Applicability of Hyperdimensional Computing for Seizure Prediction using LBP and PSD Features from iEEG

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***Abstract*— Hyperdimensional computing (HDC) has been assumed to be attractive for time-series classification. These classifiers are ideal for one or few-shot learning and require less resources. These classifiers have been demonstrated to be useful in seizure detection. This paper investigates seizure prediction using HDC from intracranial electroencephalogram (iEEG) from the publicly available Kaggle dataset. In comparison to seizure detection (interictal *vs.* ictal), seizure prediction (interictal *vs.* preictal) is a more challenging problem. Two HDC-based encoding strategies are explored: local binary pattern (LBP) and power spectral density (PSD). The average performance of HDC classifiers using the two encoding approaches is computed using the leave-one-seizure-out cross-validation method. Experimental results show that the PSD method using a small number of features selected by the minimum redundancy maximum relevance (mRMR) achieves better seizure prediction performance than the LBP method on the training and validation data.**

***Index Terms*— Hyperdimensional computing (HDC), local binary pattern (LBP), power spectral density (PSD), minimum redundancy maximum relevance (mRMR), and seizure prediction.**

I. Introduction

In recent years, there has been a surge of interest in hyperdimensional computing (HDC) since it was proposed in 1988 [1]. As a brain-inspired computing paradigm, HDC manipulates its unique data points, which are referred to as *hypervectors* for data representation, transformation, and interpretation. The dimensionality d of these hypervectors is typically in thousands of bits, e.g., d=10,000 bits. Though still in its infancy, HDC has been widely studied to demonstrate its potential: comparable performance to traditional machine learning techniques, high energy efficiency, high noise tolerance, massive parallelism, and ideal realization in nanoelectronics. Applications of HDC include but are not limited to: language recognition [2], image classification [3], bio-signal classification [4, 5, 6], etc.

Numerous prior studies have addressed seizure detection (*interictal vs. ictal*) [7, 8, 9, 10, 11, 12, 13] and seizure prediction (interictal *vs. preictal*) [14, 15, 16]. Among these prior studies, the HDC-based local binary pattern (LBP) method, proposed in [8], can achieve 99.36% sensitivity and 95.67% specificity for seizure detection over the SWEC-ETHZ iEEG database [17]. In [11], the applicability of seizure detection using the HDC approach with frequency spectrum features is proven for the CHB-MIT dataset [18]. Additionally, the power spectral density (PSD) method using traditional support vector machines (SVMs) can achieve high performance for both seizure detection and prediction.

Though [10] has studied the applicability of HDC using both LBP and PSD methods for seizure detection, whether these two HDC-based strategies are suitable for seizure prediction has not been investigated. This paper applies these two HDC-based encoding approaches for subject-specific seizure prediction using the publicly available Kaggle dataset. The LBP strategy extracts the features from the time domain, whereas the PSD method uses the frequency-domain information. Experimental results indicate that the features generated by the aforementioned two methods are not suitable for an HDC classifier for seizure prediction for this dataset. It has been believed that HDC is applicable to most time-series classification problems. In this paper, we show that HDC classifiers using the PSD method with a small number of features achieve better performance on the training and validation data as compared to the LBP method.

This paper is organized as follows. Section II presents the classification overview for HDC. Section III elaborates the two HDC-based encoding strategies: LBP and PSD. The corresponding results are summarized and discussed in Section IV. Section V finally concludes this paper.

II. Preliminaries

A. Basics of HDC

Starting with the *seed* hypervectors, HDC maps the original data into the hyperdimensional space. With an encoding approach, those seed hypervectors are manipulated to form a compound hypervector, which corresponds to the input data. Typically, three point-wise operations are involved: addition (+), multiplication (*), and permutation (ρ).

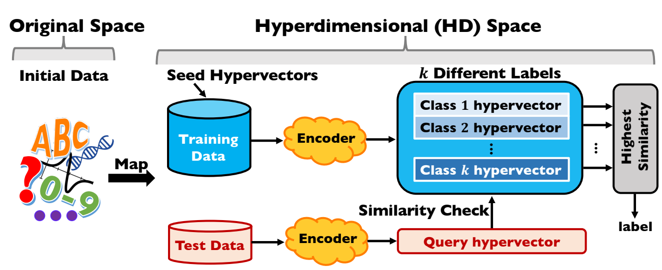

Fig. 1: Classification overview with HDC [19].

Take a k-class classification problem as an example. As shown in Fig. 1, during the training phase, k different *class* hypervectors are generated by encoding the training data.

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During the inference phase, a *query* hypervector, corresponding to an unknown test data, is encoded. To predict this test data, a similarity measurement is computed between the pre-trained class hypervectors and the query hypervector. The label is determined by the class which shows the highest similarity with the query one. In terms of the similarity measurement, since the employed seed hypervectors are composed of binary values ($\in \{0,1\}^d$), the experimental results throughout this paper are measured by Hamming distance as calculated in (1), where d is the dimensionality of the two hypervectors $\mathbf{A}$ and $\mathbf{B}$. Note that we use d=10,000 for the hypervectors in this paper.

$$\mathrm{Ham}(\mathbf{A},\mathbf{B}) = \frac{1}{d}\sum_{i=1}^{d} 1_{\mathbf{A}(i)\neq\mathbf{B}(i)}. \qquad (1)$$

In this paper, the seed hypervectors are either *random* or *level* hypervectors. To put it simply, *1).* random hypervectors are quasi-orthogonal to each other and are mainly employed to represent the independently categorical data, e.g., 256 pixel values; *2).* level hypervectors are usually linearly correlated and are used to represent the sub-intervals of a given range, e.g., the quantized magnitude of a given time series. The reader is referred to [19, 20] for more details.

B. Seizure Prediction Dataset

The term "ictal" refers to the period when the subject has a seizure. "Interictal" and "preictal", respectively, represent the time period at baseline and just before the onset of the seizure. Preictal often refers to the period an hour before the seizure with a 5-minute offset, i.e., the 5-minute period just before the seizure onset is not considered preictal.

The dataset considered in this paper is publicly available as part of the Kaggle seizure prediction contest [21]. Such data are provided as 10-min interictal and preictal clips. In total seven subjects are involved: five dogs and two humans. Table I lists the basic dataset information, including the number of interictal-, preictal-, and test-clips, the number of channels for the iEEG recordings, and the sampling frequency f_s. Each clip is a 10-min iEEG recording. For more detailed data description, interested readers are referred to [22].

TABLE I: Dataset Information

Subject	#interictal	#preictal	#test	#ch	f_s (Hz)
Dog_1	480	24	502	16	400
Dog_2	500	42	1000	16	400
Dog_3	1440	72	907	16	400
Dog_4	804	97	990	16	400
Dog_5	450	30	191	15	400
Patient_1	50	18	195	15	5000
Patient_2	42	18	150	24	5000

One thing that should be emphasized is that the seizure prediction in this paper is a binary classification problem, which identifies the preictal clips among a large number of interictal clips. Ictal clips, which represent the iEEG during the seizure period, are not analyzed. The goal of predicting the preictal clips is to provide sufficient time for warning or prevention before the actual seizure occurs.

C. Flow Chart of the Employed Approaches

Figure 2 shows the flow chart of the employed HDC-based approaches for seizure prediction. For the given multi-channel iEEG recordings, two different types of features are investigated as the input for the HDC classifier: LBP and PSD. To be more specific, the LBP method essentially extracts the time-domain information, whereas the PSD features reflect the frequency-domain information. Note that, there are three types of PSD features: absolute power spectral density (ASP), relative power spectral density (RSP), and the ratio of two ASPs [16]. Finally, after encoding the input features (LBP codes or PSD values), an HDC-based classification is performed for this dataset.

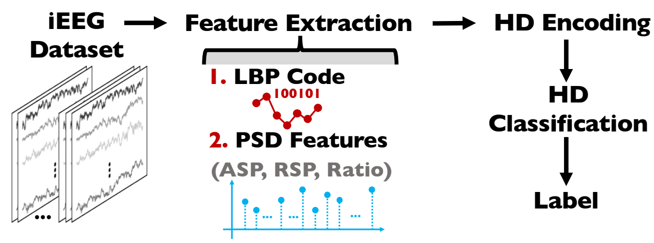

Fig. 2: Flow chart of the employed approaches.

D. Training and Test Workflow

We conduct the leave-one-seizure-out cross-validation over this seizure prediction dataset. This Kaggle dataset mentioned earlier comes with pre-specified training and test data. Thus the original given training data are separated into the training and validation sets. Note the validation sets are not used for updating the learned HDC model but for evaluating the generalizability of the trained model. To elaborate further, based on the number of seizures (S), the original training data are divided into S folds. Within each fold, both the interictal and preictal clips are split into S groups. To be more specific, the preictal clips belonging to the same single seizure form one group, whereas the interictal clips are nearly equally distributed among all S groups. After the data are split, we learn from ($S-1$) groups, validate the trained model on the remaining one group, and test the model over the given test data. The final performance is the average of the results for all S folds.

III. Methodology

A. LBP Method

This work employs the HDC-based LBP method, which is originally proposed in [8] for seizure detection using the SWEC-ETHZ iEEG database [17]. Given the raw iEEG data, LBP codes are extracted as the features, which reflect the time-domain information and are then fed to the HDC classifier.

To extract the LBP codes, consecutive iEEG samples are converted into a bit stream whose components are determined by the sign of the temporal difference of the two adjacent samples. If the difference is positive, then the LBP code is set to be "1"; otherwise it is assigned as "0". Generally, the length of LBP code l should be specified. To obtain a length-l (l-bit) LBP code, $(l+1)$ consecutive time-series data are required. Equations (2a)-(2e) describe how the class hypervector is generated for either the preictal or interictal class. The parameters, l, N, W, P, K, respectively, represent the length of LBP code, the number of channels, the number of samples within a window, the number of windows, and the number of clips for a single class.

$$\bar{\mathbf{hv}}_{\mathbf{LBP}_{\mathbf{Ch}_{j,i}}} \in \{\mathbf{hv}_{\mathbf{LBP}1}, \cdots, \mathbf{hv}_{\mathbf{LBP}2^l}\} \tag{2a}$$

$$\mathbf{hv}_{\mathbf{spatial}_i} = \Big[\sum_{j=1}^{N} \bar{\mathbf{hv}}_{\mathbf{LBP}_{\mathbf{Ch}_{j,i}}} \oplus \mathbf{Ch}_j\Big], \tag{2b}$$

$$\mathbf{hv}_{\mathbf{win}_p} = \Big[\sum_{i=1}^{W-l} \mathbf{hv}_{\mathbf{spatial}_i}\Big], \tag{2c}$$

$$\mathbf{hv}_{\mathbf{clip}_k} = \Big[\sum_{p=1}^{P} \mathbf{hv}_{\mathbf{win}_p}\Big], \tag{2d}$$

$$\mathbf{hv}_{\mathbf{class}} = \Big[\sum_{k=1}^{K} \mathbf{hv}_{\mathbf{clip}_k}\Big]. \tag{2e}$$

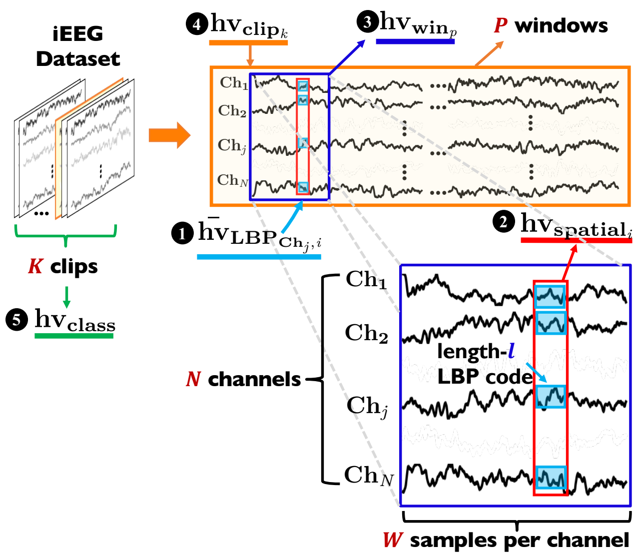

Fig. 3: HDC classification using LBP method.

Figure 3 illustrates the HDC-based LBP method for seizure prediction. To begin with, we generate the seed hypervectors $\{\mathbf{hv}_{\mathbf{LBP}1}, \mathbf{hv}_{\mathbf{LBP}2}, \cdots, \mathbf{hv}_{\mathbf{LBP}2^l}\}$ and $\{\mathbf{Ch}_1, \mathbf{Ch}_2, \cdots, \mathbf{Ch}_N\}$ to represent all the 2^l LBP code patterns and N channel indices, respectively. Both of these two sets of hypervectors are random hypervectors. *1).* Within each window, the temporal iEEG data are converted into LBP codes $\bar{\mathbf{hv}}_{\mathbf{LBP}_{\mathbf{Ch}_{j,i}}}$, where Ch_j specifies the channel information and i indicates the temporal index. These hypervectors are selected from the seed hypervectors according to their code patterns (see (2a)). *2).* Computed by (2b), the spatial information across all N channels is encoded by $\mathbf{hv}_{\mathbf{spatial}_i}$, which associates the LBP code patterns with the specific channel. *3).* Since there are W samples within a window, the entire window information is represented by $\mathbf{hv}_{\mathbf{win}_p}$, which is calculated by (2c) *4).* Afterwards, $\mathbf{hv}_{\mathbf{clip}_k}$ represents a 10-min data as computed in (2d). *5).* The final class $\mathbf{hv}_{\mathbf{class}}$ is generated by summing up its constituent clips (as shown in (2e)). For this seizure dataset, we use a 1s-window for each 10-min clip.

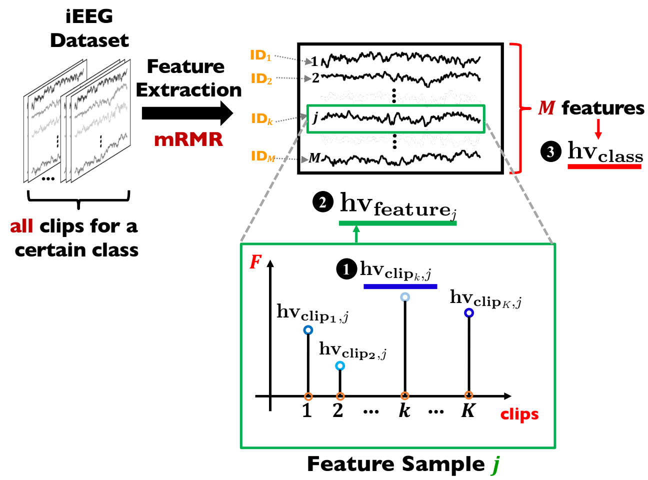

Fig. 4: HDC-based PSD method for seizure prediction.

B. PSD Method

PSD features manifest the frequency-domain information. Unlike [15], where only RSP and ratio of spectral powers are considered, this paper employs one more type of PSD features—ASP. How these three PSD features are computed is described in [23] (see page 2).

We follow the same sub-band split for the PSD feature extraction as described in [15], whose classifier is polynomial SVM. *1).* For dogs, the frequency band is divided into 10 sub-bands (Hz): 3-8, 8-13, 13-30, 30-55, 55-80, 80-105, 105-130, 130-150, 150-170, 170-200. *2).* For human patients, two more sub-bands are included: 200-225 and 225-250. Note that the power line noise at 60 Hz and its harmonics should be eliminated. The reader is referred to Sec.II.C of [15] for more details. In this paper, we have $65(= 10 + 10 + \binom{10}{2})$ PSD features for dogs and $90(= 12 + 12 + \binom{12}{2})$ for human patients. Equations (3a)-(3c) describe how the class hypervector is generated for the PSD method. The parameters, q, K, M, respectively, represent the quantization level, the number of clips for a single class, and the number of selected features.

$$\mathbf{hv}_{\mathbf{clip}_k,j} \in \{\mathbf{L_1}, \mathbf{L_2}, \cdots, \mathbf{L}_q\}, \text{ where } k \in [1, K], \tag{3a}$$

$$\mathbf{hv}_{\mathbf{feature}_j} = \Big[\sum_{k=1}^{K} \mathbf{hv}_{\mathbf{clip}_k,j}\Big], \tag{3b}$$

$$\mathbf{hv}_{\mathbf{class}} = \Big[\sum_{j=1}^{M} \mathbf{hv}_{\mathbf{feature}_j} \oplus \mathbf{ID}_j\Big]. \tag{3c}$$

We employ the record-based encoding (summarized in [19] and is the "Approach 3" in [10]) using a small number of features that are selected by minimum redundancy maximum relevance (mRMR). After calculating PSD values for each feature, we concatenate the corresponding interictal and preictal categories of the training data together and normalize them into the range of [0,1]. Then use the training information to scale both the validation and test data. Figure

TABLE II: Experimental Results For LBP Method With The Code Length $l = 6$

Patient	Training Data				Validation Data				Test Data			
	ACC	**Sen.**	**Spec.**	**AUC**	**ACC**	**Sen.**	**Spec.**	**AUC**	**ACC**	**Sen.**	**Spec.**	**AUC**
Dog_1	67.33	59.72	67.71	0.64	64.29	8.33	67.08	0.38	58.72	39.58	59.68	0.50
Dog_2	70.13	67.46	70.36	0.69	69.02	66.67	69.22	0.68	58.41	40.63	60.17	0.50
Dog_3	66.41	69.19	66.27	0.68	63.43	54.17	63.89	0.59	63.51	23.41	65.45	0.44
Dog_4	69.84	74.04	69.33	0.72	68.76	73.53	68.34	0.71	68.50	67.39	68.56	0.68
Dog_5	68.07	69.17	68.00	0.69	67.08	66.67	67.11	0.67	37.70	8.33	39.66	0.24
Patient_1	63.64	77.78	58.33	0.68	27.27	11.11	33.33	0.22	44.27	80.56	41.89	0.61
Patient_2	77.50	66.67	82.14	0.74	56.67	38.89	64.29	0.52	47.78	38.10	48.77	0.43
mean	68.99	69.15	68.88	0.69	59.50	45.62	61.89	0.54	54.13	42.57	54.89	0.49

TABLE III: Experimental Results For PSD Method With The Quantization Level $q = 21$

Patient	Training Data				Validation Data				Test Data			
	ACC	**Sen.**	**Spec.**	**AUC**	**ACC**	**Sen.**	**Spec.**	**AUC**	**ACC**	**Sen.**	**Spec.**	**AUC**
Dog_1	91.53	33.33	94.44	0.64	90.48	0.00	95.00	0.48	87.00	11.46	90.79	0.51
Dog_2	89.39	64.68	91.48	0.78	88.13	47.62	91.55	0.70	65.83	33.02	69.07	0.51
Dog_3	95.01	34.85	98.02	0.66	94.51	30.56	97.71	0.64	81.25	16.67	84.38	0.51
Dog_4	86.83	34.84	93.14	0.64	85.96	26.08	93.24	0.60	93.04	8.77	98.18	0.53
Dog_5	95.94	65.83	97.94	0.82	95.83	66.67	97.78	0.82	93.72	0.00	100.00	0.50
Patient_1	92.42	72.22	100.00	0.86	83.33	44.44	97.92	0.71	63.59	44.44	64.85	0.55
Patient_2	90.00	66.67	100.00	0.83	51.67	16.67	66.67	0.42	62.22	19.05	66.67	0.43
mean	91.59	53.20	96.43	0.75	84.27	33.15	91.41	0.62	78.09	19.06	81.99	0.51

4 shows the HDC-based classification for seizure prediction using PSD features. First, seed hypervectors are generated $\{\mathbf{ID}_1, \mathbf{ID}_2, \cdots, \mathbf{ID}_M\}$ and $\{\mathbf{L}_1, \mathbf{L}_2, \cdots, \mathbf{L}_q\}$ to represent the feature identifiers and the quantized PSD values, respectively. Note that the feature identifier hypervectors are random hypervectors, whereas the quantization hypervectors are level hypervectors. The class hypervectors are generated following these steps: *1).* According to the quantized PSD values, hypervectors $\mathbf{hv}_{\mathbf{clip}_k, j}$ are selected from the seed hypervectors, where "clip_k, j" specifies that this PSD value is calculated from the clip_k to form the feature j (as shown in (3a)). *2).* As described in (3b), for the feature j, the corresponding $\mathbf{hv}_{\mathbf{feature}_j}$ hypervector is obtained by adding all its constituent K clip hypervectors. *3).* The class hypervector $\mathbf{hv}_{\mathbf{class}}$ is generated as shown in (3c). *4).* Similar to [15], we use a 2s-window with 50% overlap to generate the PSD feature values for each 10-min clip.

IV. Experimental Results

Using the aforementioned LBP and PSD methods, the corresponding experimental results are reported in Tables II and III, respectively. We can observe from these two tables that: *1).* the LBP method achieves the on average 0.69 training AUC, 0.54 validation AUC, and 0.49 test AUC (Table II), whereas the PSD method leads to 0.75 training AUC, 0.62 validation AUC, and 0.51 test AUC (Table III). Therefore, the PSD method performs better than the LBP method for seizure prediction on the training and validation data. However, both methods perform no better than a random guess for the test data. *2).* The HDC-based LBP method achieves 99.36% sensitivity and 95.67% specificity for seizure detection in [8]. However, this method does not perform well in seizure prediction. The LBP method could be suitable for Dog_4 since it achieves 0.72, 0.71, and 0.68 AUC for training, validation, and test data. The best result using the LBP method is achieved for Dog_4. *3).* The PSD method can achieve 0.98 validation AUC in [15] using polynomial SVM. However, only 0.64 validation AUC is achieved by the HDC-based PSD method in this paper. Note that, the HDC-based PSD method has been investigated in [10] to demonstrate that HDC is suitable for seizure detection. However, the PSD features cannot always predict seizures using HDC for the test data in this dataset.

The results of the top ten competitors from the Kaggle seizure prediction contest have been summarized in [22], where the test AUC scores range from 0.82 to 0.86 (see Table 2 in [22]). None of them is based on HDC, which can be beneficial for lightweight classifiers and wearable devices.

V. Conclusions

The HDC PSD method works well for the two human subjects and two dogs for the training data. Generally, the PSD method achieves better performance than LBP using HDC; however, neither of them is practically applicable for seizure prediction by testing over the Kaggle dataset. Significant portions of the test samples in the Kaggle dataset are from out-of-distribution data as reported in [22]. Predicting seizures is a hard problem due to the highly non-stationary nature of brain signals. Thus, further research needs to be directed towards the development of HDC approaches that are robust to classifying out-of-distribution data. Although the LBP approach exploits some aspects of temporal properties, the PSD method does not. Future work should, therefore, be directed towards exploiting temporal properties in the context of PSD features. In addition, new encoding approaches that can take advantage of temporal properties in the context of HDC classifiers could be explored. Features could also be generated by neural networks such as autoencoders.

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