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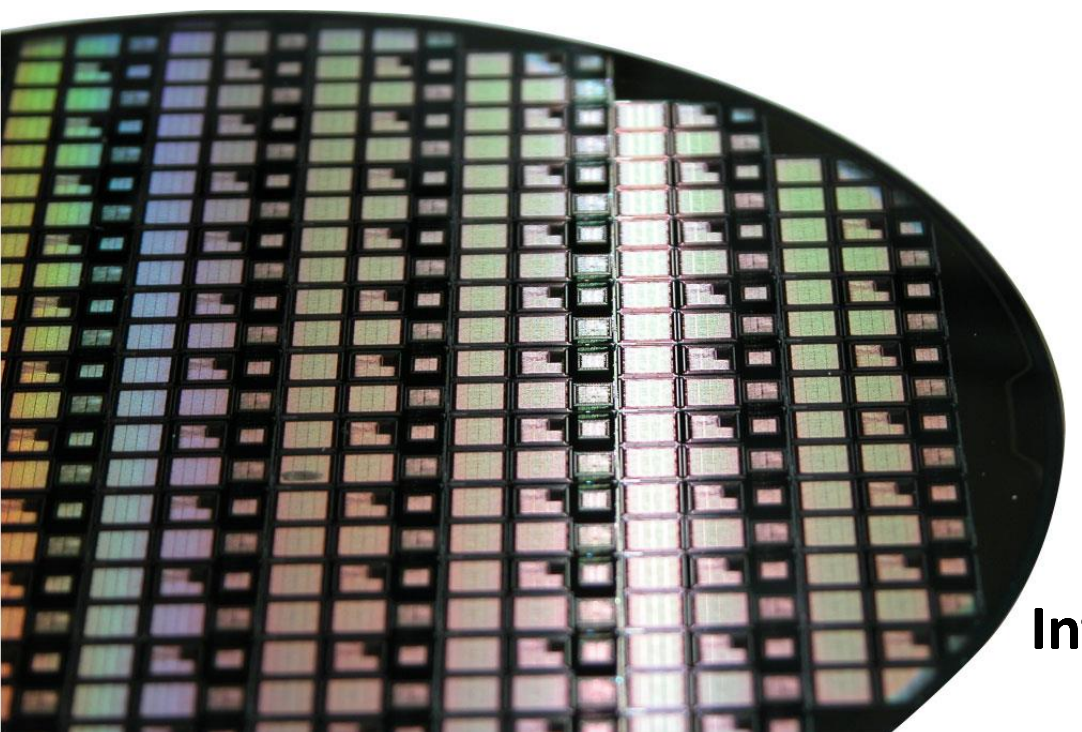
# Fast and Accurate Multiclass Inference for MI-BCIs Using Large Multiscale Temporal and Spectral Features



6 September 2018

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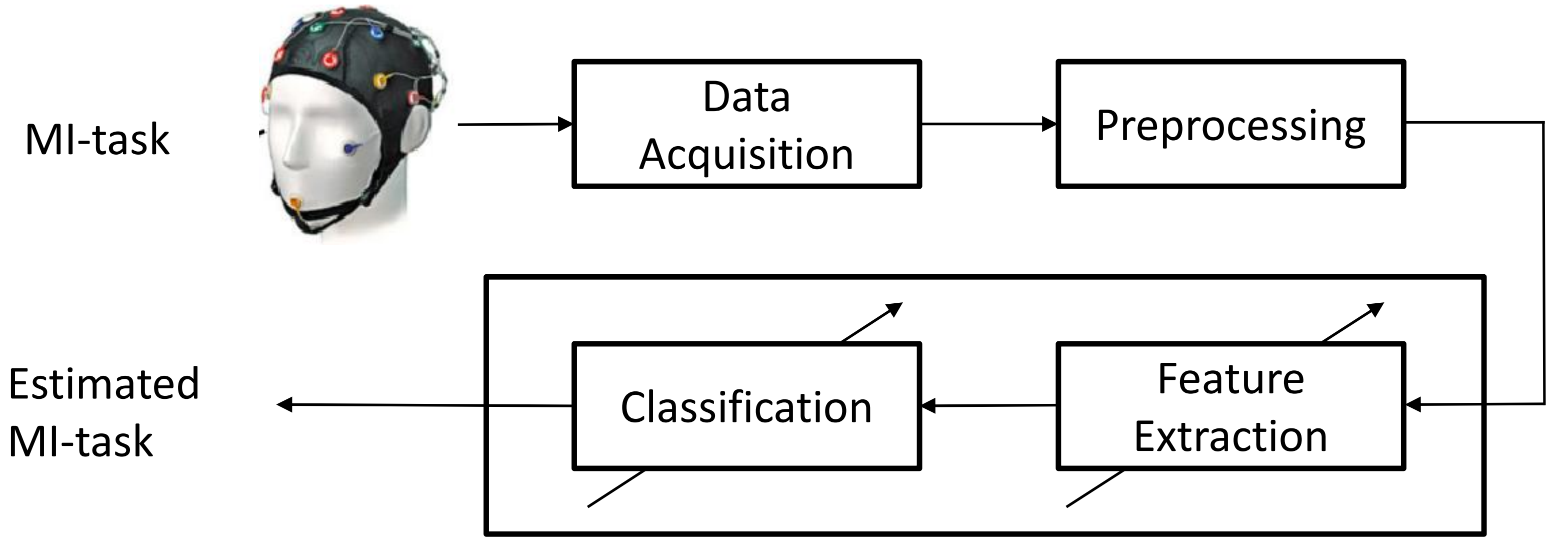
# Brain-Computer Interface (BCI)




# EEG signals are hard to classify

- **High variance**
- **Low SNR**
- **Limited training data**

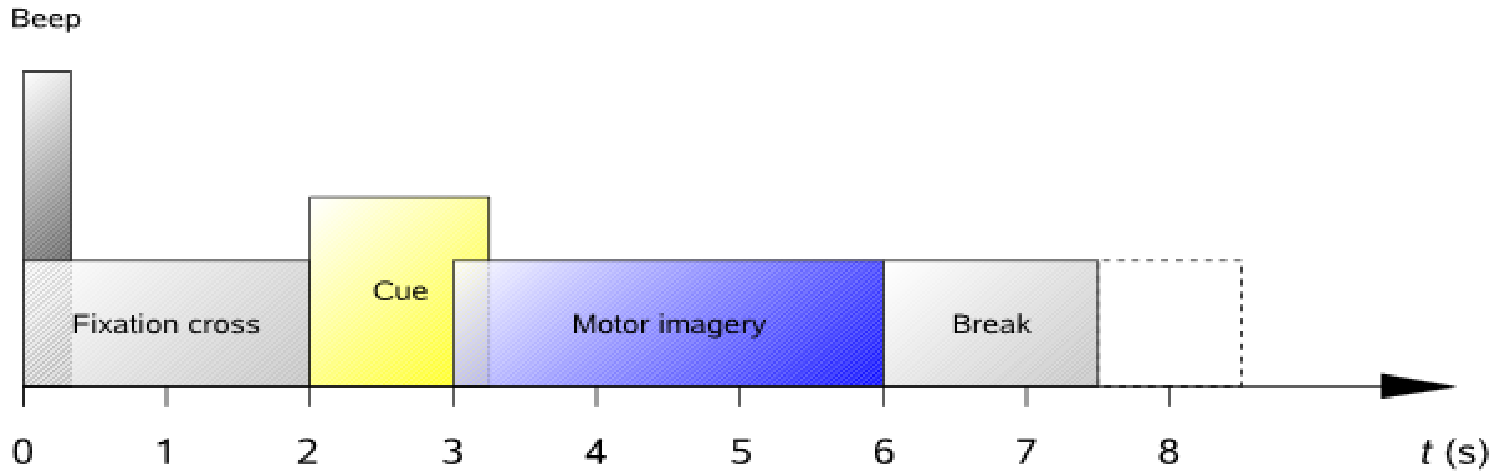
**Our Contribution**

- **Evaluate and compare feature extractors**
  - CSP
  - Riemannian
- **Extend to multiscale spectral and temporal feature extractors**
- **Increase the classification accuracy by 5% compared to state-of-the-art (CNN[1] 70.6%)**

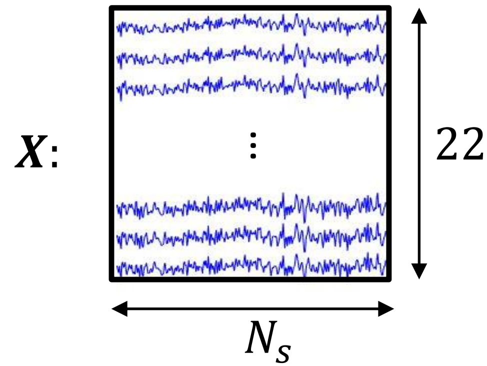
1. [Sakhavi et al., "Parallel convolutional-linear neural network for motor imagery classification," EUSIPCO 2015]

# The BCI competition IV 2a data set is still a challenge

- **9 subjects**
- **2 sessions each: training and test set**
- **288 trials per session and subject**
- **4 different MI tasks initiated by visual cue**
  - Left hand / right hand / feet / tongue
- **22 EEG channels sampled with 250 Hz**



# Common spatial pattern (CSP) maximizes the variance between two classes




- **Spatial covariance matrix**

$$C = XX^T \qquad C \in \mathbb{R}^{22 \times 22}$$

- **Find spatial filter $w \in \mathbb{R}^{22}$ to maximize variance on average**

$$\boxed{\max_{w} \frac{w^T \overline{C}_1 w}{w^T \overline{C}_2 w}}$$

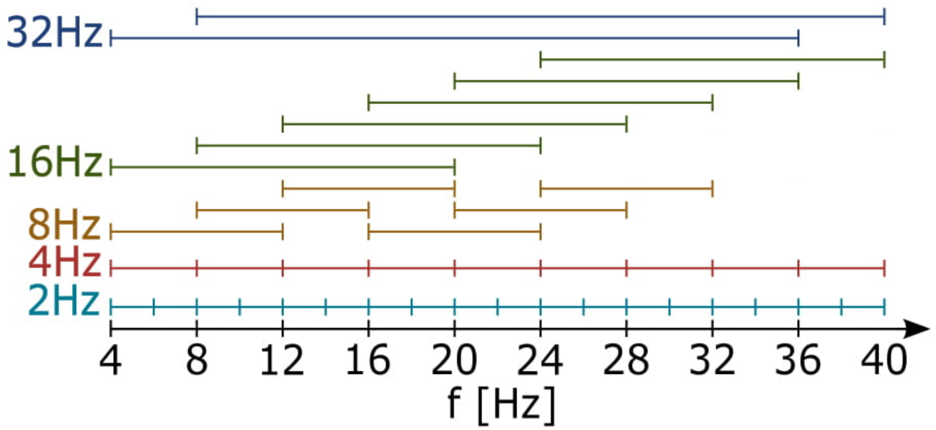
$\overline{C}_1$: average covariance matrix **class 1**
$\overline{C}_2$: average covariance matrix **class 2**

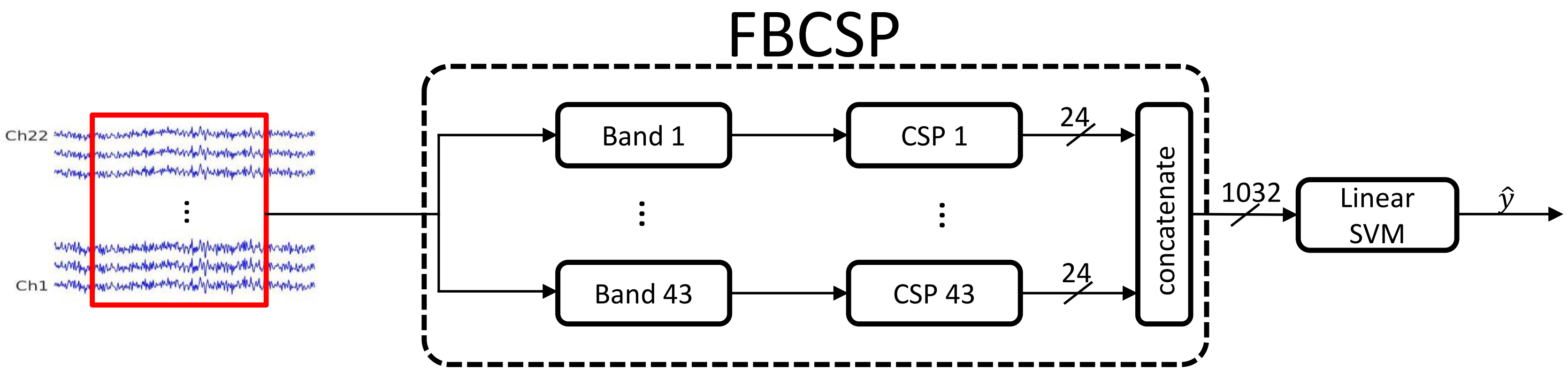
- **Multiclass implementation**
  - 6 pairs of classes
  - 4 spatial filters per pair
  - Total 24 spatial filters
- **Feature calculation**

$$f_i = \log\left(\frac{w_i^T C w_i}{\sum_k w_k^T C w_k}\right) \qquad i = \{1,2,\dots,24\}$$

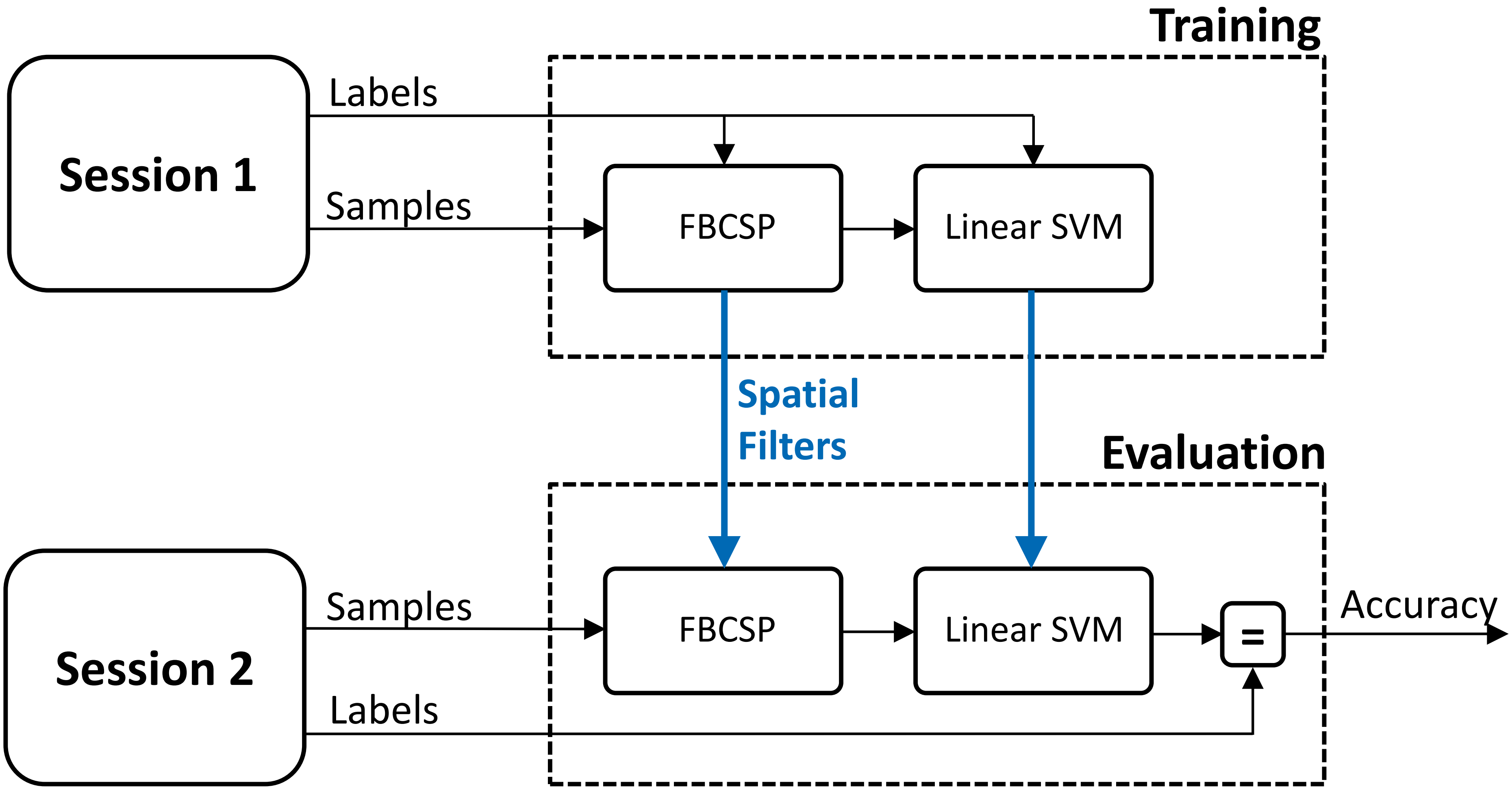
# Adding spectral information leads to Frequency Band CSP (FBCSP)

- **Filterbank with 2nd order Butterworth bandpass filter**
- **Total of 43 overlapping frequency bands**
- **1,032 features**
  (24 CSP) x (43 bands)

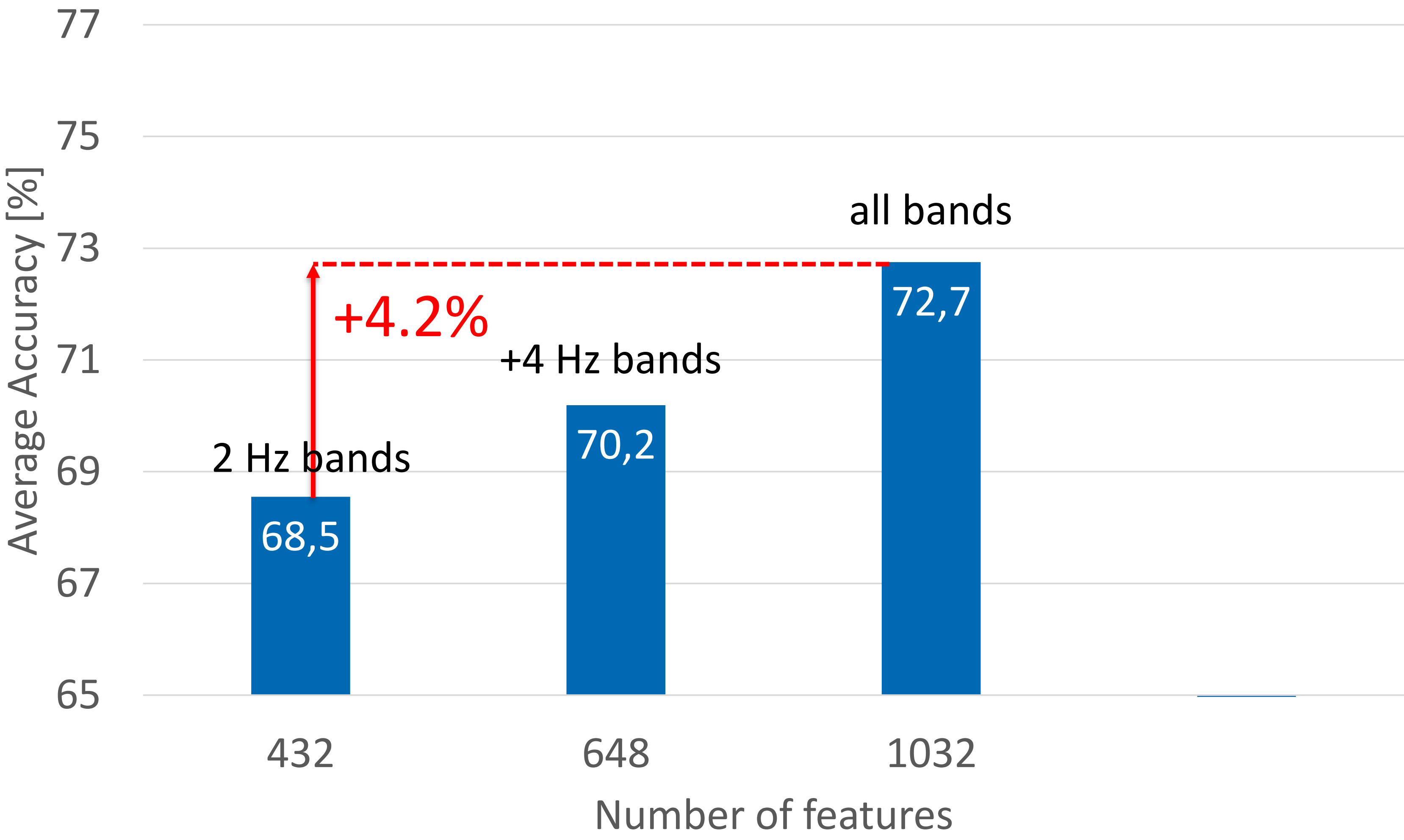


# Training & Evaluation Methods

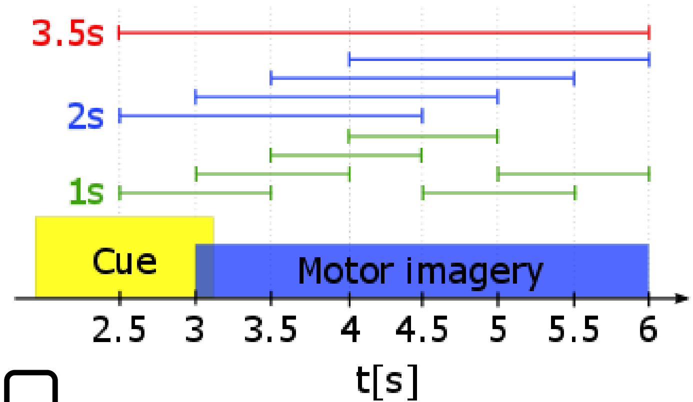


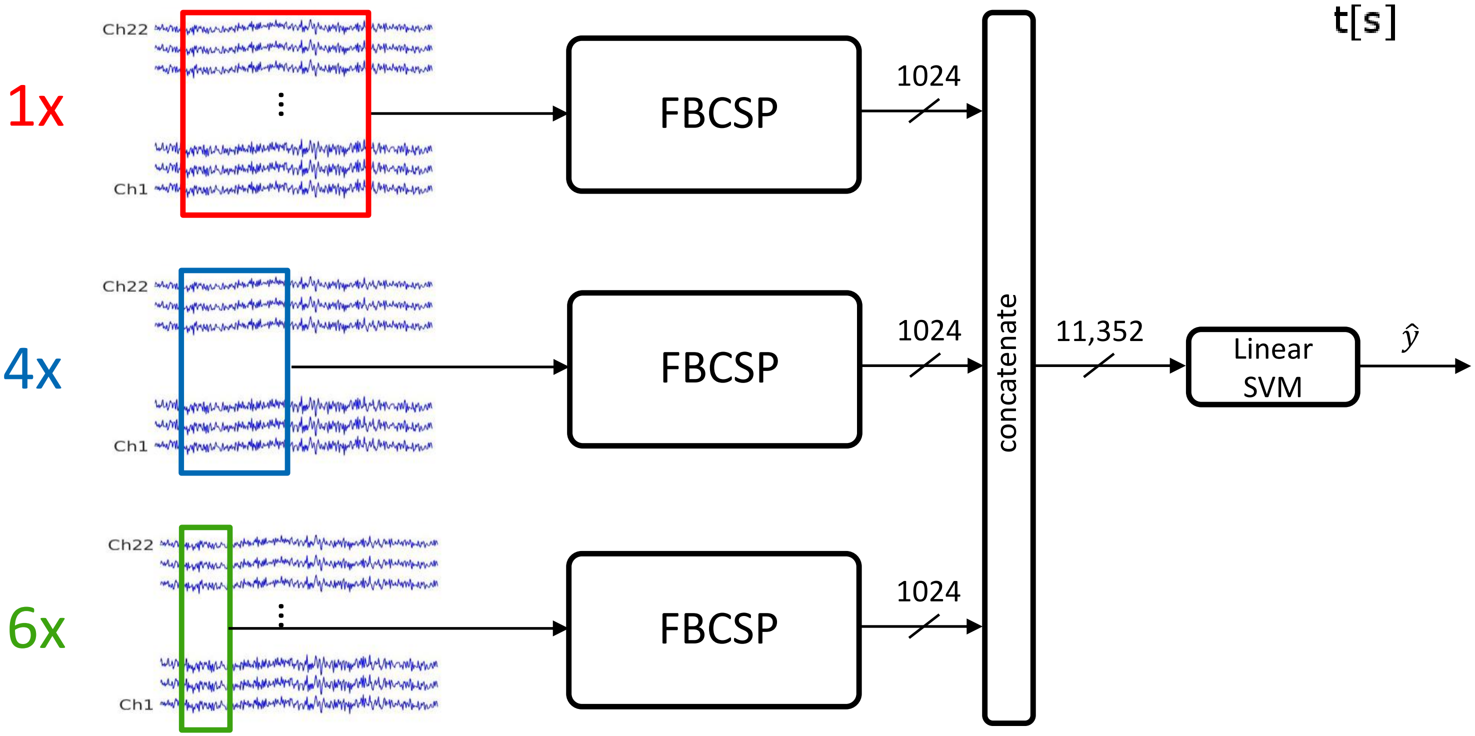
# Redundant spectral features improves the accuracy



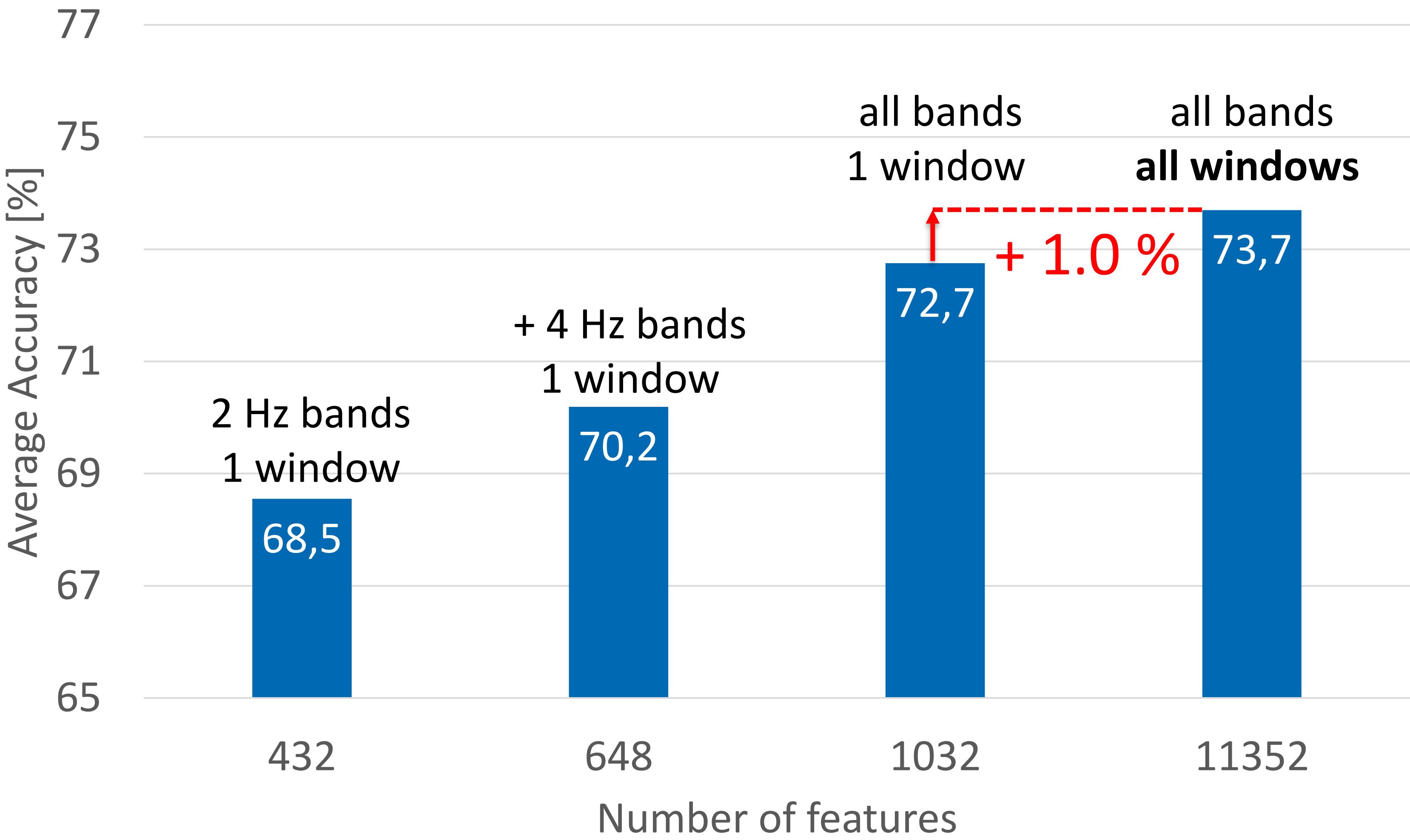
# Adding temporal features further adds redundancy

- **11 overlapping temporal windows**
- **11’352 features**
  (24 CSP) x (43 bands) x (11 temp)



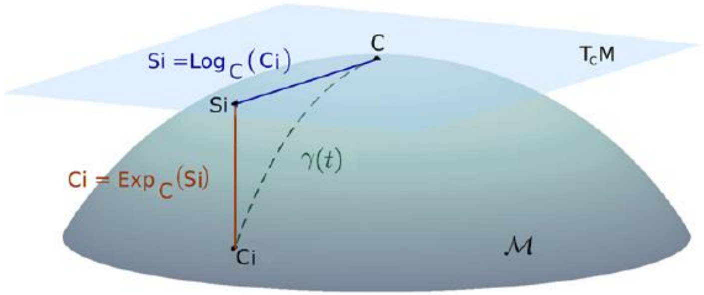



# Redundant spectral AND temporal features improves accuracy



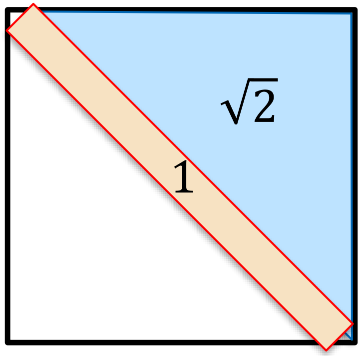
# Riemannian covariance method is an unsupervised alternative to CSP

$$\boldsymbol{\widetilde{C}} = \operatorname{logm}(\boldsymbol{C}_{\boldsymbol{ref}}^{-1/2}\boldsymbol{C}\boldsymbol{C}_{\boldsymbol{ref}}^{-1/2})$$

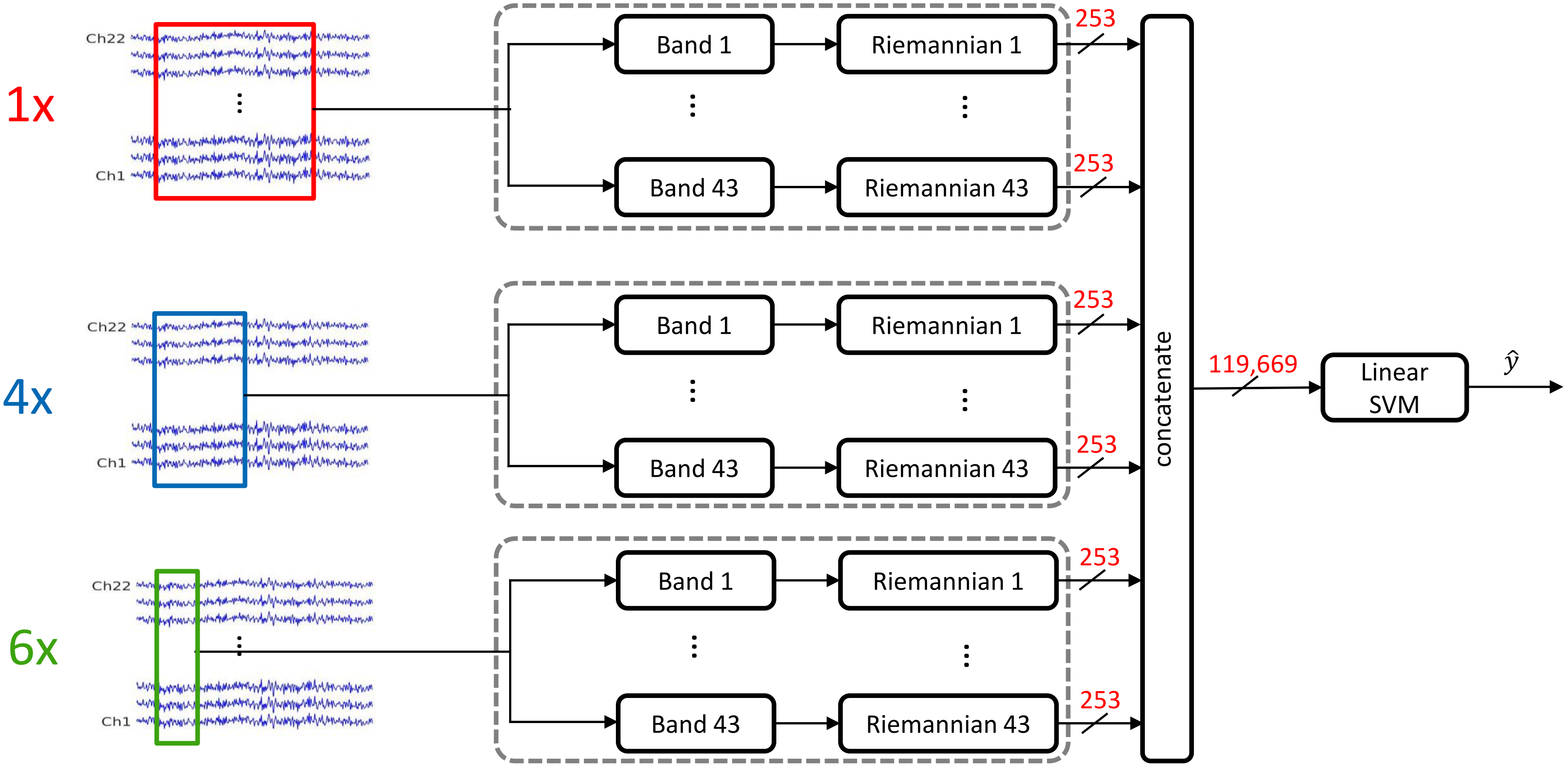



- **Reference matrix $\boldsymbol{C}_{\boldsymbol{ref}}$**
  Average over **all** covariance matrices in training (unsupervised)
- **Half vectorization gives 253 features**

$$\boldsymbol{f} = \operatorname{vect}(\boldsymbol{\widetilde{C}})$$

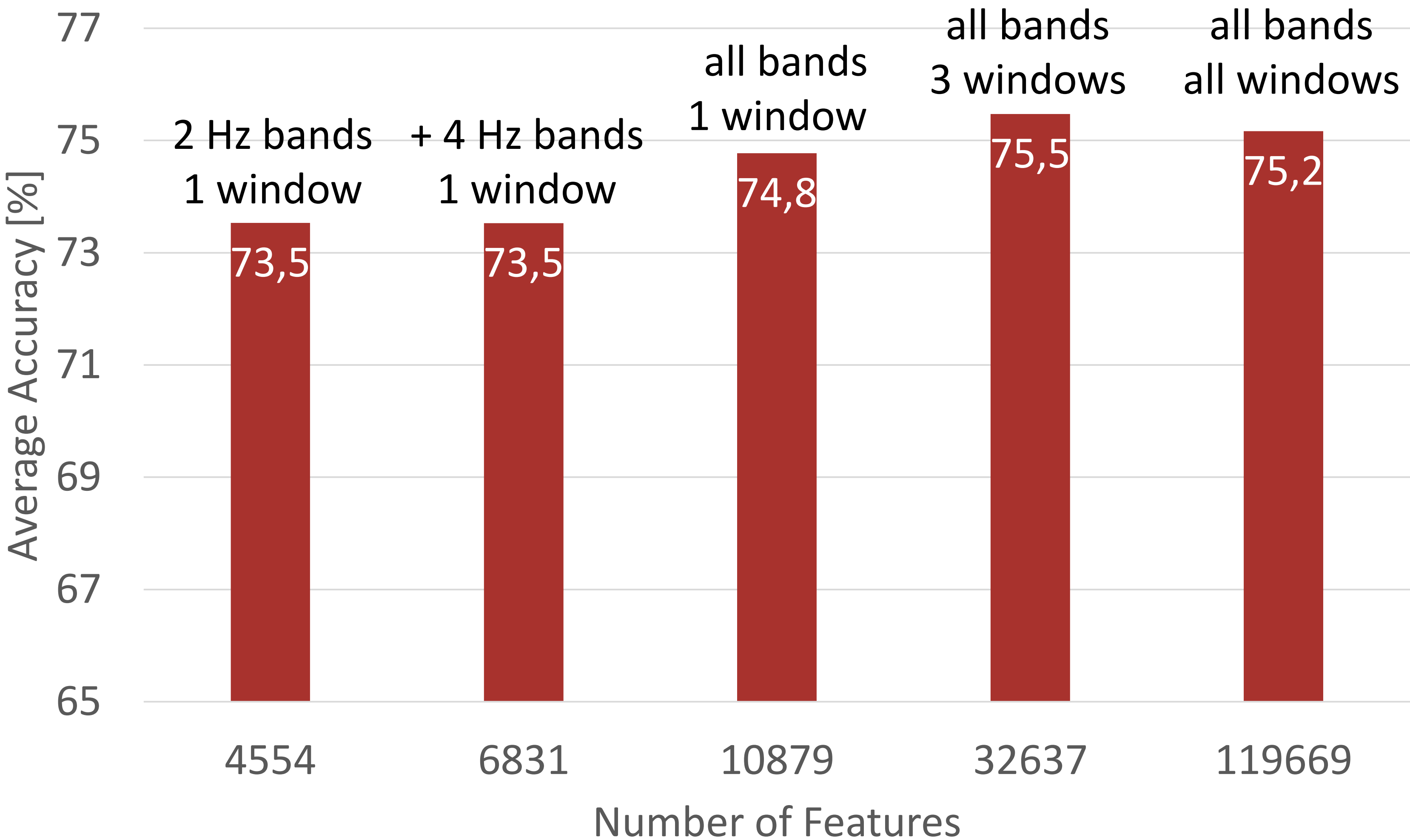


# Riemannian covariance method increases the number of features significantly

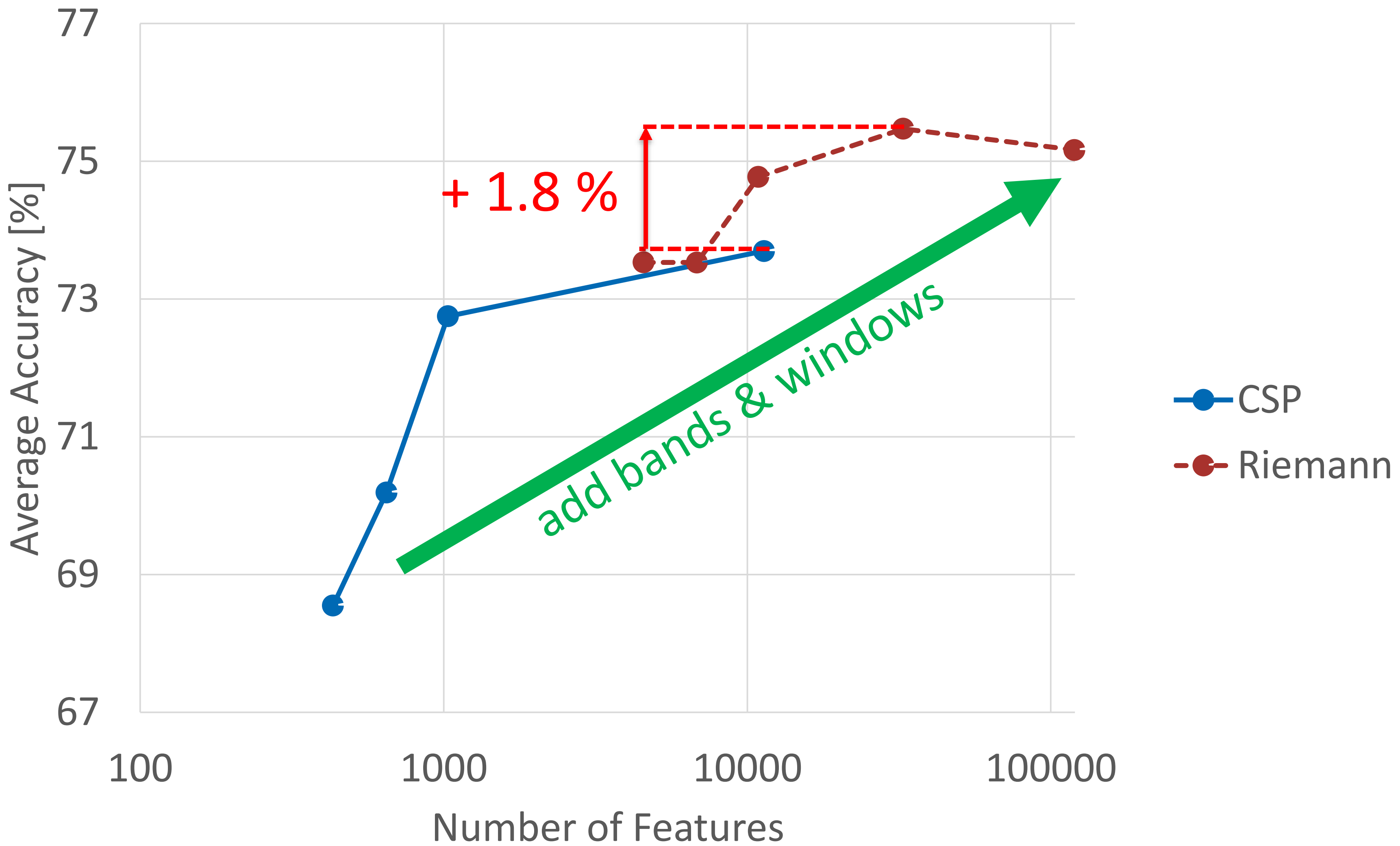



**(253 Riemannian) x (43 bands) x (11 temp) = 119,669 features**

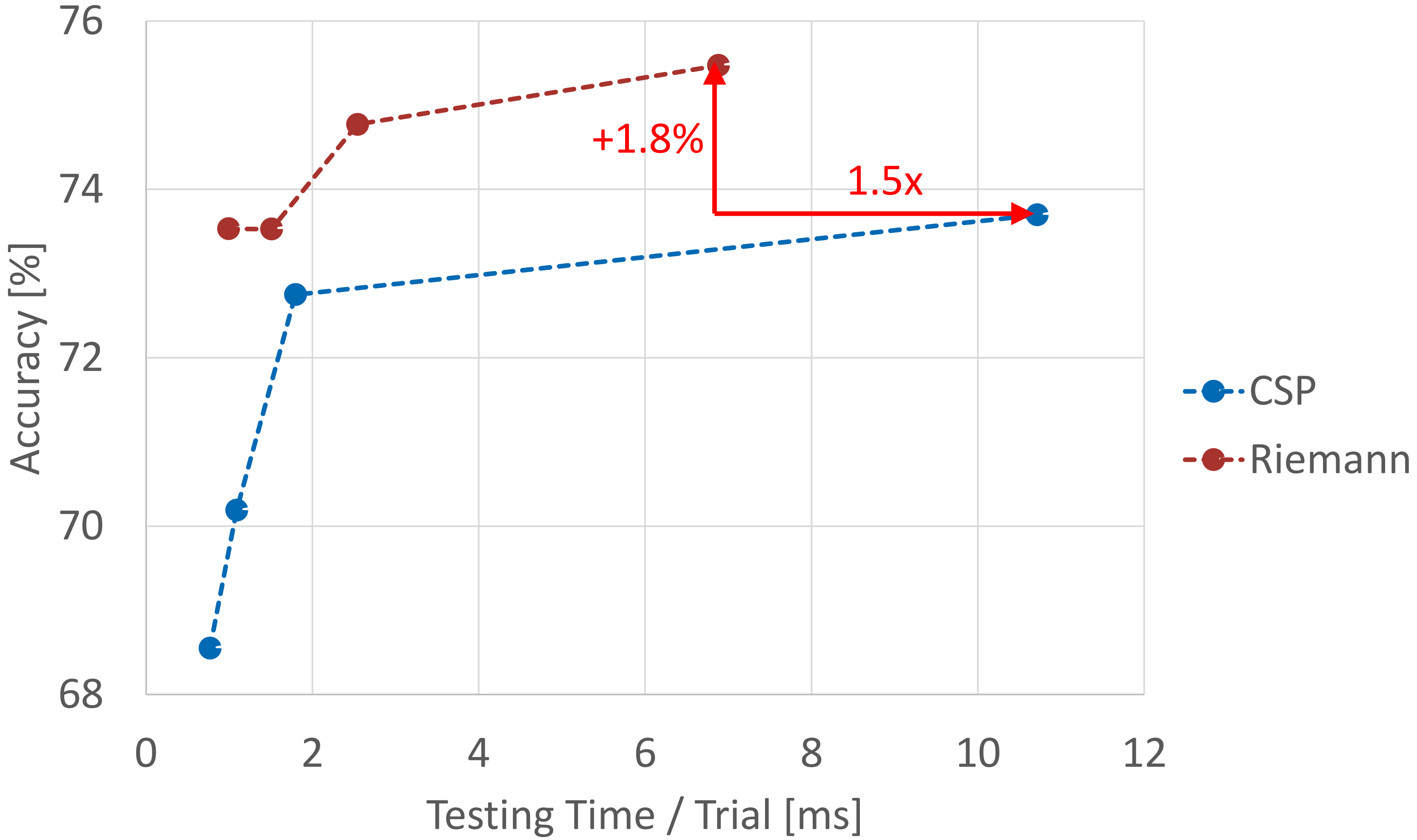
# Riemannian covariance features improve when adding temporal and spectral information



# Riemannian covariance features outperform CSP



# Improving accuracy comes with costs in testing time



# Conclusion

- **Adding spectral and temporal information increased state-of-the-art accuracy by 5%**
- **Riemannian covariance feature extraction outperforms CSP**
  - Unsupervised feature learning
  - Higher Accuracy (+1.8%)
  - Shorter testing time (1.5x)

https://github.com/MultiScale-BCI/IV-2a

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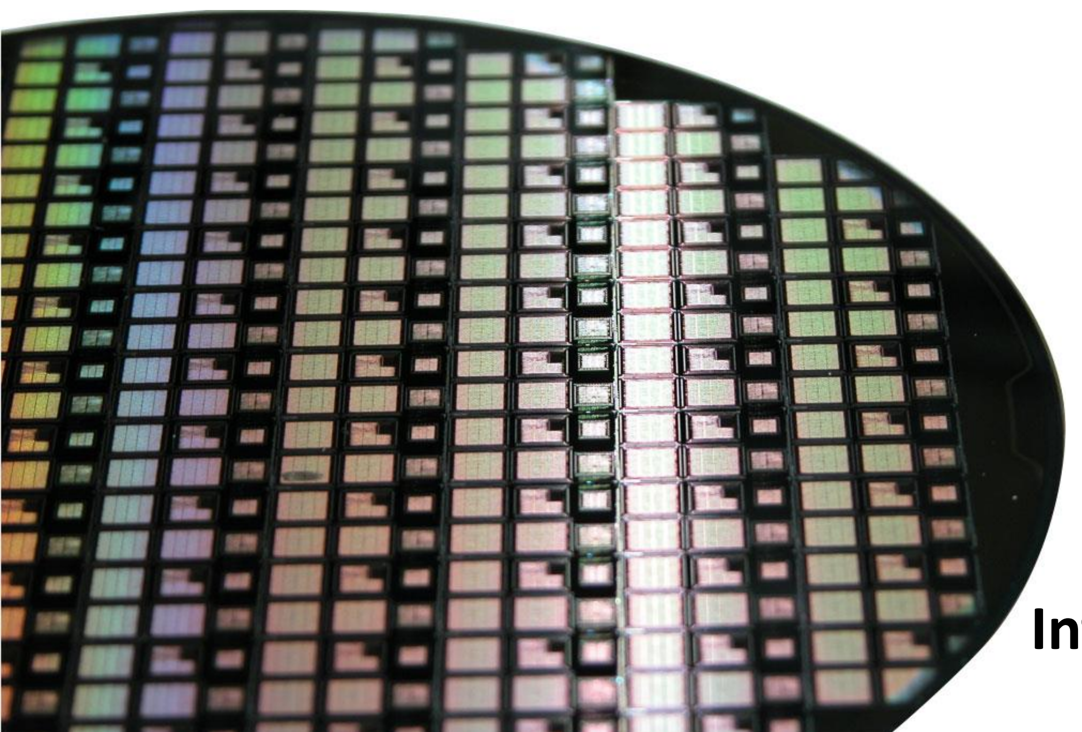

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