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Active Selection of Source Patients in Transfer Learning for Epileptic Seizure Detection using Riemannian Manifold

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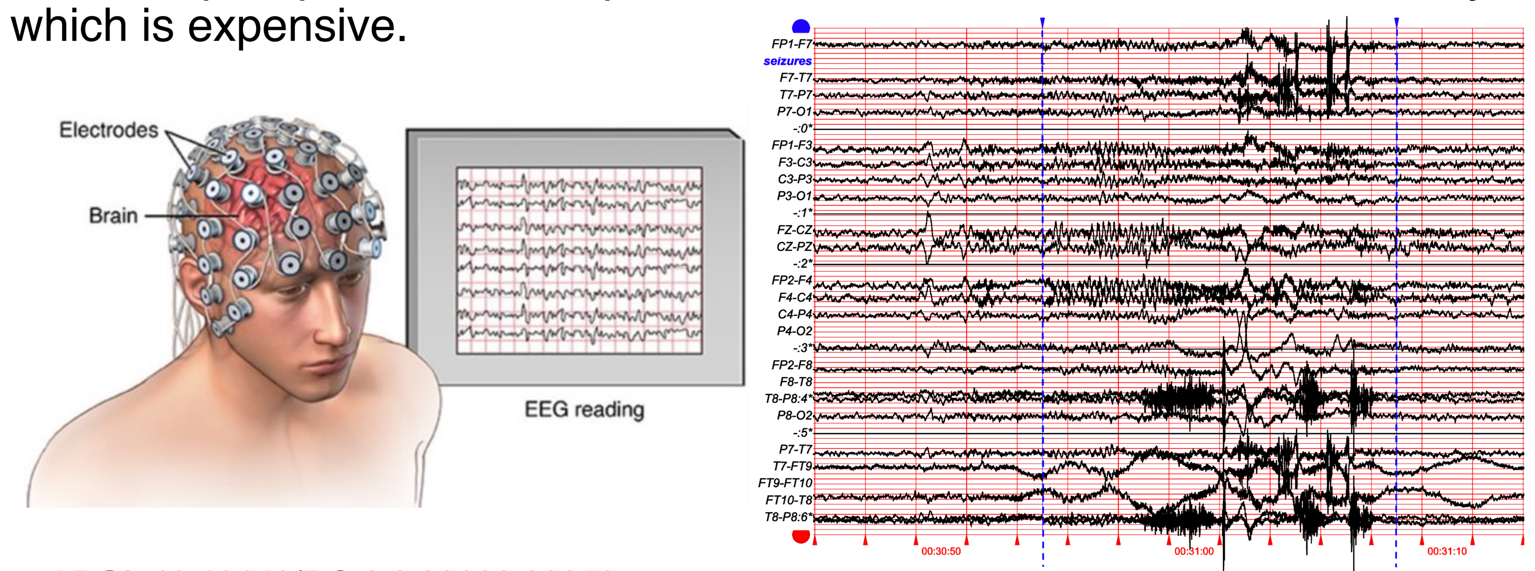
Introduction

Epilepsy

- a group of neurological disorder, characterized by repeated seizures.
- The recurrent occurrence of seizures caused by excessive discharge from cerebral cortex neurons independently without any obvious rhythm.

Motivation

- Epileptic seizure event detection in long electroencephalogram (EEG) recordings is a time-consuming, tedious and error-prone process.
- needs expert practitioner's opinion to detect the seizure event correctly which is expensive.



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Seizure Event in EEG recordings

Research Goal

- Epileptic seizure detection from long EEG recordings of epileptic patients using machine learning based approach.

Focus A solution to mitigate the subject-dependent nature of seizure data in case of designing seizure detection model from EEG recordings.

Riemannian Manifold

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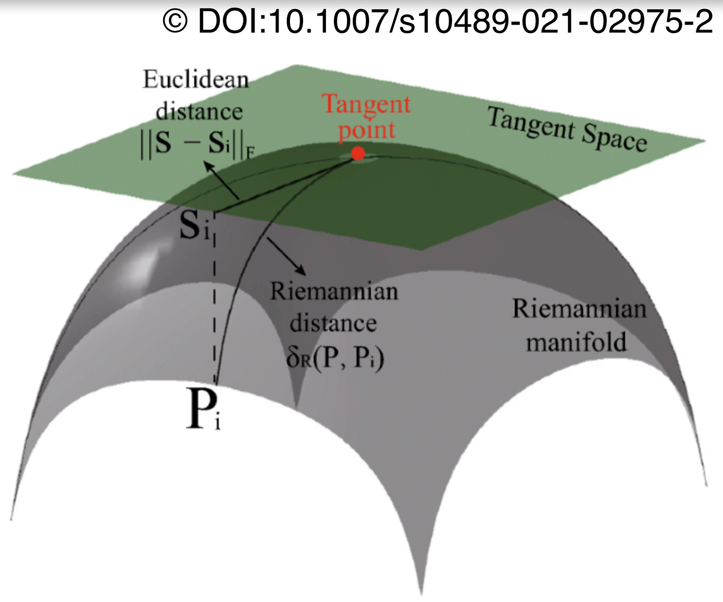
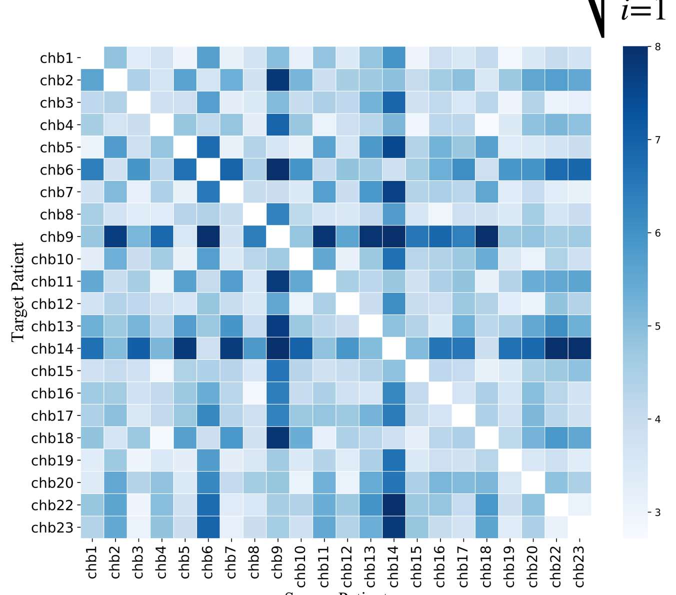
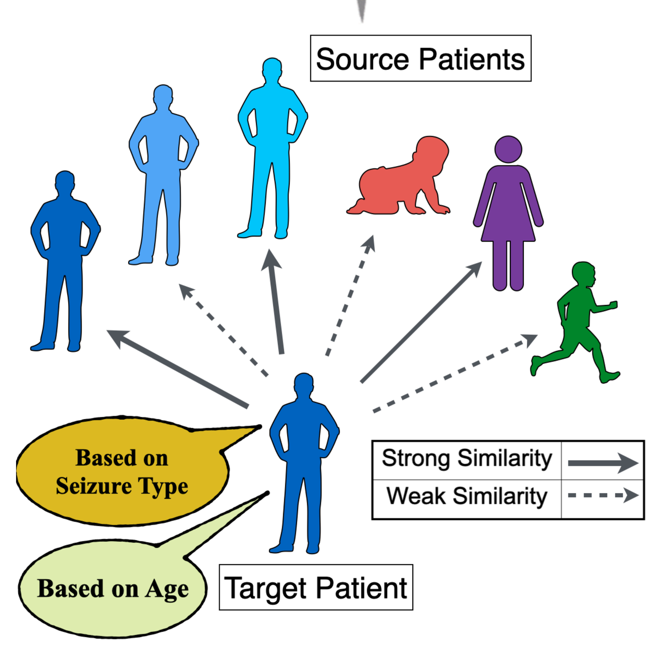
- It has ability to unfold the hidden structure of complex brain signal organization in non-Euclidean space.
- Riemannian distance could measure the similarity among EEG data of different patients.
- Riemannian Distance between A and B:

$$\delta_R(A,B) = \left\| \log\left(A^{-1}B\right) \right\|_F = \sqrt{\sum_{i=1}^{M} \log^2 \lambda_i}$$

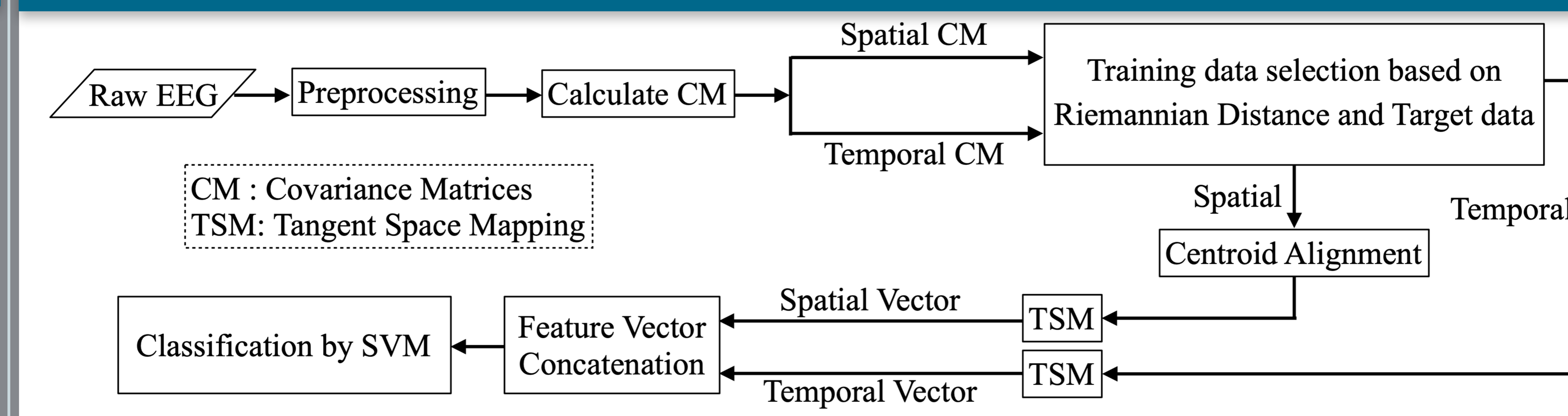




Inter patient Riemannian distance matrix



Method



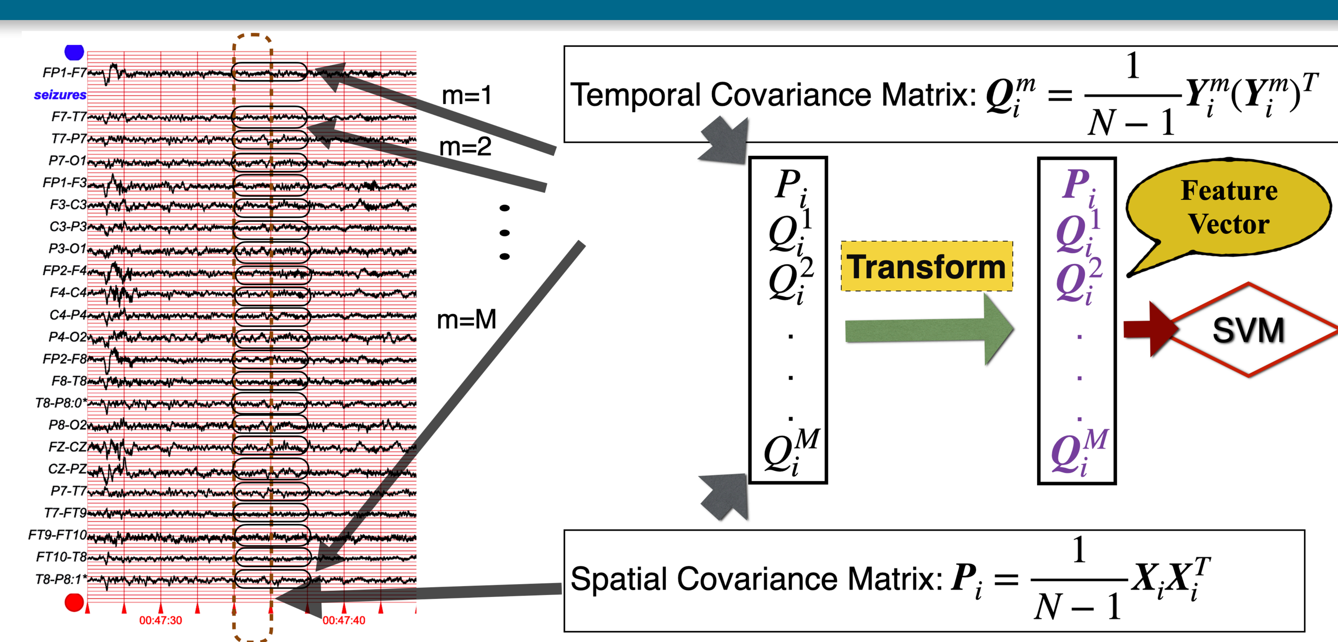
Our Approach

Preprocessing

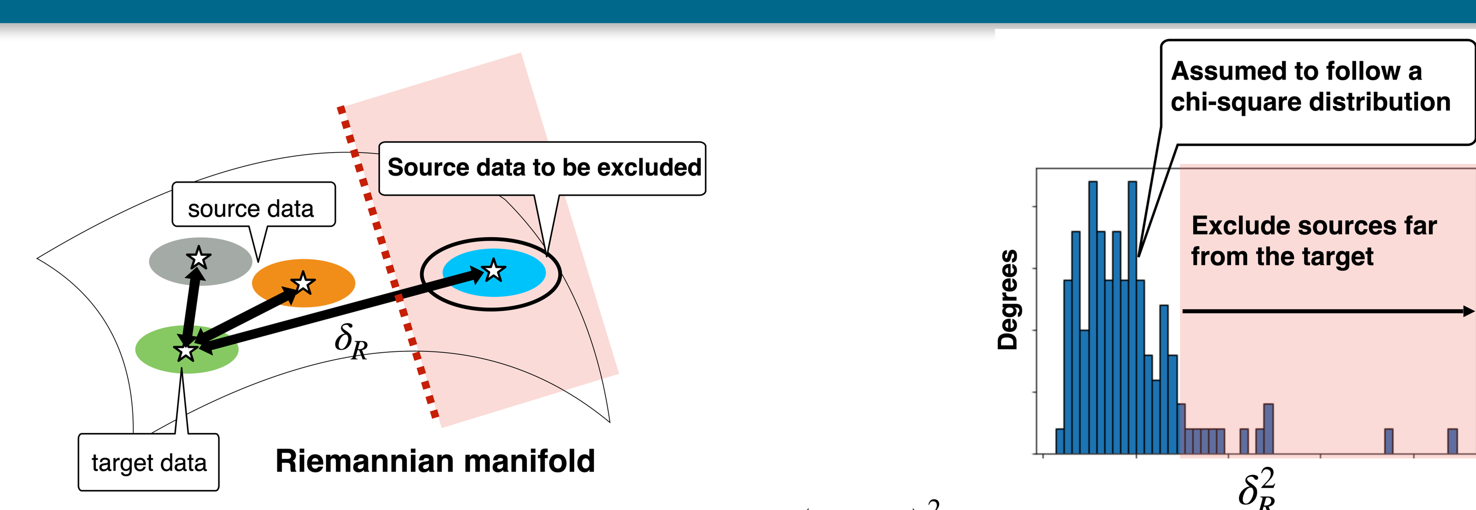
- FIR bandpass filtering 4-35 Hz and z-score normalization of each Channel
- Non-overlapping Segmentation (2 seconds) of continuous EEG

① Calculate Covariance Matrices in Spatial (SCM) and Temporal (TCM) domain
② Selection of Training data based on Target Patients Riemannian Mean
③ Applied Centroid Alignment on Spatial Covariance Matrices
④ Applied Tangent Space Mapping to the SCM and TCM
⑤ Concatenate the output vectors from Tangent Space Mapping
⑥ Train Support Vector Machine Model for the classification

Raw EEG to Feature Vector



Active Selection of Data for Training Model

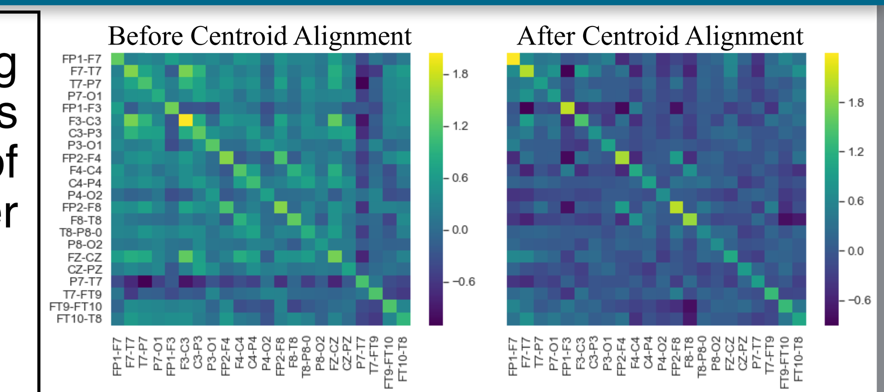


1. Calculate the abnormality $a(\delta_R) = \frac{(\delta_R - \mu)^2}{\sigma^2}$, mean μ and variance σ^2 of the Riemannian distances.
2. Under the assumption that $a(\delta_R)$ is chi-square distributed, select the source patient whose Riemannian distance δ_R has a significant probability of 0.75 or greater.

Centroid Alignment and Tangent Space Mapping

Centroid Alignment is a transfer learning technique on a manifold that minimizes the marginal probability distribution shift of different domains and enables transfer from multiple source domains.

$$P_i^{CA} = M_{ref}^{-\frac{1}{2}} P_i M_{ref}^{-\frac{1}{2}}$$



Centroid Alignment effects on SCM

Tangent space mapping (TSM) is a nonlinear mapping of the covariance matrices to the linear tangent space of a Riemannian manifold, converts them to a transformed vector form as a feature.

$$P = \text{upper}\left(\log\left(M^{-\frac{1}{2}} C M^{\frac{1}{2}}\right)\right)$$

Result

Dataset: recorded by Children's Hospital Boston–MIT, 23 pediatric patients, number of common channels: 23, Sampling frequency: 256 Hz https://www.physionet.org/content/chbmit/1.0.0/

Validation: Leave-one-patient-out
Classifier: Support Vector Machine (SVM)

Tab1: Patient-wise Performance

Patient	AUC(%)	Acc(%)	Sen(%)	Spe(%)
chb01, 21	99.6	98.1	99.1	97.1
chb02	97.2	93.5	92.9	94.0
chb03	99.9	95.4	100.0	90.7
chb04	93.9	84.5	81.8	87.1
chb05	99.0	90.1	98.6	81.5
chb06	62.7	58.2	91.4	21.9
chb07	98.6	89.4	81.7	97.3
chb08	88.6	82.5	72.0	93.1
chb09	99.9	97.8	100.0	95.5
chb10	98.2	87.6	97.3	77.7
chb11	98.9	96.3	95.5	97.0
chb12	81.4	75.7	73.5	78.0
chb13	62.1	52.0	16.2	88.6
chb14	93.9	68.6	100.0	35.1
chb15	95.7	88.2	90.5	85.8
chb16	89.4	73.0	54.5	93.3
chb17	99.4	95.2	97.9	92.4
chb18	95.4	88.1	87.7	88.6
chb19	100.0	98.3	97.4	99.1
chb20	95.2	89.6	85.7	93.6
chb22	99.9	98.5	100.0	96.9
chb23	98.8	94.7	96.2	93.3
Mean	**93.1**	**86.1**	**86.8**	**85.4**
Median	**96.8**	**90.3**	**93.8**	**92.5**

Tab2: Performance of the model's components

Method	AUC(%)	Acc(%)	Sen(%)	Spe(%)
SCM	89.8	81.9	86.4	77.2
SCM+CA	91.4	85.4	86.8	83.9
(SCM+TCM)+CA	92.4	85.3	85.7	84.8
AL+(SCM+TCM)+CA	93.1	86.1	86.8	85.4

Tab3: Comparison with state-of-the-art

Work	AUC	Acc.	Sen.	Spe.
Single-channel EEG+ wavelet features + SVM (Janjarasjitt, 2017)	–	96.87	72.99	98.13
DWT + CNN + BLSTM (Liu et al., 2022)	90.82	97.51	83.11	97.58
DWT + 1-D CNN (Halawa et al., 2022)	–	87	84.40	–
Multiscale CNN (Thuwajit et al., 2022)	–	96.74 ± 4.04	75.32 ± 20.46	95.96 ± 4.38
Proposed Model	**93.1**	**86.1**	**86.8**	**85.4**

Observation

- Selection of source patient data for training helps to tune model for target patient.
- Low performing patients are quite different from the majority of the patients.
- There is a scope to improve the Specificity in future for practical implementation.

Acknowledgment

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