Sub-microwatt KNN Classifier for Implantable Closed-loop Epileptic Neuromodulation System

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Abstract—The implantable closed-loop system for epileptic seizure detection and neuromodulation is getting more attention in recent years. The architecture design for seizure signal sensing and analyzing has been proposed, but the implementation of the classifier for unsupervised seizure detection is still strongly desired. The *k*-nearest neighbor (KNN) classification algorithm is one commonly used classifiers in previous researches, yet it needs the training data from both non-seizure and seizure EEG/ECoG states, which are difficult to be collected. Also, the large size of the training set and the concept of the exhaustive search for nearest neighbors make the classification procedure power-consuming. In this paper, we propose a sub-microwatt KNN classifier which only requires the non-seizure EEG/ECoG for training. The size of the training set memory as well as the leakage power is saved by 50%. The processing dynamic power is further reduced by 93.9% due to the early termination scheme. This work achieves the sensitivity of 98.04% and the false alarm rate of 1.97% with optimized power consumption at sub-microwatt, and is suitable for the implantable devices.

1 Introduction

In the last decade, an emerging therapy for the epilepsy control is the neuromodulation, or the electrical stimulation of the brain [1], [2]. By sending stimulating current to break down the epileptic neural firing, this treatment has been proven to be effective for interrupting the onset of upcoming seizures. However, traditional open-loop system performs continuous stimulation without analyzing the states of the brain, and many studies suggest that the efficacy of the treatment could be further enhanced by making it a closed-loop system featuring brain state feedback mechanism [3]. Thanks to the aid of electroencephalogram (EEG) and electrocorticogram (ECoG), more insights about the dynamics of the epileptic brain are discovered, and the rapid development of the seizure detection and prediction techniques [4], [5] make the closed-loop neuromodulation system feasible.

A general closed-loop system for automated seizure detection and neuromodulation consists of the EEG/ECoG sensing unit, the signal characteristics analyzing/decision unit and the neurostimulator. Current development on the system is toward an implantable miniaturized device. For such power-limited application, low-power design for each component in the system becomes the most important issue. In previous researches, several prototype implementations are presented. A spectral analysis IC was proposed by Avestruz and *et al*. for neuronal biomarkers sensing and analyzing [6], and the power consumption achieves $5\mu W$ per channel. Aziz and *et al*. realized an microsystem featuring the wavelet transform processor for epileptic brain dynamics characterization [3], and the system consumes power at microwatt order. However, none of these works have realized the automated decision unit, i.e. the classifier, for the system. The classifier is an essential component responsible for classifying the epileptic biomarkers or features. Therefore, the implementation of the classifier for the implantable system is highly desired.

Several different approaches are applied to construct the classifier for epileptic seizure detection. The artificial neural networks (ANNs) are commonly adopted [3], [7], but the ANN can hardly be implemented into low-power hardware for its high complexity. The *k*-nearest neighbor (KNN) classifier is an alternative choice having good performance for epileptic seizure detection [8] with low computational complexity. Nevertheless, the direct implementation of the KNN algorithm cannot meet the low-power requirement of the system. The large size of the training set memory and the exhaustive searching for nearest neighbors make the classifier power-consuming. On the other hand, the training of the KNN classifier requires the seizure EEG/ECoG data, but the sudden onset of seizures makes it difficult to be acquired. For these reasons, more efficient and low-power design is required for the KNN classifier.

In this paper, we propose the hardware architecture for an on-chip KNN classifier. The modified version of KNN classifier only requires non-seizure EEG data at the training stage. Moreover, several low-power techniques are applied and substantially reduce the power consumption to the sub-microwatt order. The remainder of this paper is organized as follows. In section 2, we introduce the closed-loop neuromodulation system. The algorithm of the proposed KNN classifier is explained in section 3, and the architecture design methodology is revealed in section 4. In section 5, the simulation and implementation results are presented. Finally, we draw conclusion in section 6.

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2 The Closed-loop Neuromodulation System

The closed-loop neuromodulation system is an implantable miniaturized device that could detect and break down the epileptic seizures. Limited power supply of this device implies

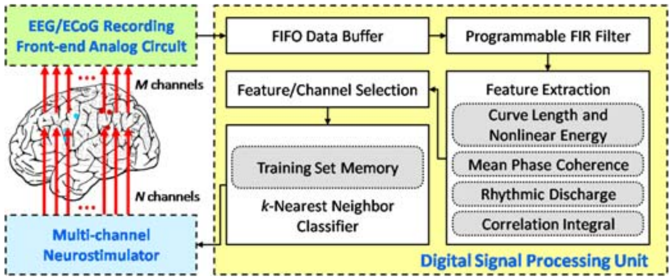


Fig. 1. The detailed block diagram of a epileptic neuromodulation system.

that low-power design is very important to the system. Several techniques are usually adopted to achieve this goal. For example, the ASIC implementation is preferred to the design with general purpose microprocessors because of the reduced overhead. Also, advanced process could benefit the power dissipation performance. More important, the hardware area and computational cost would directly affect the leakage and dynamic power, respectively. Therefore, in the system design, these factors should be considered.

2.1 System Architecture

Fig. 1 illustrates the detailed block diagram of a neuromodulation system. With total M channels of EEG/ECoG processing capability, the system consists of three major components: 1) the front-end analog circuit for EEG/ECoG recording, 2) the digital signal processing unit (DSPU) and 3) the multi-channel neurostimulator. The EEG/ECoG captured by the electrodes are first amplified, digitized and time-multiplexed by the recording circuit. Then, the DSPU are responsible for the early detection of seizures. If there are upcoming seizures, the N-channel neurostimulator would be actuated, and stimulating current is sent to break down the seizures.

The DSPU contains several different modules. First, the programmable FIR filters remove the noise and reserve the signal in a specific bandwidth. Next, some features are extracted from the preprocessed signal. In the implementation, we apply a multi-feature scheme. The curve length (CL) and non-linear energy are features from time domain analysis [7]. The mean phase coherence [9] and the rhythmic discharge (RD) [10] are features from spatial domain and frequency domain analysis, respectively. The correlation integral (CI) is from the non-linear analysis [11] to estimate the brain chaoticity. Employing several features from different analyzing way not only enhances the seizure detection accuracy, but also envisions a possibility of discovering more properties about the epileptic brain dynamics in the future. After the feature extraction, a subset of the biomarkers from M channels are selected to preserve useful information and to reduce the total quantity of data. Finally, the KNN classifier decides the states of the incoming features by comparing with the training set.

2.2 System Specification

Our design targets at the system with 16 channels processing capability, i.e. $M = 16$. The sampling rate of the EEG/ECoG from each channel is 256Hz with input bit precision of 9 bits, and the system clock rate would be 4096Hz by multiplexing signals from 16 channels. To achieve real time response for more accurate detection of seizures, the detecting rate is set to be 10 times/sec.

3 k-Nearest Neighbor Algorithm

The k-nearest neighbor (KNN) algorithm is a lazy learning classification algorithm. An object or sample is classified to one class by a majority vote of its k-nearest neighbors from the training set. Fig. 2(a) is an example of the original KNN classification. On the 2D feature space, the red triangles and the blue circles are data from non-seizure and seizure class collected in the training stage, respectively. In the processing stage, the incoming unknown object, the green cross, is to be classified. The KNN algorithm finds k-nearest neighbors of the cross from the training set. Then, if more than half of these neighbors are from the seizure class, the cross is classified as epileptic seizure, and vice versa. The cross in Fig. 2(a) would be assigned to the seizure class if $k = 3$.

However, if high accuracy of the classification results is required, a large memory space is needed to store enough training set data from both classes, which would increase the hardware area and is not very power-effective. Furthermore, larger training set implies higher computational power consumption for searching nearest neighbors. Also, because of the sudden onset of the seizure state, the seizure training set is hard to obtain.

To improve the original algorithm, we propose the modified KNN classifier for the implantable epileptic neuromodulation system. As shown in Fig. 2(b), only non-seizure EEG/ECoG data, the red triangles, are collected in the training stage, and we preset a distance threshold D and the parameter k. In the processing stage, we compare the distance of the incoming object, the green cross, with all of the non-seizure data in the training set. If more than k non-seizure data whose distance to the incoming object is less than D, then the state of the incoming object would be assigned to non-seizure. Otherwise, the incoming object would be identified as seizure. The proposed algorithm do not need to collect the seizure training data, and both the memory size and the processing time could be reduced by half because of the comparison with only the non-seizure training data.

4 Architecture Design

Based on the proposed algorithm, Fig. 3 illustrates the hardware architecture of the proposed KNN classifier, and the operation of the finite state machine (FSM) is revealed in Fig. 4(a). In the training stage, the non-seizure features from the previous stage are directly stored into the training set memory until the memory is full. In the processing stage, the incoming unclassified features are temporarily saved into the FIFO data buffer for further operation. The distance comparator first computes the distance between the data in the data buffer and all the the data in the training set memory, and then compares the result with the distance threshold D. If the computed distance is smaller than D, the match number would be accumulated by the match accumulator. Finally, a

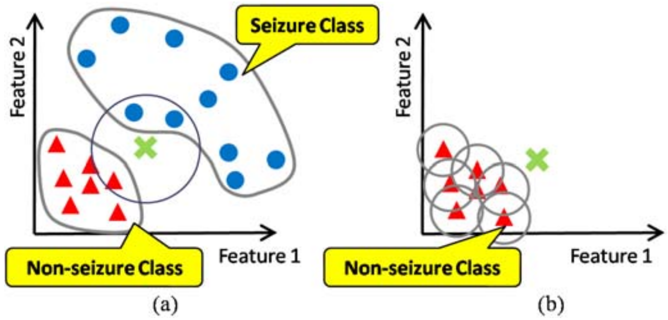


Fig. 2. The comparison between (a) the original KNN classifier and (b) the modified KNN classifier on a 2D feature space. The red triangles are training set from the non-seizure class, the blue circles are training set from the seizure class, and the green cross is the incoming unknown object.

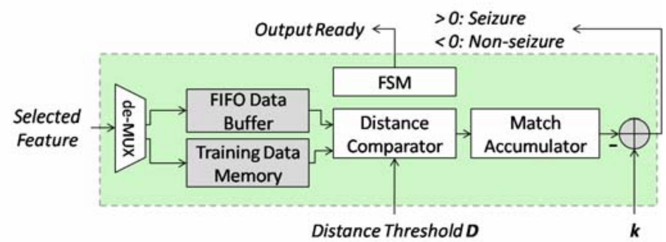


Fig. 3. The hardware architecture of the proposed KNN classifier.

subtractor is used to compare the match number with k to give the classification result.

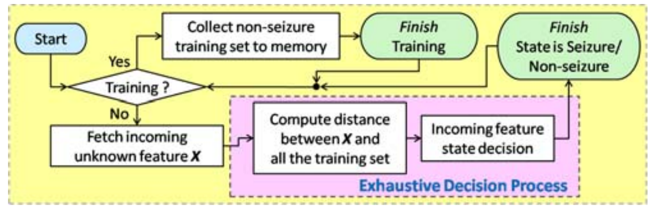
Because the proposed algorithm only requires the training data from the non-seizure EEG/ECoG, the size of the training set memory and the computational complexity of on-line matching could both be reduced by 50%. The reduced memory size not only lower the hardware implementation cost, but also reduce the power consumption. The cell leakage power of the hardware is directly proportional to its area. The reduced memory contributes to the reduction on the leakage power. The saving in the computational complexity provides the reduction on the dynamic power.

The proposed algorithm requires that the data to be classified should be compared with all of the training data in the training set memory, then the output could signal ready. However, this approach is power-wasting in that the match number might already much larger than k. Therefore, We further modify the operation of the FSM, and it is presented in Fig. 4(b). The new FSM possesses the early termination scheme that the operation terminated when the match number is larger than k instead of waiting until the end of the exhaustive distance comparison. The modified FSM could significantly shorten the processing time when the brain state is non-seizure, which is most of the case, and the dynamic power consumed at the processing stage is thus further reduced.

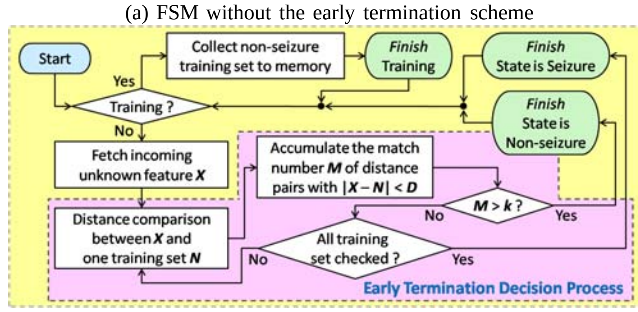
5 Simulation and Implementation Results

5.1 Simulation Results

The proposed KNN classifier is tested with the system presented in section 2 for the ability of seizure detection. The data applied are real ECoG recorded from



(a) FSM without the early termination scheme



(b) FSM with the early termination scheme

Fig. 4. The FSM operation of the proposed KNN classifier.

the Epilepsy Center at the University of Bonn, Germany. The data are made available online by Dr. R. Andrzejak (http://www.meb.unibonn.de/epileptologie/science /physik/eegdata.html). We used data from three groups and divided them into two classes: the non-seizure class (group Z and group N) and the seizure class (group S).

For ease of demonstration, we show the 3D feature space consisting of normalized RD, CL and CI in Fig. 5. The blue circle are from the non-seizure class and the red triangles are from the seizure class. Two clusters could be clearly identified in this plot, and the data from the non-seizure class are more densely located with each other while the data from the seizure class are more scattered. This property implies that the distances of nearby non-seizure features are more likely to be bounded by a threshold, which makes the application of the proposed KNN algorithm more convincible and practical.

To examine the seizure detection capability, we apply the following figure of merit: the sensitivity, i.e. the true positive rate, and the false alarm rate, i.e. the false positive rate. To find the distance threshold for optimized system performance, Fig. 6 shows the receiver operating characteristic (ROC) curves of the proposed KNN classifier when k equals to 3, 7 and 11 as its distance threshold D is varied. Each of these curves passes through the upper left corner of the ROC space, which means that the proposed KNN classifier is effective. For the choice of k, we note that larger values of k generally reduce the effect of noise, but it also increases the processing latency. In our simulation, we tried to decrease the value of k while still maintaining the classification performance. The ROC curves in Fig. 6 reveal that the proposed KNN classification performance is almost unchanged with different k values. Therefore, the k value of 3 is suggested in the case of the applied data.

Table 1 shows the performance comparison between the original and the proposed KNN classifiers with the early termination scheme. Both of the classifiers could achieve the sensitivity around 98% and the false alarm rate less than 2%. However, the proposed algorithm requires less implementation cost and computational complexity, which effectively reduces

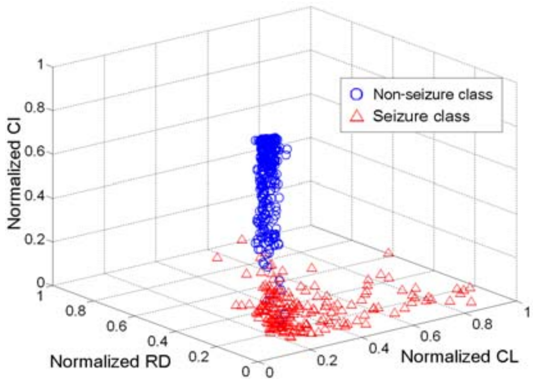


Fig. 5. The 3D feature space consisting of normalized RD, CL and CI. The blue circles are from the non-seizure class and the red triangles are from the seizure class.

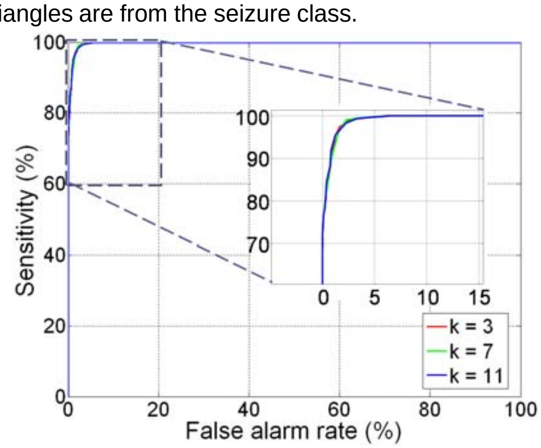


Fig. 6. The ROC curve of the proposed high-efficiency KNN classifier for k = 3, 7 and 11.

the leakage and dynamic power dissipation.

The reduction of the computational complexity as well as the dynamic power brought by the proposed KNN algorithm is revealed in Fig. 7. In the simulation, 30 non-seizure and 30 seizure training set are applied. When the training with only the non-seizure data is adopted, the computational complexity at both the seizure and non-seizure state could be reduced by 50%. If the early termination scheme is added, the complexity at the non-seizure state could be further saved by 87.9%. Compared with the original KNN algorithm, the total reduction of the computational cost at the seizure state is 93.9%. Also, the patients would stay in the non-seizure state in most of the time. Therefore, the dynamic power consumption of the KNN classifier is approximately saved by 93.9%.

5.2 Implementation Results

We use the 90nm low-K CMOS process to implement the proposed KNN algorithm, and Table 2 presents the synthesis result. The training set memory size of 7680 bits and the system clock rate of 4096Hz are set, and the core area is about $0.031mm^2$. Different from conventional chip implementation, the cell leakage power is about 57.4 times higher than the dynamic power due to the low clock rate. As we know, the cell leakage power is proportional to the chip size, which implies that the area becomes a more critical issue in this design.

TABLE 1
Performance comparison of the KNN classifiers

Feature	Sensitivity (%)	False alarm rate (%)
Original KNN	98.7429	1.5529
Proposed KNN	98.0400	1.9714

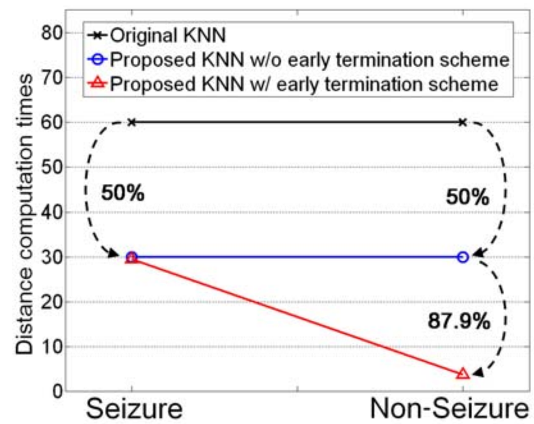


Fig. 7. The comparison of the average distance computation times required by different KNN algorithms.

Moreover, the memory occupies about two third of the total core area. Under such condition, the proposed KNN classifier has the advantage that the required memory size is only 50% of the size required by the original KNN classifier.

6 Conclusion

In this paper, the algorithm and hardware architecture design of a sub-microwatt KNN classifier for the implantable closed-loop system are presented. The training of the proposed algorithm only requires the non-seizure EEG/ECoG data instead of both non-seizure and seizure signals. The performance of this work achieves the sensitivity of 98.04% and the false alarm rate of 1.97%, which is as well as the original method. For the hardware implementation, the proposed KNN classifier only demands half size of the training set memory, which reduces 50% leakage power dissipation. Furthermore, the average computational complexity as well as the dynamic power consumption is reduced by 93.9% due to the reduced training set memory size and the early termination scheme. The synthesis result shows that the core area is $0.031mm^2$, and the dynamic power and cell leakage power are 6.77nW and 388.89nW, respectively.

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TABLE 2
Synthesis result of the proposed KNN classifier

Memory size	256x30bits
Operation frequency	4096Hz
Core area (Memory %)	$31468\mu m^2$ (65.33%)
Total gate count (Memory excluded)	2728 (2-port NAND gate)
Total dynamic power	6.77nW
Cell leakage power	388.89nW

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