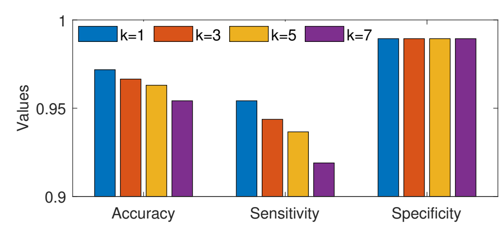

Fig. 2. Comparison bar plot of Accuracy, Sensitivity, and Specificity of an unweighted k-NN classifier for $k = 1, 3, 5, 7$

IV. k-Nearest Neighbor (k-NN) Classifier

The feature vectors derived in Section III is then used by the k-NN algorithm for classifying records into acceptable (0) and unacceptable (1) categories. k-NN is used for this classification task because it is well-suited for case-based decision-making [4]. k-NN is a distance-based classifier wherein a query object is classified based on the classes of its k nearest neighbors, where k is a user-defined number. A majority voting approach is used to determine the class of the query object.

k-NN has been used for real-time ECG Arrhythmia classification, as discussed in [13]. The k-NN classifier can be modified with new training data easily in an edge wearable device if required during update stages. In this experiment, the k-NN feature space is 6 dimensional and populated with 512 objects (number of training examples) during the training phase. Euclidean distance was chosen as the distance measure. The selection of the hyperparameter k for this experiment was chosen based on the performance of various k values for voting as shown in Fig. 2 The performance of the different methods were analyzed in terms of accuracy (Acc), sensitivity (Se) and specificity (Sp) which are calculated from the confusion matrix

From the figure, it is observed that the classifier has the highest accuracy and sensitivity when $k = 1$, and therefore the k value is set to 1 for this experiment.

V. Approximate Multiplier

The implementation of the proposed technique requires several multiplication operations. Multipliers are usually costly in terms of power and complexity. The possibility of using an approximate 16×16 multiplier for feature extraction and classification for the implementation of the data integrity assessment in an IoT device is explored. An area-optimized low-latency multiplier is used for this purpose [14]. This approximate multiplier offers 25% – 31.5% area reduction, 8.6% – 53.2% reduction in latency, and 8.86% – 67% gains in Energy-Delay-product (EDP) when compared to the accurate multiplier implementation offered by Xilinx Vivado [15]. The multiplier method utilizes 6-input Look Up Tables (LUTs) for the generation of approximate partial products. The approximate multiplier works based on the approximate multiplication of a 4-bit number $A(A_3A_2A_1A_0)$ to a 2-bit number $B(B_1B_0)$, which generates a 6-bit output. Truncation of the last bit in the product, P_0, limits the output error to the least significant product bit and the final output accuracy to 75% with a maximum error magnitude of "1" for all input combinations. The approximation of any other product bit results in a higher magnitude of error in the final output. This method of approximation uses four 6-input LUTs for its implementation by truncating "P_0".

The implementation of a 4×4 multiplier requires two 4×2 multipliers, consuming 8 LUTs for partial products generation. As shown in Fig. 3, the accurate summation of the approximate partial products generated by the two 4×2 multipliers requires the use of two carry chains. Therefore, the approximate 4×4 multiplier, with an accurate summation of partial products, requires 16 LUTs (2 LUTs wasted by the second carry chain). However, the 4×4 multiplier design utilizes approximate addition of the partial products and employs only 4 LUTs for the computation of the final product.

For the design of higher-order approximate multipliers, the approximate 4×2 and 4×4 multipliers are utilized recursively. For example, an approximate 8×8 multiplier can be implemented by accurately adding the approximate partial products generated by four instances of approximate 4×4 multipliers. Although in [14], the authors discuss unsigned number multiplications, we use a signed-unsigned converter to carry out signed number multiplication using the approximate unsigned multiplier. The approximate 16×16 multiplier discussed has an average dynamic power of 2535.1323 μW with a total delay of 7.328 ns, yielding an EDP of 0.5445×10^{-18} Js.

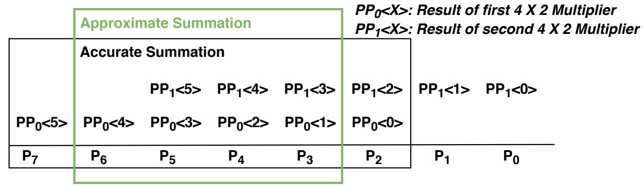

Fig. 3. 4×4 multiplier using two 4×2 multipliers [14].

TABLE I
Performance of k-NN in identifying noisy records

	Acc (%)	Se (%)	Sp (%)
Accurate Multiplier	97.18	95.42	98.94
Approximate Multiplier	96.48	94.01	98.94

VI. Results

A. Performance Analysis

The results and performance comparison of the k-NN classifier with the 10-fold cross-validation method, utilizing the features generated using both accurate and approximate multipliers is shown in Table I. During prediction, the k-NN classifier presented an accuracy of 97.18% and a high detection sensitivity of 95.42%. Energy consumption drops significantly when using a 16×16 approximate multiplier, instead of accurate multipliers, and these results are discussed in the next section. However, as a tradeoff, the detection sensitivity drops to an acceptable 94.01%. Utilizing a large and diverse dataset can further improve the performance of the k-NN classifier, but this leads to an increase in the number of objects stored in the feature space and thereby increases the search cost.

The box plot of accuracy values over 10-fold cross-validation with the accurate multiplier and approximate multiplier is as shown in Fig. 4 for performance comparison over all folds testing.

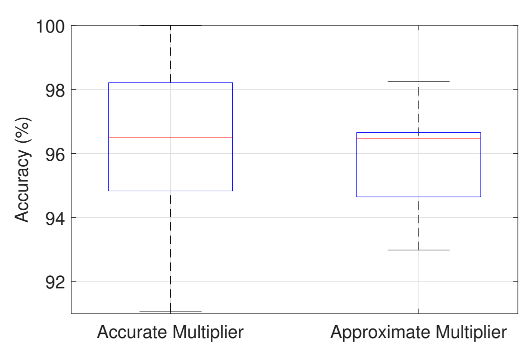

Fig. 4. Boxplot of accuracy values during testing over the 10 folds.

TABLE II
MULTIPLIERS REQUIRED AT EACH STAGE FOR QUALITY ASSESSMENT OF ONE RECORD

Multiplications				Total EDP (f Js)		
Feature Generation	Normalization	k-NN Classification	Total	AOAM	SOAM	Approximate
6585	6	8704	15301	12.728	8.974	8.332

TABLE III
COMPARISON OF THE BEST PERFORMING CLASSIFIER WITH STATE-OF-THE-ART ECG RECORD QUALITY ASSESSMENT ALGORITHMS

Article	G. Clifford et. al [7]	Q. Li et. al [6]	This work
Dataset	CinC 2011 challenge: Set B	CinC 2011 challenge: Set B	Subset of Cinc '17 challenge: training
Method	F and NF SQIs; ML and fusion	F and NF SQIs, SVM	NF SQIs; ML
Accuracy	**92.6%**	**80.26%**	**96.48%**

B. Complexity Calculation

The computational complexity of the proposed algorithm is evaluated in terms of the number of multiplications required for quality assessment of a 30-second long record. Feature extraction and normalization stages require a total of 6591 multiplications. Computations of kSQI and SSQI can share a few multipliers. The shared number of multipliers required was 4386. Computation of kSQI alone using the shared values requires 2187 multiplications while sSQI specific calculation requires 12 multiplications. Six multipliers are required for the normalizing stage.

For estimating the computational complexity of the k-NN classifier, the Euclidean distance calculation complexity to each object needs to be evaluated. k-NN- with 512 training examples- requires approximately 8704 multiplications for classifying a record based on its features. Table II summarises these values as well as the improvement in EDP when using an approximate multiplier compared to accurate multipliers. For this comparison, Xilinx's area/speed optimized accurate 16×16 signed multiplier is used. All the values of power and total delay are obtained using Vivado 17.4 for Xilinx Virtex-7 xc7v585tffg1157-3 FPGA for verification purposes and the results could be extended to a standard cell-based or custom integrated circuit implementation. The EDP of the area optimized 16×16 accurate multiplier (AOAM) with a total delay of 5.035 ns and dynamic power of 8203.109 μW was found to be 0.8318×10^{-18} Js, while the EDP of the speed optimized 16×16 accurate multiplier (SOAM) with a total delay of 4.269 ns and dynamic power of 8045.487 μW was found to be 0.5864×10^{-18} Js. From Table II, we observe that the proposed use of an approximate multiplier in place of an accurate multiplier exhibits good improvements in EDP.

The performance of the discussed SQI-based k-NN classifier using approximate multiplications is compared against the performance of state-of-the-art ECG record quality assessment algorithms in Table III and it can be observed that the proposed algorithm exhibits the best performance.

VII. CONCLUSIONS

This article explores the possibility of data integrity assessment of ECG signals on wearable devices using approximate multiplier based computing. To improve the quality of the signal acquired, records of poor signal quality need to be discarded and re-recorded, calling for algorithms that are highly sensitive to poor signal quality. The method discussed uses kurtosis SQI and skewness SQI as features for data integrity assessment using a k-NN classifier. The experiment carried out proves that approximate multipliers can be used for data integrity assessment, in place of accurate multipliers, with just a slight drop in sensitivity but with gain in EDP, which is an important consideration in wearable devices. This would be a helpful add-on to IoT physiological monitoring devices that are currently available.

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