DTU

Towards Enhanced EEG-based Authentication with Motor Imagery Brain-Computer Interface

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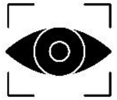
Biometric Authentication

- Physiological characteristics
  - fingerprint 
  - face 
  - iris 

  → Suffer from spoofing attacks
- Behavioural characteristics
  - signature 
  - voice 
  - EEG（brainwave） 

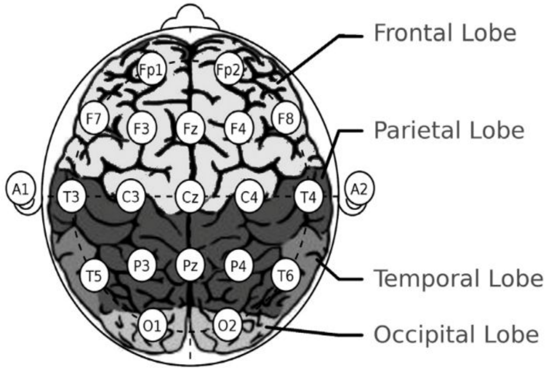
  → Cannot be forcibly acquired

EEG Background

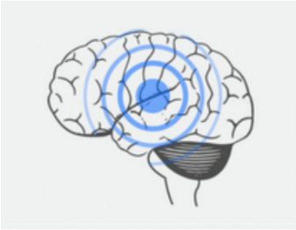
recording of electrical activities of the brain, usually along the scalp surface

Functions associated to different parts of the brain(Demos, 2005).

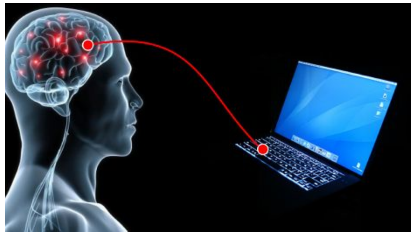
Region	Local channels	Functions
Frontal Lobe	Fp1, FP2, FPz, Pz, F3, F7, F4, F8	Memory, concentration, emotions.
Parietal Lobe	P3, P4, Pz	Problem Solving, attention, grammar, sense of touch.
Temporal Lobe	T3, T5, T4, T6	Memory, face recognition, hearing, word recognition, social clues.
Occipital Lobe	O1, O2, Oz	Reading, vision.
Cerebellum	–	Motor control, balance.
Sensorimotor Cortex	C3, C4, Cz	Attention, mental processing, fine motor control, sensory integration.



- Delta (1 − 4Hz)
- Theta (4 − 8Hz)
- Alpha (8 − 12Hz)
- Beta (12 − 25Hz)
- Gamma (over 25Hz)



detect and investigate disease
(e.g. epilepsy)



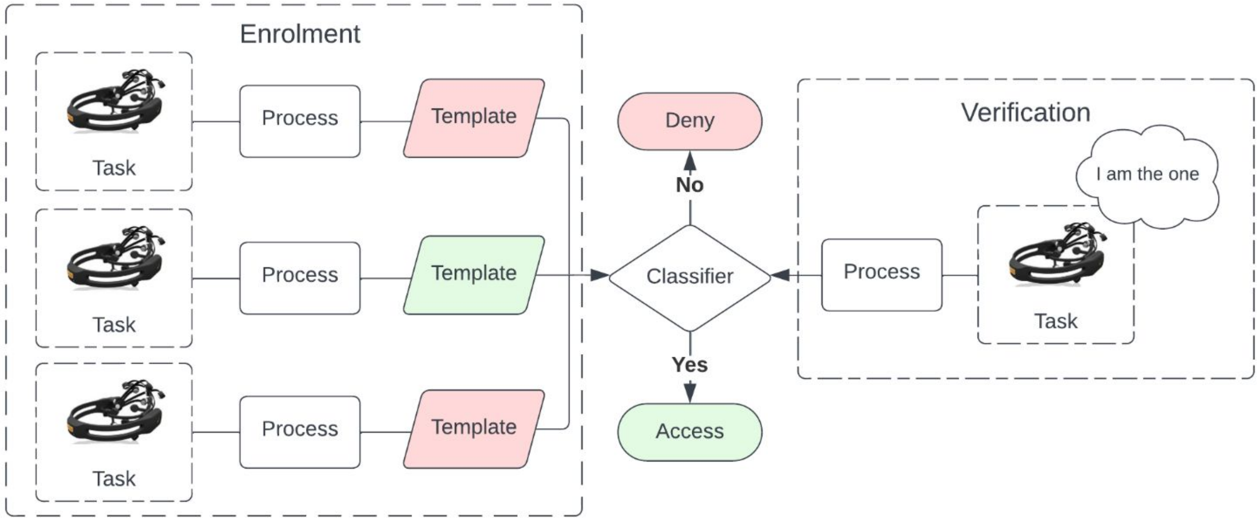
brain computer interface
(e.g. motion control)

security

Amir Jalaly Bidgoly, Hamed Jalaly Bidgoly, and Zeynab Arezoumand. 2020. A survey on methods and challenges in EEG based authentication. Computers and Security 93 (2020), 101788.

EEG Authentication

- Authentication: to prove or disprove
- Identification: determine who the user is



Task: Motor Imagery

- Help user concentrate
- Have been extensively studied

Motivation

Study	Year	Type	Task	Subject	Channel	Feature	Method	Performance
[8]	2011	auth	resting state/ motor imagery/ thinking stimuli	5	14	AR/ PSD/SP/ IHPD/ IHLC	SVM	100%
[12]	2013	auth	resting state/ motor imagery/ visual/ auditive stimuli	15	1	time series	Cosine Similarity	1.1% HTER
[35]	2016	auth	motor imagery	20	2 ~6	STFT	SVM/NN	98%
[28]	2016	iden	motor imagery/ movement	5	1	Wavelet Decomposition	NN	95% TAR 4.44 %FAR
[15]	2018	iden	motor imagery	40	17	time series	CNN	99.3%
[5]	2018	iden	motor imagery/ movement	10/11	64	MOFPA-WT	NN	85.71% TAR 14.28% FAR
[47]	2019	iden	motor imagery	109	16	time series	CNN-LSTM	99.58%
[4]	2022	iden	motor imagery/ movement	109	23	AR	SVM-RBF	94.13%
[7]	2015	iden	text reading (ERPs)	45	3	time series	NN	82% ~97%
[25]	2016	auth	visual stimuli/ thinking stimuli	12	14	CSP	LDA	96.97%
[14]	2016	auth	visual stimuli	50	19	time series	Similarity	95% EER confidence intervals
[27]	2017	auth	gesture patterns	50	14	DFT	SVM/HMM	25% Global HTER 2.01% Local HTER
[32]	2018	auth	resting state/ math computation/ speech imagery	45	19	AR/ MFCC/ Bump	HMM	<2% EER
[37]	2019	iden	RSVP Keyboard (RSVP)	10	16	time series	Adversarial CNN	99% within-session 72% across-sessions

EEG Biometric evaluation

- uniqueness (50 subjects)
- collectability
- persistence

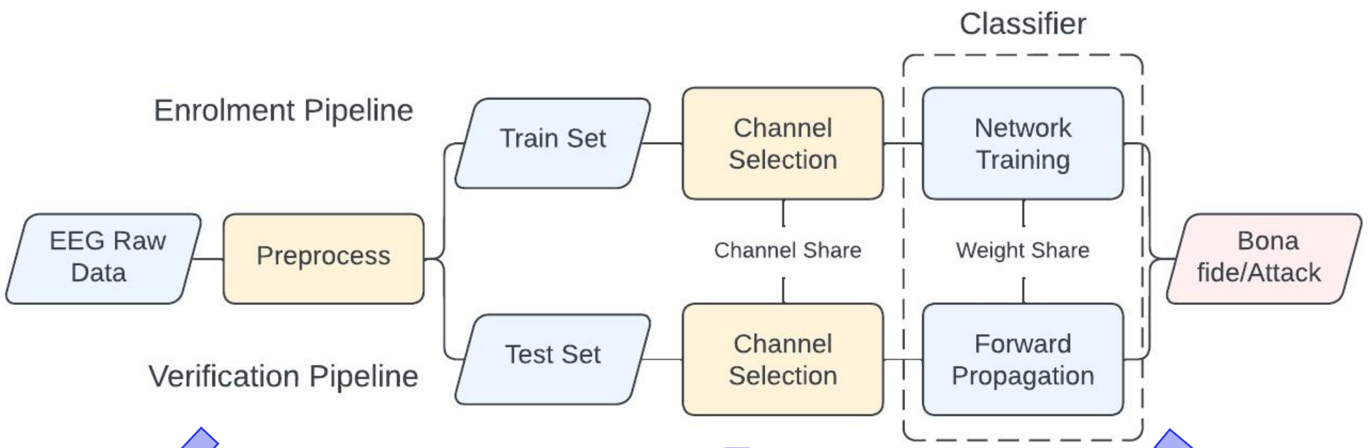
Transfer methods to Authentication

- brain connectivity
- DL classifier

An end-to-end Authentication framework

Our Approach

- Propose an enhanced EEG authentication framework with Motor Imagery

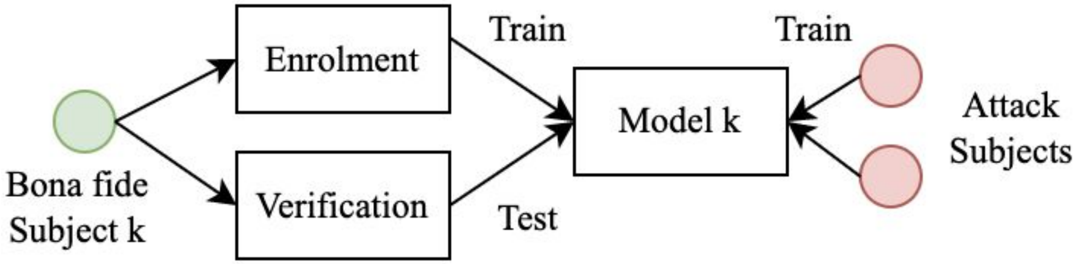


ICA Artifacts Removal
(*identify sources from all sources*)

Effective Connectivity
(*reduce the number of electrodes*)

Deep Learning
(*encode temporal, spatial and spectral characteristics*)

Protocol



The classifier model is trained for each subject:

- subject k => model k
- same attackers => fairness

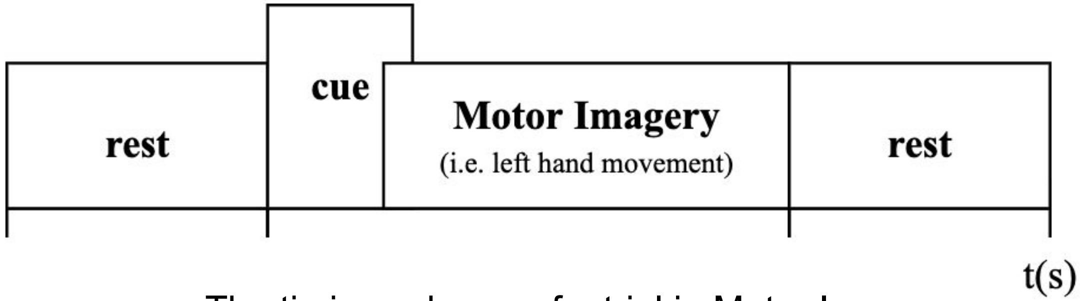
one trial => one imagination => one sample

body parts of imagination:

- left hand
- right hand
- left foot
- right foot

mixed

try to find universal characteristics



The timing scheme of a trial in Motor Imagery

Preprocessing

Independent Component Analysis (ICA):

separating a multivariate signal into subcomponents

Raw EEG signal E is assumed to be a linear mixture of source S and white noise N

$$E = A \times S + N$$

A is the matrix expressing the linear combination of sources,

And the inverse $W = A^{-1}$ is therefore the unmixing matrix to separate the sources

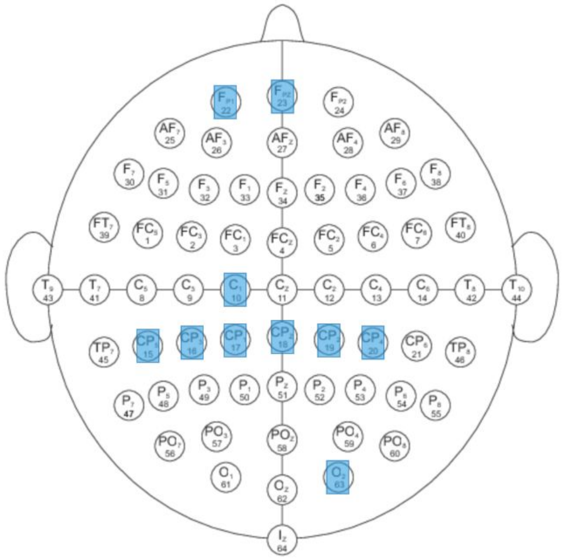
$$S' = W \times E$$

<u>The majority components with similar statistical characteristics is the dominant component</u>

Algorithm 1 K-means and ICA artifact removal

1: Raw EEG data of shape $(N_{trial} \times N_{channel} \times N_{sample})$, N_{trial}—number of trials, $N_{channel}$—number of channels, N_{sample}—number of time samples
2: **for** $i = 1, 2, \ldots, N_{trial}$ **do**
3: Z-score normalization of each trial
4: **end for**
5: Reshape EEG data to a matrix of $(N_{channel} \times N_t)$ where $N_t = N_{trial} \times N_{sample}$.
6: Calculate ICA linear combination matrix W, using the Picard ICA algorithm.
7: Calculate ICA components of sources $S' = WK \times E$, K is the whitening matrix.
8: Derive descriptors, including variance, amplitude, range, max derivative, kurtosis, entropy, mean local variance and mean local skewness of each ICA component.
9: $\boxed{\text{Utilize K-means clustering based on above features into two classes. Class with less components is considered as suspected artifacts.}}$
10: Remove two components with highest variance by setting corresponding rows of S', the S'_{clean} is derived.
11: Reconstruct EEG data $E_{clean} = K^{-1}W^{-1}S'_{clean}$

Channel Selection



Algorithm 2 PDC-based Channel Selection

Artifact removed EEG data of subject s of shape $(N_{trial} \times N_{channel} \times N_{sample})$
for $i = 1, 2, \ldots, N_{trial}$ **do**
    To calculate PDC matrix $(N_{channel} \times N_{channel})$ for i-th trial.
    To derive the mean for each column, which represents the PDC from j-th channel to all the channels.
    To sort and return the maximum M mean PDC value channels.
end for
To select M most frequent channels in N_{trial} trials.

Brain Connectivity
- Functional connectivity ✗
- Effective connectivity ✓

a node exerts over another under a network model of causal dynamics

↓ described by

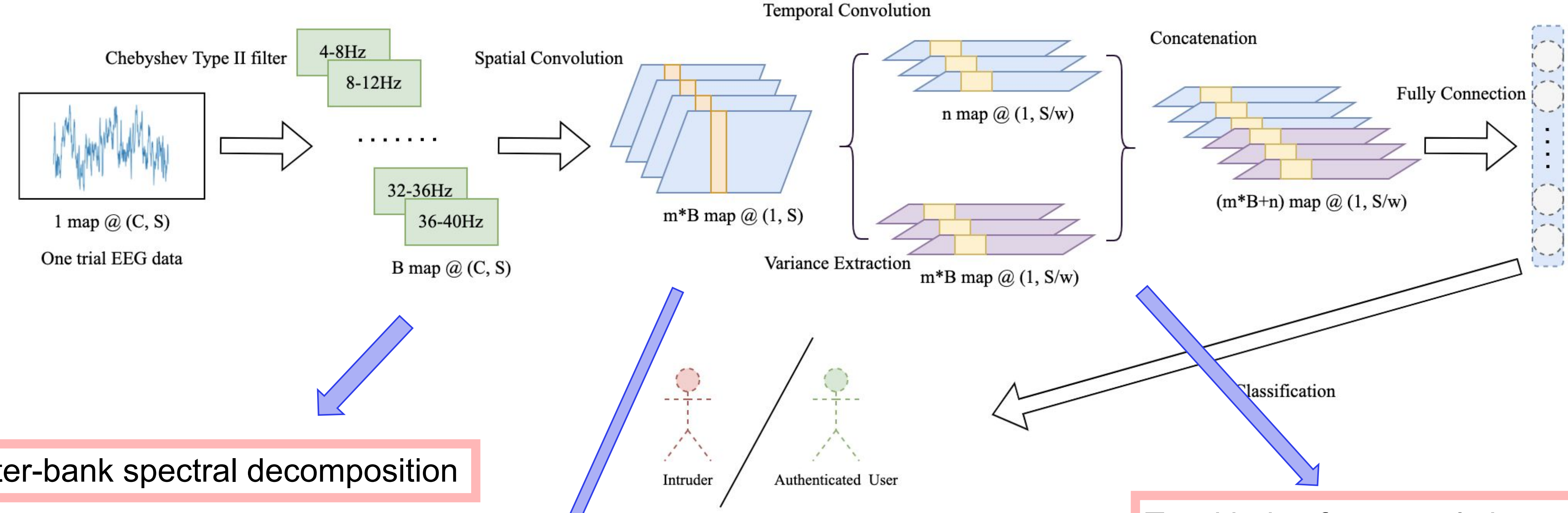
Partial Directed Coherence (PDC)

the intensity of the causal action from the j-th channel to the i-th channel

$$P_{ij}(f) = \frac{A_{ij}(f)}{\sqrt{a_j^H(f)a_j(f)}} \qquad A_{ij}(f) = I - \sum_{r=1}^{p} a_{ij} e^{-\pi i r f}$$

$A_{ij}(f)$ is the frequency domain multivariate autoregressive model (MVAR) coefficient of the i-th channel to the j-th channel coefficient, H means conjugate transpose

Deep Learning Classification



Filter-bank spectral decomposition

Spatial convolution: aggregate features along different channel

Two kinds of temporal characteristic

$$x_{var}(k) = \frac{1}{w} \sum_{t=w*k}^{(k+1)*w-1} (X_{SC}(t) - \mu(k))$$

$X_{SC} \in \mathbb{R}^{(m\times B)\times 1\times S}$ is the feature map, $\mu(k)$ is the mean value of the k-th window. k has a range of [0, S/w]

Experiments

- **Datasets**
  - Physionet EEG Motor Movement/Imagery Dataset[1]: large number of subjects (109)
  - BCI competition IV-dataset 2a[2]: two sessions on different days
- **Insider Attack Performance**: subjects have already been seen during enrolment
- **Outsider Attack Performance**: subjects have never been seen during enrolment
- **Cross-session Performance**: enrolment and verification performed on different days
- **Comparison with SOTA**: especially when using a limited number of channels
- **Influence of Channel Selection**: reducing the number of used channels

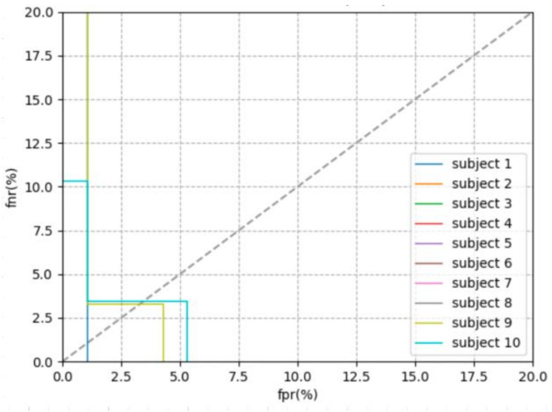
Configuration of Insider/Outsider Attack Experiment

Dataset	**Trials**	**Channels**
Physionet	60	10
Enrollment Time	**Verification Time**	**Model Parameters**
8-10 mins	4s	450,626

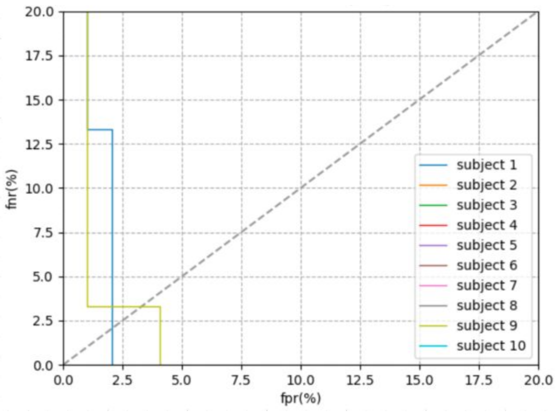
Dataset	**Trials**	**Channels**
BCI IV 2a	96	10
Enrollment Time	**Verification Time**	**Model Parameters**
14-18 mins	4.5s	450,626

[1] https://physionet.org/content/eegmmidb/1.0.0/ [2] https://www.bbci.de/competition/iv/

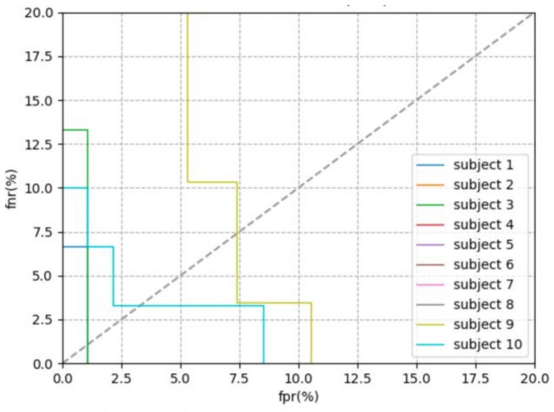
Insider/Outsider Attack Performance



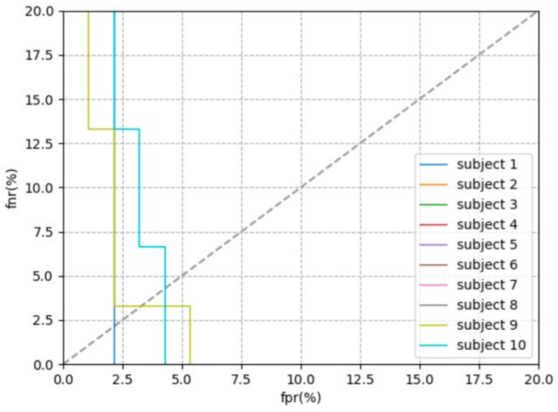
19 attackers



49 attackers



19 attackers



49 attackers

Insider: Average Equal Error Rate (EER) < 1% using 10 channels

Outsider: Average Equal Error Rate (EER) < 1.3% using 10 channels

Protocol		Subject										
		1	2	3	4	5	6	7	8	9	10	avg
Insider	EER-19	1.05	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.19	3.15	0.74
	EER-49	2.04	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.06	0.0	0.51
Outsider	EER-19	1.06	0.0	1.06	0.0	0.0	0.0	0.0	0.0	7.37	3.19	1.27
	EER-47	2.13	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.19	4.26	0.96

Single session performance

Protocol		Subject									
		1	2	3	4	5	6	7	8	9	avg
Insider	EER-4	0.0	0.0	2.34	0.0	0.0	0.58	0.0	0.0	0.0	0.32
Outsider	EER-4	9.04	0.0	20.45	1.14	0.0	0.0	1.74	12.35	0.0	4.97

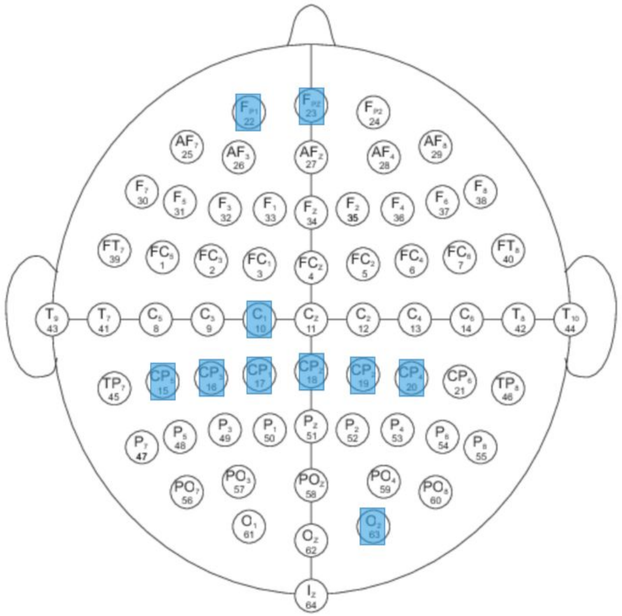
Cross session performance

Influence of Channel Selection

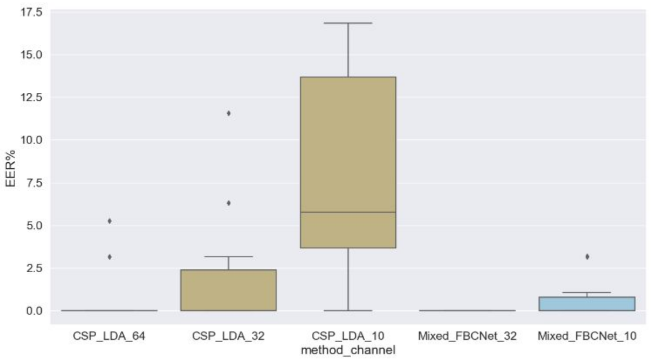
10 channels
- Insider attack performance: average EER of 0.74%
- outsider attack performance: average EER of 1.24%

32 channels
- Insider attack performance: average EER of → 0.0%
- outsider attack performance: average EER of 0.21%

Skip channel selection /
10 frequently selected channels



EER of 1.21%/1.74%



The EER-19 (%) of CSP_LDA and Mixed_FBCNet (our method) using 64, 32 and 10 channels.

Comparison with SOTA

Method	Insider			Outsider		
	Mean Accuracy (%)	Mean EER-19 (%)	Lowest Subject/EER-19	Mean Accuracy (%)	Mean EER-19 (%)	Lowest Subject/EER-19
SVM[27]	90.63	6.73	10 / 13.68	91.44	5.785	3 / 24.21
HMM[27]	76	18.23	3 / 25.85	74	20.57	7 / 27.12
CSP_LDA	98.32	0.84	1 / 5.26	96.96	1.37	1 / 5.26
energyNN	82.6	15.47	5 / 19.17	80.23	17.98	9 / 24.23
MI_CNN[15]	84.96	11.88	6 / 26.08	80.56	15.02	6 / 25.27
CNN_LSTM[47]	78.2	17.89	7 / 24.54	76	19.12	7 / 26.25
EEGNet[29]	82.16	22.04	1 / 32.97	79.6	23.44	1 / 36.17
CP_MixedNet[30]	74.97	9.95	1 / 13.6	67.87	15	1 / 18.22
FBCNet[33]	98.02	1.45	3 / 4.34	96.12	1.98	7 / 6.23
Mixed_FBCNet_10	**99.48**	**0.74**	9 / 3.19	**98.89**	**1.27**	9 / 7.37

32 channels

10 channels

Our method outperforms with less channels

Conclusion

- An end-to-end authentication framework for EEG
  – ICA Artifacts Removal
  – Channel Selection
  – Deep Learning Classification
- More comprehensive assessment in this work
  – many studies before have fewer than 20 subjects
  – collectability and user-friendliness
    - channel selection
    - enrollment time: 8-10 mins (robust classifier towards fewer enrolment data)
  – longitudinal performance
  – a large set of comparison
- Lack of data
  – dataset with >50 subjects and multiple sessions across a long time period

Entropy of different biometrics.

Biometric	Study	Entropy (bits)
Finger vein	Krivokuća et al. (2020)	4.2–19.5
Retina	Arakala et al. (2009)	16.7
Voice	K. Inthavisas (2012)	18–30
Iris	Hao et al. (2006)	44
Fingerprint	Li et al. (2012)	48
Face	Feng and Yuen (2012)	75
Iris	Kanade et al. (2009)	94
Gait	Hoang et al. (2015)	50–139
EEG	Sadeghi et al. (2017)	83
EEG	Bajwa and Dantu (2016)	82

Amir Jalaly Bidgoly, Hamed Jalaly Bidgoly, and Zeynab Arezoumand. 2020. A survey on methods and challenges in EEG based authentication. Computers and Security 93 (2020), 101788.

Q&A

Thanks!