A Novel TSK Fuzzy System Incorporating Multi-view Collaborative Transfer Learning for Personalized Epileptic EEG Detection

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Abstract—In clinical practice, electroencephalography (EEG) plays an important role in the diagnosis of epilepsy. EEG-based computer-aided diagnosis of epilepsy can greatly improve the accuracy of epilepsy detection while reducing the workload of physicians. However, there are many challenges in practical applications for personalized epileptic EEG detection (i.e., training of detection model for a specific person), including the difficulty in extracting effective features from one single view, the undesirable but common scenario of lacking sufficient training data in practice, and the no guarantee of identically distributed training and test data. To solve these problems, we propose a TSK fuzzy system-based epilepsy detection algorithm that integrates multi-view collaborative transfer learning. To address the challenge due to the limitation of single-view features, multi-view learning ensures the diversity of features by extracting them from different views. The lack of training data for building a personalized detection model is tackled by leveraging the knowledge from the source domain (reference scene) to enhance the performance of the target domain (current scene of interest), where mismatch of data distributions between the two domains is resolved with adaption technique based on maximum mean discrepancy. Notably, the transfer learning and multi-view feature extraction are performed at the same time. Furthermore, the fuzzy rules of the TSK fuzzy system equip the model with strong fuzzy logic inference capability. Hence, the proposed method has the potential to detect epileptic EEG signals effectively, which is demonstrated with the positive results from a large number of experiments on the CHB-MIT dataset.

Index Terms—EEG, Seizure classification, Computer aided diagnosis, Multi-view transfer learning, TSK fuzzy system.

I. INTRODUCTION

Epilepsy is a chronic brain disease. The World Health Organization (WHO) estimates that there are about 50 million people with epilepsy worldwide [1]. The excessive discharge of brain neurons during epileptic seizures, which can be due to a variety of reasons, cause the central nervous system to malfunction. Since seizures usually happen at night, it is inaccurate to diagnose afterwards by relying only on patient's recall of the past events. The common diagnostic methods of epilepsy detection include medical history, physical examination, and auxiliary examinations such as electroencephalography (EEG), which is indeed an important clinical examination method. EEG measures the electrical activity of brain cells. Observations from EEG activities can be used effectively for clinical diagnosis. In one study, the number of seizures detected by EEG was 29 times and 7 times higher than the number of episodes detected by family members and nurses, respectively [2].

Since Gotman [3] first proposed the widely used epilepsy detection method, the application of intelligent algorithms to assist doctors in epilepsy detection has received increasing attention [4]. The process of automatic epilepsy detection with EEG signals can be broadly divided into three steps: acquisition of EEG signals, extraction of useful features, and construction of epileptic EEG classifiers. In the paper, we focus on feature extraction and the construction of classifiers.

Feature extraction methods are often developed to capture features in the time domain, frequency domain, or time-frequency domain [5-7]. Time-domain features dominate in early feature extraction methods because they are intuitive and relatively easy to obtain. While many EEG feature extraction methods have been made available, it is difficult to determine the most appropriate one in different applications or for different datasets [8-10].

In the construction of classifiers, binary or three-class classification are generally performed for EEG signal recognition. Binary classification of epileptic EEG signals aims to differentiate seizure state from normal state. With three-class classification, EEG signals can be further classified as being corresponding to normal, interictal or ictal state. Neural networks [8, 9], Naive Bayes [10], support vector [11] and fuzzy systems (FS) [12, 13] are commonly used in binary classification. Recurrent neural networks [14], support vector machine (SVM) [15], K-nearest neighbor (KNN) [16], decision trees with C4.5 algorithm [17], and FSs [18] have been used for three-class classification of EEG signals. In addition, end-to-end deep learning
methods have been developed for EEG analysis in recent years [19-21]. Among the abovementioned methods, fuzzy rules and fuzzy inference based FSs are distinctive for the capability of maintaining a good balance between accuracy and interpretability.

However, challenges remain despite the advances in automated epilepsy detection [22, 23]. The difficulty of extracting targeted discriminatory features for identification is a key issue. Apart from conventional approaches that extract features from single view, multi-view feature extraction and learning techniques have been introduced to address this challenge, which can effectively exploit the complementary information of different views to improve the detection performance [24]. Another challenge is the lack of sufficient samples for training effective patient-specific models. Transfer learning techniques have been used here because of their ability to improve the learning of specific tasks by using the existing knowledge in the related tasks [25, 26]. While these two challenges are alleviated to some extent by multi-view learning and transfer learning respectively, they are usually not tackled at the same time and deserves in-depth research investigation.

To address the challenges, a multi-view transfer learning TSK FS (MV-TL FS) is proposed for epilepsy EEG detection by taking advantage of the interpretability and fuzzy inference abilities of fuzzy rule-based models. The proposed method extracts features from multiple views and employs transfer learning to train the model based on the data of the target domain and the knowledge of the source domain from different views. The mechanism effectively alleviates the challenge caused by the lack of data for patient-specific epilepsy detection. Notably, in the proposed method, multi-view learning is integrated with transfer learning so that the model is insensitive to the features in a certain view while learning more knowledge from multiple views. Finally, a multi-view TSK FS classifier is constructed.

The main contributions of this work are summarized as follows:

1) By introducing TSK FS as the basis model, a multi-view collaborative transfer learning based TSK FS classification method, i.e., MV-TL FS, is proposed. The method is based on fuzzy inference rules, which makes the model more interpretable when compared with black-box based methods developed for patient-specific epileptic EEG detection.

2) For patient-specific epileptic EEG detection, a collaborative multi-view transfer learning mechanism is proposed for model construction of TSK FS by integrating multi-view learning with transfer learning. The multi-view learning enables the proposed model to incorporate between-view knowledge and reduces the difficulty in selecting a specific method that is appropriate for feature extraction. At the same time, the transfer learning enables the model to have robust performance for scenes with insufficient samples. The mechanism effectively enhances the generalization ability of the trained model.

3) Extensive experimental studies are conducted on the CHB-MIT dataset to demonstrate the effectiveness of the proposed method for patient-specific epilepsy detection.

The rest of this paper is organized as follows. Section II gives the main technical background. The proposed MV-TL FS method is described in detail in Section III. Section IV discusses the procedure of epilepsy detection using MV-TL FS. Experimental validation and analysis are reported in Section V. Finally, conclusions and future works are given in Section VI.

II. RELATED WORK

A. Multi-view Learning for Epilepsy Detection

Multi-view learning is a learning paradigm to improve modeling performance using the data extracted from multiple views [27-30]. It solves the limitation of a single view by ensuring the diversity of features and integrating them to improve the performance. The existing multi-view learning algorithms can be classified into three main categories, i.e., co-training [28], multiple kernel learning [29] and subspace learning[30].

In recent years, multi-view learning has been applied for epilepsy detection. Tang et al. [31] proposed a multi-view convolutional gated recurrent unit network framework to analyze the spatiotemporal sequences of multi-view features to capture potential changes prior to seizures. Yuan et al. [32] proposed a unified multi-view deep learning framework based on multichannel scalp EEG signals to detect abnormalities associated with epileptic seizures. Liu et al. [33] used a multi-view convolutional neural network framework to predict the occurrence of seizures. Tian et al. [34] proposed a multi-view deep feature extraction method combined with interpretable classifier for epilepsy detection.

B. Transfer Learning for Epilepsy Detection

Transfer learning refers to applying knowledge and/or data from a domain to a different but related domain. Its aim is to find the similarities between the domains to deal with challenging data mining problems like big data, unlabeled learning, universal models or personalized applications [35-39]. Transfer learning and related techniques have already been used in many areas, such as WiFi signal localization, and image classification [40, 41, 65, 66].

In epilepsy detection, it is difficult to construct completely universal models because the difference in EEG signals between individuals can be significant. Transfer learning can resolve this paradox to some extent. S. Raghu et al. [36] classified seven different types of seizure versus non-epileptic EEG signals by applying convolutional neural networks(CNN) and transfer learning. Rodrigues et al. [37] proposed a transfer learning method for processing the statistical variability of EEG signals of different subjects. Jiang et al. [38] incorporated label shift vector into generalized linear model to adjust the weights in the least squares regression classifier. Xia et al. [39] proposed a cross-domain classification model with knowledge utilization maximization (CDC-KUM).

C. TSK FS for Epilepsy Detection

Fuzzy set, as a promotion of the classic crisp set, is proposed to model the vagueness of data in the real world. Representation of complex knowledge can be represented in imprecise terms using fuzzy set theory and fuzzy logic theory, and the intelligent models thus developed, i.e., fuzzy systems, have good interpretability. Since the first proposal of fuzzy system in [42], different
variations have been developed and the TSK FS is a popular one that is widely used due to its flexibility and good learning abilities [43, 44]. TSK FS has been applied to various fields, e.g., data mining and intelligent care [45-50].

TSK FS contains a fuzzy rule base. The kth rule can be defined as follows.

\[
\text{IF: } x_1 \in A_{1}^k \land x_2 \in A_{2}^k \ldots \land x_d \in A_{d}^k \\text{Then: } f_j^k(x) = p_{0j}^k + p_{1j}^k x_1 + p_{2j}^k x_2 + \ldots + p_{dj}^k x_d
\]

(1)

where \(K\) is the total number of rules, and \(d\) is the dimensionality of the sample. \(A_{i}^k\) is the fuzzy set of the \(i\)th feature in the \(k\)th rule, and \(f_j^k(x)\) is the \(j\)th output of the \(k\)th rule. \(p_{ij}^k\) is the consequent parameter of the \(j\)th output in the \(k\)th rule. \(\land\) is a fuzzy conjunction operation. The output of the TSK FS can be obtained by (2) with specific fuzzy inference operations adopted:

\[
f_j(x) = \frac{\sum_{k=1}^{K} \mu_k^i(x) f_j^k(x)}{\sum_{k=1}^{K} \mu_k^i(x)} = \sum_{k=1}^{K} \tilde{\mu}_k^i(x) f_j^k(x)
\]

(2)

where \(\mu_k^i(x)\) denotes the firing strength of the \(k\)th rule for the sample input \(x\), which can be normalized to \(\tilde{\mu}_k^i(x)\). They are usually obtained by

\[
\mu_k^i(x_i) = \prod_{j=1}^{d} \mu_{A_j}^i(x_i)
\]

(3)

\[
\tilde{\mu}_k^i(x) = \mu_k^i(x) / \sum_{k=1}^{K} \mu_k^i(x)
\]

(4)

where \(\mu_{A_j}^i(x_i)\) is the membership degree of the \(i\)th element \(x_i\) of \(x\), belonging to the fuzzy set \(A_{j}^k\). Gaussian function is commonly used as the membership function [51], i.e.,

\[
\mu_{\mu_j}(x_i) = \exp \left( -\frac{(x_i - c_j^k)^2}{2\delta_j^2} \right)
\]

(5)

The parameters \(c_j^k\) and \(\delta_j^k\) in (5) can be obtained in different ways, such as deterministic clustering [52, 53]. If the antecedent parameters of a TSK FS have been determined, for an input vector \(x\), the \(j\)th output of the model, i.e., \(y_{j, pre}\), can be expressed as a linear model in the new feature space as follows:

\[
y_{j, pre} = f_j(x) = p_{gj}^T x_g
\]

(6)

with the transformations below,

\[
x_g = [1, x]^T \in \mathbb{R}^{(d+1) \times 1},
\]

(7a)

\[
\tilde{x}_g = \tilde{\mu}(x) x_g \in \mathbb{R}^{(d+1) \times 1},
\]

(7b)

\[
x_g = [\tilde{x}_1^T, \tilde{x}_2^T, \ldots, \tilde{x}_K^T]^T \in \mathbb{R}^{K(d+1) \times 1}
\]

(7c)

\[
p_{gj}^k = [p_{0j}^k, p_{1j}^k, \ldots, p_{dj}^k]^T \in \mathbb{R}^{(d+1) \times 1}
\]

(7d)

\[
p_{g,j} = [(p_{j}^1)^T, (p_{j}^2)^T, \ldots, (p_{j}^K)^T]^T \in \mathbb{R}^{K(d+1) \times 1}
\]

(7e)

In (6), \(x_g\) is the new feature vector obtained from \(x\) after fuzzy mapping; \(p_{gj}\) is the consequent parameters combined with all the rules for the \(j\)th output. Existing optimization technologies for linear models, e.g., least squares method, can be used to solve for \(p_{gj}\) directly. Among them, ridge regression is a proven effective optimization method [11], where the optimized consequent parameters for classification can be expressed as,

\[
p_{g,j} = \left( I_{d+1} + \sum_{i=1}^{N} x_{g,i} x_{g,i}^T \right)^{-1} \left( \sum_{i=1}^{N} x_{g,i} y_{i,j} \right)
\]

(8)

where \(x_{g,i}\) is the mapped input vector in the new feature space of the \(i\)th sample in the training set and it can be obtained by (7a)-(7c); \(y_{i} = [y_{i,1}, \ldots, y_{i,C}]^T\) is a \(C\)-dimension label vector of the \(i\)th training sample, where \(C\) is the number of classes.

TSK FS have gained popularity for epilepsy detection in recent years. The advantage of using TSK FS for detecting epilepsy lies in its good interpretability and strong learning ability. Yang et al. [54] proposed a TSK FS construction algorithm based on transductive transfer learning to solve the mismatch in distribution between the training and test datasets. Xie et al. [26] proposed a generalized hidden-mapping transductive transfer learning method that implements transfer learning of several classical intelligent models, including feedforward neural networks, fuzzy systems, and kernelized linear models. Jiang et al. [24] proposed an epileptic EEG recognition method based on a multi-view learning-based TSK FS. Ni et al. [55] proposed a new noise-insensitive TSK FS based on inter-class competitive learning for EEG signal recognition. Deng et al. [13] proposed an enhanced transductive transfer learning TSK FS for epileptic EEG recognition by introducing the joint knowledge transfer mechanism. These studies demonstrate that TSK FSs have played an important role in epilepsy detection.
III. TSK Fuzzy System Based on Multi-view Collaborative Transfer Learning

The proposed TSK FS with multi-view collaborative transfer learning capability, i.e., MV-TL FS, is presented in this section.

A. Framework of the Proposed Method

The framework of MV-TL FS is shown in Fig. 1. First, knowledge extraction is performed on the data of the source domain. Afterwards, the model in the target domain is trained by the multi-view cooperative transfer learning technique. In this framework, we focus on two mechanisms: knowledge transfer from the source domain to the target domain for each view, and cooperation between different views. Detailed descriptions of these mechanisms are presented below.

B. Multi-view Transfer Learning Mechanism for Fuzzy Feature Space

1) Multi-view Distribution Adaptation of Fuzzy Feature Space

Maximum mean discrepancy (MMD) is a common metric that is used in transfer learning to match the distributions of data between source and target domains. In this study, MMD is used to match the distributions between the two domains in the fuzzy space for multi-view scene. Typically, with a source domain dataset $D_s = \{x_i\}_{i=1}^N$ and a target domain dataset $D_t = \{z_i\}_{i=1}^M$, the MMD can be expressed in the following form [56],

$$MMD^2 = \left\| \frac{1}{N} \sum_{i=1}^N \phi(x_i) - \frac{1}{M} \sum_{j=1}^M \phi(z_j) \right\|^2$$

where $\phi(\cdot)$ is a mapping function used to map the original variable to the reproducing kernel Hilbert space. $N$ and $M$ are the number of samples of the source and target domains, respectively.

In this paper, the knowledge from each view is transferred and the mapping vector in the fuzzy space that can minimize the distribution distance between a transferred view and the target is determined based on MMD. We map the source domain dataset $D_s$ and the target domain dataset $D_t$ to the fuzzy space using (7a)-(7c) to obtain $D'_s = \{x_{gi}\}_{i=1}^N$ and $D'_t = \{z_{gi}\}_{i=1}^M$.

Based on (9), the MMD of two domains in the multi-view fuzzy feature space can be expressed as follows,

$$d(P_{i,map}^tP_{i,map}^s) = MMD^2_{Multi-view}$$

$$= \sum_{i=1}^V \sum_{j=1}^C \left\| \frac{1}{N} \sum_{i=1}^N p_{j}^{v_i} x_{ti}^{v_i} - \frac{1}{M} \sum_{j=1}^M (p_{j}^{v_i})^T z_{ti}^{v_i} \right\|^2$$

$$= \sum_{i=1}^V \sum_{j=1}^C \left( \frac{1}{N^2} \sum_{i=1}^N \sum_{i=1}^N (p_{j}^{v_i})^T x_{ti}^{v_i} x_{ti}^{v_i} - \frac{1}{M^2} \sum_{j=1}^M \sum_{j=1}^M (p_{j}^{v_i})^T z_{ti}^{v_i} z_{ti}^{v_i} \right)$$

$$+ \frac{1}{M^2} \sum_{j=1}^M \sum_{j=1}^M (p_{j}^{v_i})^T z_{ti}^{v_i} p_{j}^{v_i}$$

$$- \frac{2}{NM} \sum_{i=1}^V \sum_{j=1}^C \sum_{i=1}^N \sum_{i=1}^N (p_{j}^{v_i})^T x_{ti}^{v_i} z_{ti}^{v_i} (p_{j}^{v_i})^T$$

where $x_{ti}^{v_i}$ is the $i$-th sample of the $v$-th view in the fuzzy feature space and $p_{j}^{v_i}$ is the consequent parameters of the $v$-th view for the $j$-th output. $V$ is the total number of views; $C$ is the total number of outputs (i.e., the number of classes in the classification dataset). Let

$$\Omega_o = \frac{1}{N^2} \sum_{i=1}^N \sum_{i=1}^N x_{ti}^{v_i} (x_{ti}^{v_i})^T + \frac{1}{M^2} \sum_{j=1}^M \sum_{j=1}^M z_{ti}^{v_i} (z_{ti}^{v_i})^T$$

$$- \frac{2}{NM} \sum_{i=1}^V \sum_{j=1}^C \sum_{i=1}^N \sum_{i=1}^N x_{ti}^{v_i} z_{ti}^{v_i} (p_{j}^{v_i})^T$$

$$\Omega = \frac{\Omega_o + \Omega^T_o}{2}$$

Fig. 1 The framework of the proposed multi-view collaborative transfer learning TSK fuzzy system.
Equation (10) can be simplified as
\[
d(P_{s,map},P_{t,map}) = MMD_{\text{multi-view}}^2 = \sum_{v=1}^{V} \sum_{c=1}^{C} (p_{g0,v,j}^v - p_{g0,v,j}^v)^T \Omega p_{g0,j}^v
\] (12)

2) Comprehensive Multi-view Transfer Mechanism

The consequent knowledge of the source domain is further introduced into the transfer learning process for the target domain, so that the trained model can approximate the desired parameters more easily with the guidance of the knowledge in the source domain. The knowledge transfer, denoted as $KT$, can be expressed in the following form,
\[
KT = \sum_{v=1}^{V} \sum_{j=1}^{C} (p_{g0,v,j}^v - p_{g0,v,j}^v)^T (p_{g0,v,j}^v - p_{g0,v,j}^v)
\] (13)

where $p_{g0,v,j}^v$ denotes the consequent parameter of the $j$th output in the source domain for view $v$. The $KT$ term allows the model to implement multi-view consequent knowledge transfer to estimate the desired consequent parameters of the model in the target domain.

Based on the adaptive multi-view distribution of the fuzzy feature space and the multi-view consequent knowledge transfer, we obtain the following comprehensive multi-view transfer mechanism, denoted as $T$, for the construction of TSK FS,
\[
T = \lambda_t KT + \lambda_d d(P_{s,map},P_{t,map})
\]
\[
= \lambda_t \sum_{v=1}^{V} \sum_{j=1}^{C} (p_{g0,v,j}^v - p_{g0,v,j}^v)^T (p_{g0,v,j}^v - p_{g0,v,j}^v)
\]
\[
+ \lambda_d \sum_{v=1}^{V} \sum_{j=1}^{C} \sum_{l=1}^{N} (p_{g0,v,j}^v)^T x_{g0,l}^v
\]
\[
- \frac{1}{M} \sum_{j=1}^{C} (p_{g0,j}^v)^T z_{g0}^v
\] (14)

The first term in (14), derived from (13), is to transfer multi-view consequent knowledge. The second term, derived from (10), is to measure the distribution distance between different domains in a multi-view projected fuzzy space. It is used to improve transfer learning performance. Ultimately, (14) can make the model transferable and enhance the learning ability of the model in the target domain for scenes with insufficient multi-view data.

C. A Multi-view Collaborative Learning Mechanism for TSK Fuzzy Systems Based on Fuzzy Weighting and Consistency Constraints

To further improve the learning ability of the constructed model, a collaborative learning mechanism involving multiple views, denoted as $Ψ$, is proposed and designed as follows,
\[
Ψ = \frac{1}{2} \sum_{v=1}^{V} (w_v m \sum_{i=1}^{N} \| x_{g0,l}^v - y_{ij} \|^2 + \lambda_p \sum_{v=1}^{V} \sum_{c=1}^{C} (p_{g0,v,j}^v)^T p_{g0,j}^v
\]
\[
+ \frac{\lambda_m}{2} \sum_{v=1}^{V} \sum_{c=1}^{C} \sum_{l=1}^{N} (p_{g0,v,j}^v)^T x_{g0,l}^v
\]
\[
- \frac{1}{V-1} \sum_{v=1}^{V} \sum_{l=1}^{N} (p_{g0,v,j}^v)^T x_{g0,l}^v
\] (15)

where $w_v$ is the weight of the $v$th view and $m$ is the fuzzy index; $y_{ij}$ is a $C$-dimensional label vector; $p_{g0,v,j}^v$ is a priori parameter vector of the fuzzy rule consequent obtained from other views except view $v$. The definitions of the other symbols are the same as those described in the previous sections.

In (15), the first two terms are derived from the traditional TSK FS for learning the consequent parameters of each independent view. The last term $(p_{g0,v,j}^v)^T x_{g0,l}^v$ denotes the predicted $j$th output of the $v$th view, and $(\frac{1}{V-1} \sum_{v=1}^{V} (p_{g0,v,j}^v)^T x_{g0,l}^v$ denotes the average of the prior decision values of all the views except the $v$th view. By minimizing (15), the importance of different views for the corresponding TSK FS can be obtained, and each view in the target domain can reach a consistent decision.

D. Objective Function Based on Multi-view Cooperative Transfer Learning

Based on (14) and (15), we propose the objective function for training the multi-view TSK FS as follows:
\[
\min_{p_{g0,v},w} J(p_{g0,v}, w) = Ψ + T
\] (16)
\[
s.t. \sum_{v=1}^{V} w_v = 1
\]

In (16), the first term is used for multi-view collaboration and the second is used for multi-view transfer. These two terms interact with each other to facilitate effective learning of the model parameters in the target domain.

E. Optimization

Since (16) is a nonconvex optimization problem, alternate iteration strategy can be used for parameter optimization. First, keep $w_v$ constant and set $\frac{\partial J(p_{g0,v}, w)}{\partial p_{g0,v}} = 0$. Then, we can update the consequent parameter $p_{g0,v}$ as follows:
\[
p_{g0,v} = \left( (w_v m \sum_{i=1}^{N} x_{g0,l}^v x_{g0,l}^v + 2 (\lambda_p + \lambda_t) I) + \lambda_m \sum_{i=1}^{N} x_{g0,l}^v y_{ij} + \frac{\lambda_m}{V-1} \sum_{v=1}^{V} \sum_{i=1}^{N} x_{g0,l}^v (p_{g0,v,j}^v + 2 \lambda_p p_{g0,v,j}^v) \right)^{-1}
\] (17)
Next, keep $p_{ij}^v$ constant and set $\frac{\partial f(p_{ij}^v w)}{\partial w_p} = 0$, and we can update the weights $w_p$ as follows.

$$w_p = \left(\sum_{j=1}^C \sum_{i=1}^V \left\| (p_{ij}^v)^T x_{ji}^v - y_{ij} \right\|^2 \right)^{1/m-1}$$

$$\left(\sum_{h=1}^V \sum_{i=1}^C \sum_{j=1}^C \sum_{i=1}^V \left\| (p_{ij}^h)^T x_{ji}^h - y_{ij} \right\|^2 \right)^{1/m-1}$$

The optimal $p_{ij}^v$ and $w_p$ are then obtained by iterative learning. The algorithm is described in Table I.

### F. Algorithm Complexity Analysis

Based on the above discussions and the algorithm in Table I, the computational complexity of the proposed MV-TL FS is analyzed using the Big O notation. Denote $d$ as dimension of the dataset, $K$ as the number of fuzzy rules, $S = N + M$ as the number of samples, with $N$ and $M$ being the number of samples in the source and target domains respectively, $C$ as the number of classes, and $T$ as the number of iterations. In Step 2, according to (3)-(5) and (7c), the complexity of mapping the dataset into $D_1$ and $D_2'$ is $O(2SKd)$. In Step 3, the complexity of the prior consequent parameter acquisition is $O(KdSdC+ScD)$. Step 4 solves for the consequent parameters of different views and the weights of the views iteratively. The complexity is $O(TKd(4KdS+ScD)+ScS)$ and $O(TS(KdC+ScD+S^2))$ respectively. Meanwhile, considering the existence of different views, for $V$ views, the total complexity is $V$ times of the complexity of all the steps above. Based on the analysis, Step 4 dominates the computation cost. Let $a = \max(Kd, S)$ and $b = \max(T, C, V)$, the computational cost is given by $O(a^3b^2(6a + 5b))$.

### TABLE I

**Algorithm of the Proposed MV-TL FS Method**

| Initialization | Set the number of fuzzy rules $K$, the regularization parameters $\lambda_p$, $\lambda_c$, $\lambda_{un}$ and $\lambda_d$. Obtain initial multi-view dataset from source (reference) and target (current) domains. The view weight $w_p$ is set to $1/V$. |
| Stage 1: Constructing multi-view data in fuzzy feature space | |
| Step 1 | The data in each view of the source domain (reference scene) is mapped to the fuzzy inference feature space using (3)-(5), (7a)-(7c). Deterministic clustering is used in (5) to evaluate the antecedent parameters. |
| Step 2 | Transfer the antecedent parameters from the source domain (reference scene) to the target domain (current scene) for the construction of the corresponding fuzzy feature space. That is, we get $D_1 = \{x_{ji}\}_{ji}$ and $D_2 = \{x_{ji}\}_{ji}$. |
| Stage 2: Building a TSK fuzzy system based on multi-view transfer and collaborative learning | |
| Step 3 | Use (8) to obtain $p_{ij}^v$ from the source domain (reference scene) and the prior consequent parameter $\phi_{ji}$. |
| Step 4 | The consequent parameters of different views in the target domain (current scene) and the view weights are updated using (17), (18) and the knowledge from the source domain (reference scene). |
| Step 5 | The final multi-view transfer model is constructed using the antecedent and consequent parameters obtained in Step 2 and Step 4. |

![Fig. 2 Framework of the epileptic seizure detection based on the proposed MV-TL FS.](image)

**IV. EPILEPTIC EEG DETECTION BASED ON MULTI-VIEW COLLABORATIVE TRANSFER LEARNING TSK FUZZY SYSTEM**

This section presents a new scheme for epileptic EEG detection based on the proposed MV-TL FS. The method uses raw EEG signals as the initial dataset from which multi-view features are extracted. These features are then used to train the MV-TL FS classifier, which is ultimately used to produce prediction results for the test data. In this section, the framework of epilepsy detection based on MV-TL FS is first presented. The views features generated by the feature extraction module are then described, followed by the training of the MV-TL FS module and finally the testing process of the test data.
A. Framework of Epilepsy Detection Based on MV-TL FS

The framework shown in Fig. 2 consists of three core components, namely, initial EEG multi-view feature extraction, training of the MV-TL FS classifier, and the test process for the future EEG signal of the test sample. Based on the framework, the algorithm of MV-TL FS based epilepsy EEG detection is given in Table II.

| TABLE II | ALGORITHM OF THE MV-TL FS BASED EPILEPSY EEG DETECTION. |
|----------|------------------------------------------------------|
| **Stage 1: Multi-view feature extraction** | **Step 1** | The EEG data from existing reference scenes (source domain) and the raw EEG data from patients in the current scenes (target domain) are passed into the feature extraction module. Obtain multi-view feature datasets in time domain $x$, frequency domain $x'$, and time-frequency domain $x''$ using the feature extraction module, i.e., $D_x = [x_{1}]_{l=1}^{L}$ and $D_f = [x'_{1}]_{l=1}^{L}$.
| **Stage 2: Training of the multi-view transfer learning classifier MV-TL FS** | **Step 2** | Process $D_x$, $D_f$ with the MV-TL FS module in Section III.
| **Step 3** | Train the MV-TL FS classifier using the algorithm in Table I.
| **Step 4** | Obtain the multi-view dataset $T = [x_{1}]_{l=1}^{L}$ by the same feature extraction module in Stage 1 using the raw EEG test data.
| **Step 5** | Test the trained classifier in Stage 2 using the dataset $T$.

B. Multi-view Feature Extraction Module

In this study, time domain features, frequency domain features, and time-frequency domain features are adopted as the three views for the proposed multi-view feature extraction module for epileptic EEG detection. We first obtain the EEG signal in the time domain. The corresponding feature extraction modules are described below.

1) Time domain features use time as a variable in the EEG signal. It can be obtained based on the waveform characteristics of the original signal or the waveform characteristics of the decomposed signal. However, the spikes appear in the signal of seizures cause signal nonlinearity, leading to a significant increase in linear prediction error. Common time domain features include mean, variance, and median. These parameters are often used to identify signal states [57]. In this module, the time domain features are directly inherited from the original time-varying and energy-related EEG signal, which has good temporal characteristics without extra processing.

2) Frequency domain features represent the EEG signal in terms of energy changes in frequency. In frequency domain analysis, fast Fourier transform (FFT) [2] is commonly used to convert time domain signals to frequency domain. In this module, epileptic frequency domain features are extracted using the fast Fourier transform (FFT) [58, 59] from the frequency band between 4 Hz and 30 Hz where features appear during seizures. Fourier transform assumes that the signal is locally smooth [60].

3) Time-frequency analysis combines the advantages of both time domain analysis and frequency domain analysis, which is not limited by the assumption of locally smooth signals in Fourier transform. A commonly used method for time-frequency analysis is wavelet transform [61], which uses a decaying orthogonal basis to model the original signal. It obtains the position of a frequency in the time domain. Among the wavelets, Daubechies (dbN) are a popular one that has the high classification accuracy. In this module, we adopt dbN and set the wavelet order to 4.

Finally, the multi-view feature extraction module outputs these three different types of features for the subsequent training of the MV-TL FS classifier.

C. Training of MV-TL FS

After obtaining different views of the EEG dataset, we need to train the multi-view collaborative transfer learning fuzzy system classifier, i.e., MV-TL FS. From Section III, it is clear that MV-TL FS inherits the advantages of existing multi-view learning and transfer learning methods while overcoming the existing challenges. It makes full use of the obtained view information and reduces the impact due to insufficient data and the different distribution between the training and test data. Meanwhile, it has an interpretable method through fuzzy inference capability.

When the multi-view features of the data in the current scene (target domain) and the reference scene (source domain) are obtained, we first train the TSK FS for the reference scene and then extract the knowledge from the obtained models. Furthermore, the knowledge in the reference scene is used for transfer learning for the current scene. By using the algorithm in Table I, the MV-TL FS can be trained based on the data in both scenes and the knowledge of the reference scene.

D. Testing Process

Once the feature extraction module is constructed and the training of MV-TL FS is completed, they are used to classify the test samples. The overall process is as follows. First, the test sample $x$ is processed by the feature extraction module to get the required three views $x^1, x^2, x^3$. Afterwards, the samples are passed into the trained MV-TL FS for classification and the final decision value is given by

$$ f(x) = [f_1(x), ..., f_C(x)] = \sum_{v=1}^{V} w_v (p_{v, l})^x x_v^l $$

(19)

which is a linear combination of the decision values from different views. With the one-hot strategy, the final class label is given by $\hat{y} = [y_1, ..., y_l, ..., y_C] \ (1 \leq l \leq C)$. If $f_l(x) = \max_{1 \leq l \leq C} f_l(x), y_l = 1$, else $y_l = 0$. It means that $x$ belongs to class $l$.

V. EXPERIMENTAL STUDIES

A. Datasets

The CHB-MIT dataset from the Boston Children's Hospital is used here for experimental studies. The dataset contains 23 records of EEG signals acquired from 22 subjects (5 males: 3-22 years; 17 females: 1.5-19 years). Signals of 23 scalp EEG electrodes were collected based on the international 10-20 system, acquired at the sampling rate of 256 Hz with 16-bit resolution. The dataset is available on the Physionet website (https://archive.physionet.org/pn6/chbmit/).
To evaluate the performance of MV-TL FS, we select the EEG signals of the first five subjects for performance comparison, denoted as S1, S2, S3, S4, and S5, respectively. The corresponding datasets to be generated are D1, D2, D3, D4 and D5. For each subject, based on the EEG signal at seizure and without seizure, positive samples and negative samples are extracted respectively. In our experiments, each sample corresponds to one-second of EEG signal segment, i.e., 56 sampling points for each channel. To prevent overfitting, a portion of the normal state signal (without seizure) is discarded in the experiment and a sliding window technique is used to increase the number of epileptic seizure samples. The sliding window takes a fixed length of EEG signal sampled within one second and oversampling is implemented by overlapping windows. Finally, the five datasets D1-D5 are generated for the experimental studies.

### B. Experimental Settings

In order to simulate the scene of personalized epileptic detection when the training data are insufficient, 5% of samples in datasets D1, D2, ... , D5 are first adopted in our experiments for performance comparison. They are denoted as P1, P2, ..., P5, respectively. The total number of samples, the number of seizure samples, and the number of non-seizure samples are shown in Table III. To implement transfer learning, 20 different transfer tasks are constructed by selecting any two from the five datasets as reference (source) or current (target) scenes, e.g., P1→P2, P1→P3, ..., P5→P4. All the datasets in the experiments are normalized.

#### TABLE III

**DATASETS USED IN THE EXPERIMENTS**

| ID | Total number of samples | Number of seizure samples | Number of non-seizure samples |
|----|-------------------------|---------------------------|-----------------------------|
| P1 | 268                     | 108                       | 160                         |
| P2 | 105                     | 37                        | 67                          |
| P3 | 258                     | 89                        | 169                         |
| P4 | 225                     | 63                        | 162                         |
| P5 | 336                     | 108                       | 228                         |

Three multi-view learning methods and two non-multi-view learning methods are used for comparison. The three multi-view learning algorithms adopted are MV-TSK-FS [24], AMVMED [62], and MV-TL FS ($\lambda_1=0$, $\lambda_2=0$), where the last algorithm MV-TL FS ($\lambda_1=0$, $\lambda_2=0$) denotes the proposed MV-TL FS without the transfer learning abilities. The two non-multi-view learning algorithms adopted are the traditional TSK Fuzzy System (TSK FS) and Transfer Adaboost based on the TSK FS learner (Tradaboost) [63], where Tradaboost (TSK) is a transfer learning method. All the algorithms are related to fuzzy systems except AMVMED.

In order to verify the proposed MV-TL FS, five-fold cross-validation is used. The number of iterations is set to 10 for all the algorithms except AMVMED which do not require iterations. The trade-off parameters and regularization parameters of the algorithms are optimally set by searching the grid {0.01, 0.1, 1, 10, 100}. For the algorithms incorporating the TSK fuzzy system, the number of rules is set to 3. The fuzzy index of the weighting term of the proposed MV-TL FS is optimized by searching the grid {0.25, 0.5, 1, 2, 4}.

The performance index in the experiments is accuracy, which indicates the percentage of correctly classified test samples.

C. Results Analysis

Table IV shows the accuracy of the proposed MV-TL FS on different tasks for various current scenes (target domains) and reference scenes (source domains). Table V shows the accuracy of all the algorithms on the CHB-MIT datasets. In the experiments, non-multi-view algorithms are applied for each of the different views (time domain, frequency domain and time-frequency domain) respectively. For the transfer learning-based methods, i.e., Tradaboost and MV-TL FS, the average of the accuracies based on different source domains is given. The following observations can be made.

1) It can be seen from Table V that the same single view algorithm gives different results under different views. The best results are obtained in the frequency domain, while the worst is obtained in the time domain. Although TSK FS achieves good results when compared to the non-multi-view algorithms in the frequency domain, this advantage is valid only in one view, which does not hold when considering the performance in all the views together. In addition, the Tradaboost algorithm, based on the TSK FS, has a certain degree of negative transfer when compared to using TSK FS alone.

2) Consider the algorithms that are related to fuzzy systems, i.e., TSK FS, Tradaboost(TSK), MV-TSK FS and MV-TL FS ($\lambda_1=0$, $\lambda_2=0$). The multi-view algorithms MV-TSK FS and MV-TL FS ($\lambda_1=0$, $\lambda_2=0$) outperform the non-multi-view algorithms. Therefore, taking all the views available into account can effectively avoid instability caused by considering only a specific view. At the same time, the performance can be improved by the collaboration of the views.

3) Compared with multi-view classifiers, the proposed MV-TL FS enables view enhancement by introducing the transfer learning mechanism, and therefore the performance of the MV-TL FS is better than the other algorithms. It is obvious that the performance is improved when MV-TL FS ($\lambda_1=0$, $\lambda_2=0$) restores its transfer learning capability, and the effectiveness of the mechanism is demonstrated.
In summary, considering the average performance on all the datasets, the proposed MV-TL FS achieves the best performance compared to the algorithms under comparison when the training samples are insufficient, as shown in Fig. 3. The experimental results show that MV-TL FS reduces performance fluctuations caused by different views. The proposed MV-TL FS has a clear advantage over other algorithms, attributed to knowledge leverage from the source domain and the collaboration of different views at the same time.

D. Model Analysis

1) Effect of Sample Size

In the previous experiments, we have constructed the datasets P1-P5 by extracting 5% samples from the original datasets D1-D5 respectively. To study the influence of sample size on the stability of the proposed method, we vary the sample size of the datasets P1-P5 by extracting 10%, 20% and 30% samples for the original datasets D1-D5.

The experimental results are given in Table VI. It can be seen that the performance of the algorithms fluctuates with the size of the training datasets. Among the algorithms of the same mechanism, the performance of multi-view algorithms are always better than or similar to that of the non-multi-view algorithms. In addition, while the sample size is varied, the performance of the MV-TL FS is always superior to other algorithms and the performance is improved gradually with the sample size. To this end, MV-TL FS achieves the best result when considering the performance of the algorithms on all the tasks on average.

![Fig. 4. Effect of the number of rules](image)

**TABLE IV**

| Datasets (source) | P2  | P3  | P4  | P5  | P1  | P3  | P4  | P5  |
|-------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Datasets (target) | P1  | P2  | P3  |     |     |     |     |     |
|                   |     |     |     |     |     |     |     |     |
| Accuracy          | 98.50 | 99.62 | 98.50 | 99.25 | 98.00 | 95.10 | 98.00 | 96.05 |
| SD                | 0.0246 | 0.0084 | 0.0246 | 0.0106 | 0.0047 | 0.0099 | 0.0047 | 0.0061 |
| Average           | 98.97 (0.0056) | 96.79 (0.0146) | 98.46 (0.0084) |

SD denotes standard deviation. It is also given inside bracket.

**TABLE V**

| Dataset     | No multi-view methods | Multi-view methods | MV-TL FS* |
|-------------|-----------------------|--------------------|-----------|
|             | TSK FS | Tradaboost* | TSK FS | Tradaboost* | TSK FS | Tradaboost* | TSK FS | Tradaboost* | MV-TS-KFS | AMVMED | MV-TL FS* (λ₁ = 0, λ₂ = 0) | MV-TL FS* (λ₁ = λ₂ = 0) |
| P1          | 68.98 | (0.0984) | 96.65 | (0.0259) | 94.95 | (0.0169) | 74.99 | (0.0759) | 68.83 | (0.0439) | 98.13 | (0.0263) | 61.84 | (0.0654) | 98.50 | (0.0157) | 98.97 | (0.0056) |
| P2          | 67.14 | (0.0196) | 93.24 | (0.0434) | 79.32 | (0.0211) | 76.95 | (0.1024) | 65.27 | (0.0080) | 92.33 | (0.0720) | 64.90 | (0.0725) | 93.24 | (0.0274) | 96.79 | (0.0146) |
| P3          | 72.12 | (0.0931) | 96.11 | (0.0309) | 91.16 | (0.0318) | 86.05 | (0.0209) | 77.70 | (0.0300) | 98.08 | (0.0236) | 66.14 | (0.0190) | 98.06 | (0.0273) | 98.46 | (0.0084) |
| P4          | 76.00 | (0.0823) | 90.67 | (0.0531) | 84.67 | (0.0367) | 79.11 | (0.0512) | 71.11 | (0.0719) | 92.89 | (0.0727) | 72.77 | (0.0364) | 92.44 | (0.0461) | 95.00 | (0.0067) |
| P5          | 74.12 | (0.0738) | 91.37 | (0.0488) | 89.97 | (0.0342) | 77.36 | (0.0685) | 74.58 | (0.0422) | 91.09 | (0.0453) | 68.44 | (0.0739) | 92.85 | (0.0387) | 94.57 | (0.0075) |
| Average     | 71.67 | (0.0363) | 93.61 | (0.0726) | 88.01 | (0.0271) | 78.89 | (0.0624) | 71.55 | (0.0598) | 94.50 | (0.0335) | 66.82 | (0.0409) | 95.02 | (0.0300) | 96.76 | (0.0199) |

* MV-TL FS (λ₁ = λ₂ = 0) is a version of the proposed MV-TL FS where the transfer learning abilities are disabled.
+ For transfer learning-based methods, i.e., Tradaboost and MV-TL FS, the results are the average of the accuracies based on different source domains.
Standard deviation is inside bracket.
TABLE VI
COMPARISON OF ALGORITHM PERFORMANCE UNDER DIFFERENT SIZE OF DATASETS.

| Size of datasets | MV-TSFS | AMVMED | MV-TLFS (λ_\text{P}=0) | Time Domain | Frequent Domain | Time-Frequency | MV-TLFS |
|------------------|---------|--------|------------------------|-------------|----------------|----------------|---------|
|                  | TSK     | Trada boost | TSK | Trada boost | TSK | Trada boost | TSK | Trada boost |
| 5%               | 94.50   | (0.0335) | 66.82 | (0.0409) | 95.02 | (0.0300) | 71.67 | (0.0363) | 63.99 | (0.0726) | 93.61 | (0.0271) | 88.01 | (0.0624) | 78.89 | (0.0426) | 71.55 | (0.0598) | 96.76 | (0.0199) |
| 10%              | 95.51   | (0.0291) | 67.88 | (0.0104) | 95.78 | (0.0315) | 72.59 | (0.0319) | 58.87 | (0.0913) | 95.46 | (0.0392) | 88.19 | (0.0767) | 82.62 | (0.0394) | 72.73 | (0.0428) | 97.03 | (0.0221) |
| 20%              | 95.23   | (0.0247) | 67.95 | (0.0159) | 96.49 | (0.0176) | 73.81 | (0.0331) | 56.11 | (1.022) | 96.10 | (0.0383) | 88.85 | (0.0750) | 82.86 | (0.0551) | 73.51 | (0.0475) | 97.72 | (0.0137) |
| 30%              | 96.85   | (0.0207) | 63.31 | (0.0643) | 96.86 | (0.0217) | 74.75 | (0.0325) | 54.36 | (0.0908) | 96.55 | (0.0191) | 90.46 | (0.0765) | 82.71 | (0.0600) | 71.30 | (0.0548) | 98.10 | (0.0106) |
| Average          | 95.52   | (0.0098) | 66.49 | (0.0218) | 96.04 | (0.0081) | 73.21 | (0.0135) | 58.26 | (0.04192) | 95.43 | (0.0113) | 88.81 | (0.0113) | 81.77 | (0.0192) | 72.27 | (0.0103) | 97.40 | (0.0062) |

Standard deviation is inside bracket.

2) Effect of the Number of Fuzzy Rules

The number of fuzzy rules in the TSK FS influences the performance of the proposed MV-TL FS. It is desirable to use as few rules as possible while maintaining the performance of the algorithm [64]. We analyze the effect by varying the number of fuzzy rules from 2 to 10 and run the experiments on the constructed datasets P1-P5. It can be seen from the results in Fig. 4 that the performance of MV-TL FS is relatively stable under different numbers of rules. The average accuracy is the highest when the number of rules is 6, but the advantage is not significantly better than the other settings.

The results show that the proposed MV-TL FS can attain high accuracy with a small number of fuzzy rules, indicating that concise model with good interpretability can be built using fewer rules while high classification performance can be maintained at the same time. In our experiments, the number of rules is set to 3. Furthermore, based on the complexity analysis in Section III-F, computational complexity of MV-TL FS increase greatly with the number of rules. The ability for MV-TL FS to use fewer rules is also desirable from this perspective.

3) Parameter Sensitivity Analysis

To analyze the sensitivity of proposed method on the parameters \( \lambda_\text{P}, \lambda_\text{T}, \lambda_\text{A} \) and \( \lambda_\text{un} \), we evaluate the classification performance with the parameters varying within the range \( \{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 10^0, 10^1, 10^2, 10^3, 10^4\} \). Taking the dataset P2 as an example, Figs. 5(a) to 5(d) show the classification accuracy under different parameter settings in different multi-view transfer tasks. Fig. 5(a) shows that the classification accuracy changes significantly when the value of \( \lambda_\text{P} \) is greater than 1. Fig. 5(b) shows that stable classification performance can be obtained when \( \lambda_\text{T} \) is less than 1. It can be seen from Fig. 5(c) that the proposed method is not sensitive to the change of \( \lambda_\text{A} \). Meanwhile, from Fig. 5(d), we can see that the proposed method is sensitive to \( \lambda_\text{un} \).

![Fig. 5. Parameter sensitivity analysis](image-url)
VI. CONCLUSION

In this paper, we propose a TSK fuzzy system that incorporates multi-view collaborative transfer learning abilities for epilepsy EEG detection. It integrates multi-view learning, transfer learning and fuzzy system to enhance the detection performance. The proposed MV-TL FS makes full use of the information from different views and applies transfer learning for each view to solve the issues caused by the insufficient data for personalized diagnosis. The experimental studies show that MV-TL FS is a stable method with higher classification accuracy than the methods under comparison.

Future research on the following aspects will be conducted. In the proposed MV-TL FS, the transfer learning between different domains in the fuzzy inference feature space is paired, which limits the flexibility of the model. We will explore a more flexible and general multi-view transfer framework to enhance the transfer learning abilities. The cross-validation strategy in MV-TL FS for parameter optimization is time-consuming. It is necessary to investigate more effective approaches for determining the appropriate values for different hyperparameters. From clinical point of view, since epileptic seizure often occurs suddenly, it is important to study the feasibility of MV-TL FS for online epilepsy prediction to generate real-time alerts.

The effectiveness of the proposed MV-TL FS in epilepsy detection is validated in this paper. It can also be applied to other EEG signal-based recognition tasks [67], such as motor imagination and emotion recognition. The effectiveness of MV-TL FS in these fields will be carried out in our future work.

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