Embedded EEG Feature Selection for Multi-Dimension Emotion Recognition via Local and Global Label Relevance

Subject : Feature Selection | name : 김지윤

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- **Skills and Expertise: EEG, Feature Selection**
- **11 times citation**

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EEG Machine Learning Affective computing

标题	引用次数	年份
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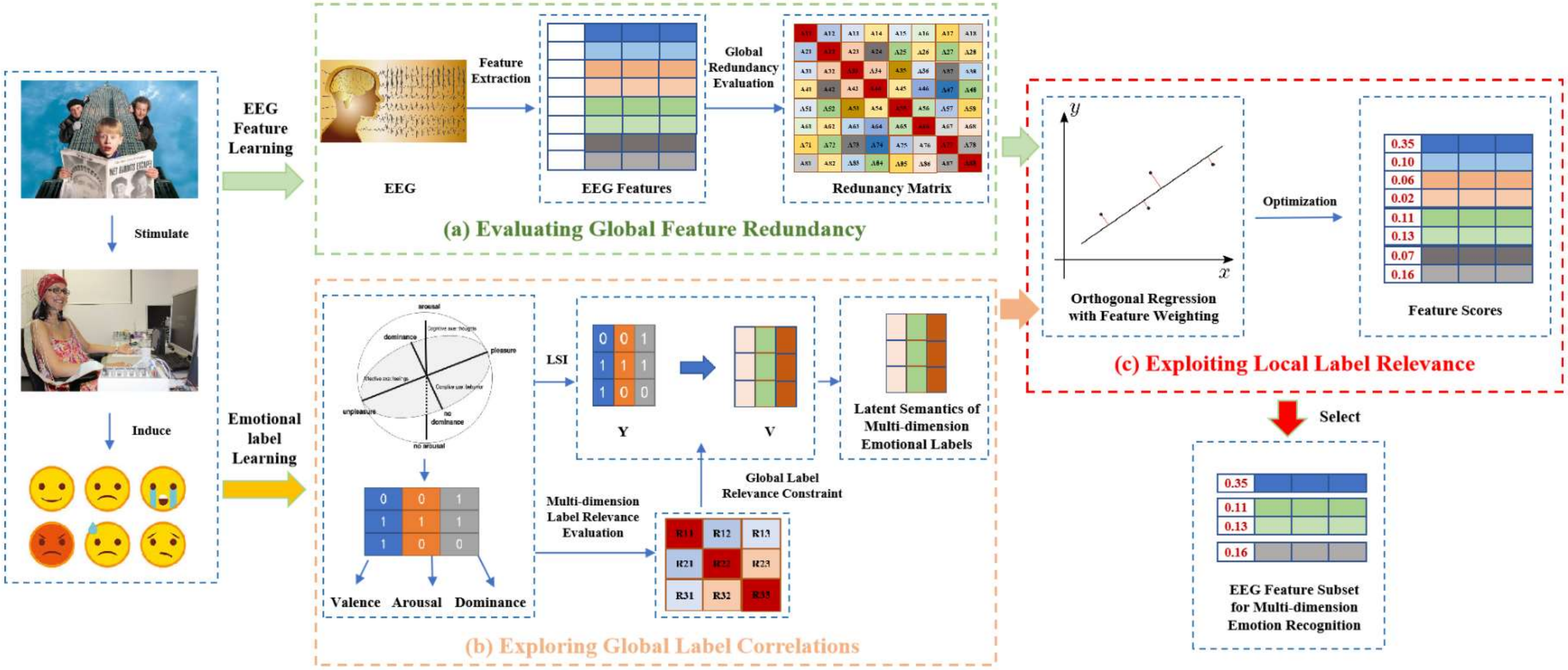
BLSAN: A Brain Lateralization-guided Subject Adaptive Network for Motor Imagery Classification F Wei, X Xu, Q Li, X Li, X Wu IEEE Signal Processing Letters 31, 2630 - 2634		2024
BDAN-SPD: A brain decoding adversarial network guided by spatiotemporal pattern differences for cross-subject MI-BCI F Wei, X Xu, X Li, X Wu IEEE Transactions on Industrial Informatics	3	2024
Embedded Multi-label Feature Selection via Orthogonal Regression X Xu, F Wei, T Jia, L Zhuo, F Nie, X Wu arXiv preprint arXiv:2403.00307		2024
Embedded EEG Feature Selection for Multi-Dimension Emotion Recognition via Local and Global Label Relevance X Xu, F Wei, T Jia, L Zhuo, H Zhang, X Li, X Wu IEEE Transactions on Neural Systems and Rehabilitation Engineering 32, 514 - 526	11	2024

II Introduction

- Current EEG-based emotion recognition studies transform multi-dimension emotional labels into single-dimension labels.
- Then implement used single-label feature selection methods to search feature subsets, which ignores the relations between different emotional dimensions.
- Also, EEG features are often high-dimensional and inevitably contains irrelevant, redundant, and noise information, which can easily deteriorate the emotion recognition performance due to the relatively small amount of EEG samples.

III EFSMDER Framework



III EFSMDER Framework

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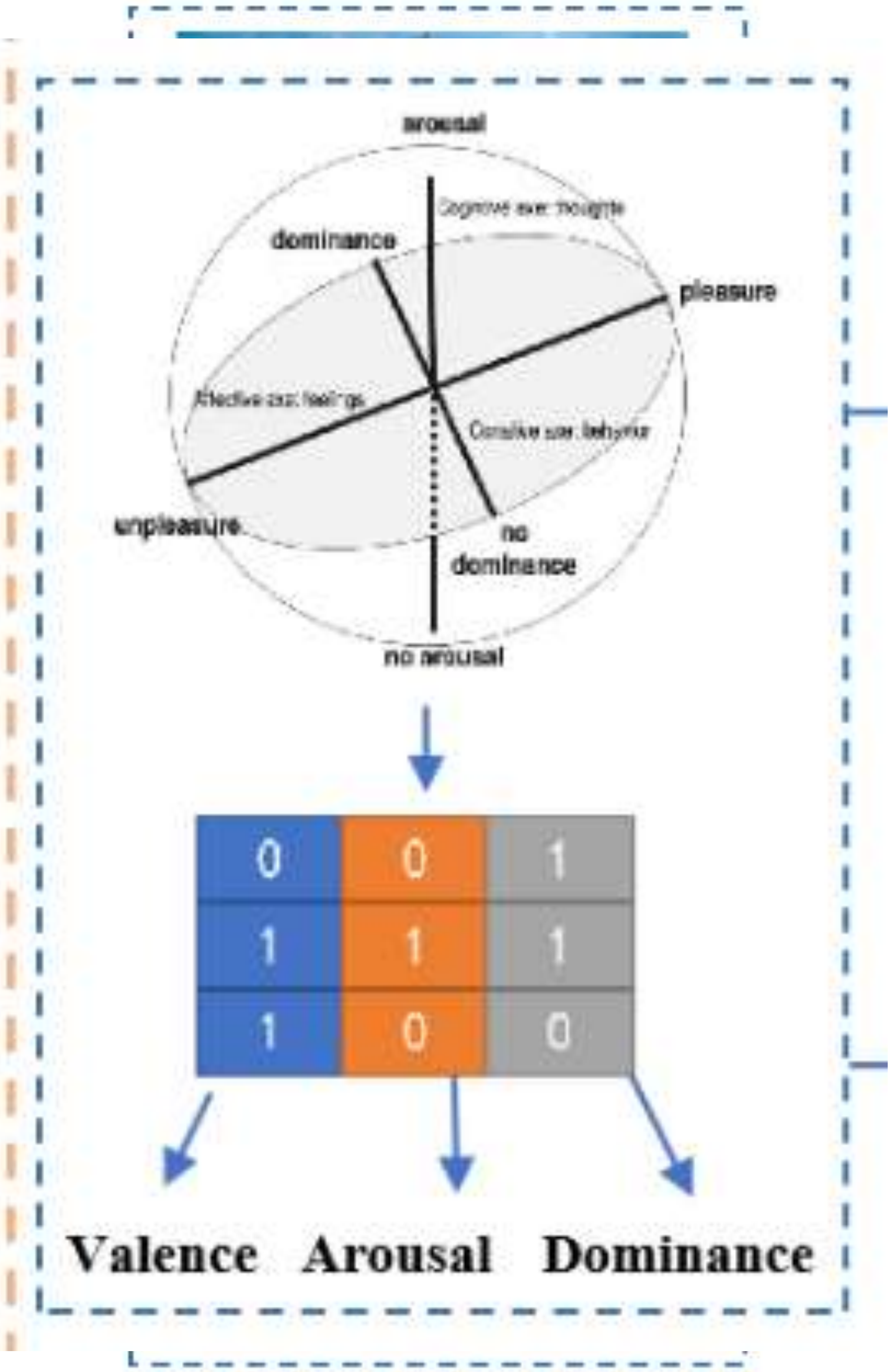
- **Database(EEG Dataset) Description**

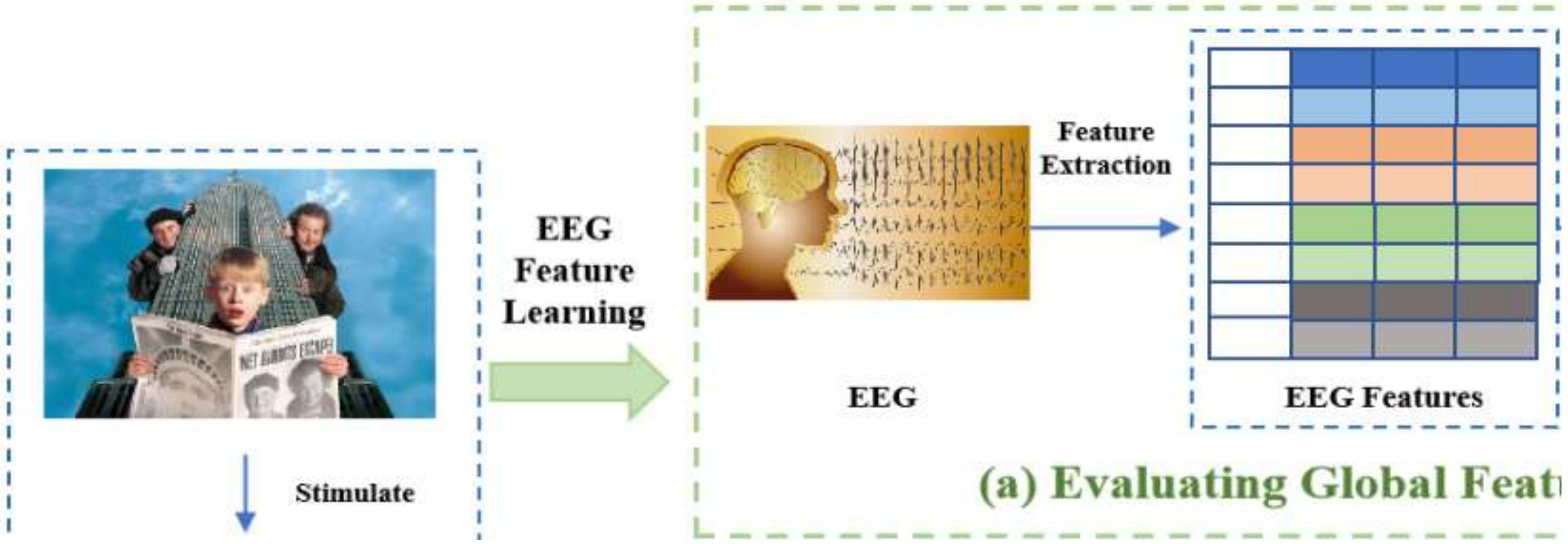
  All the databases(DREAMER, DEAP, HDED) adopt the VAD model(valence-arousal-dominance model) to represent human emotions.

TABLE I
COMPARISONS AMONG THE THREE EEG DATABASES

Data set	DREAMER	DEAP	HDED
Channel no.	14	32	90
Subject no.	23	32	16
Video no.	18	40	12
Sample no.	414	1280	192
Stimulus materials	film clips	music videos	film clips



III EFSMDER Framework



- **Feature Extraction From EEG Recordings**

  EEG signals were filtered out the noise by 1-50 Hz band-pass filter.
  ICA(Independent Component Analysis) was then used to suppress muscular and eye movement artifacts.

  The following thirteen kinds of features were extracted for EEG-based multi -dimension emotion recognition:

  NSI, HOC, spectral entropy, shannon entropy, CO complexity, DE, AP, AP_B/AP_θ, AHTIMF, IPHTIMF, DASM, RASM, FC

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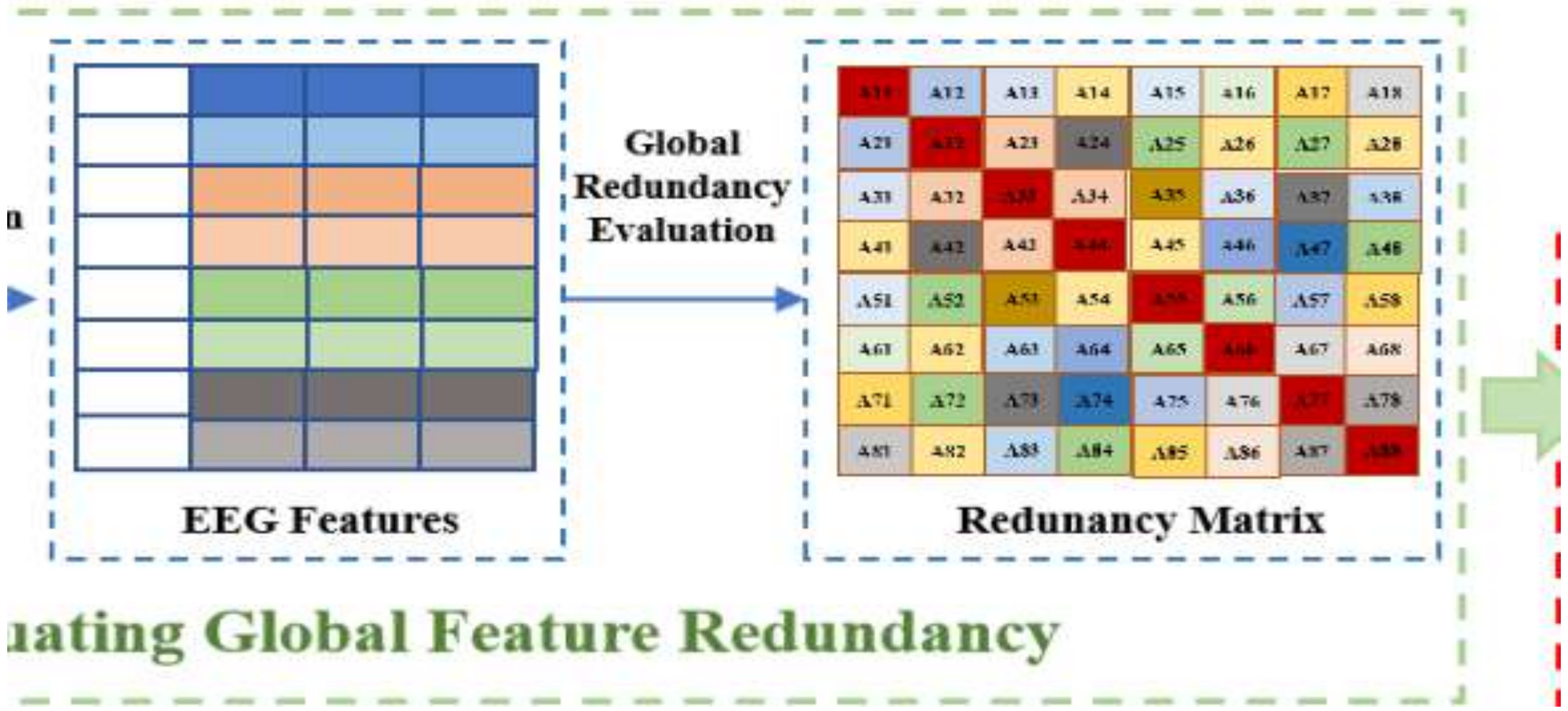


$$A_{i,j} = (O_{i,j})^2 = \left(\frac{\boldsymbol{f}_i^T \boldsymbol{f}_j}{\|\boldsymbol{f}_i\| \, \|\boldsymbol{f}_j\|} \right)^2$$

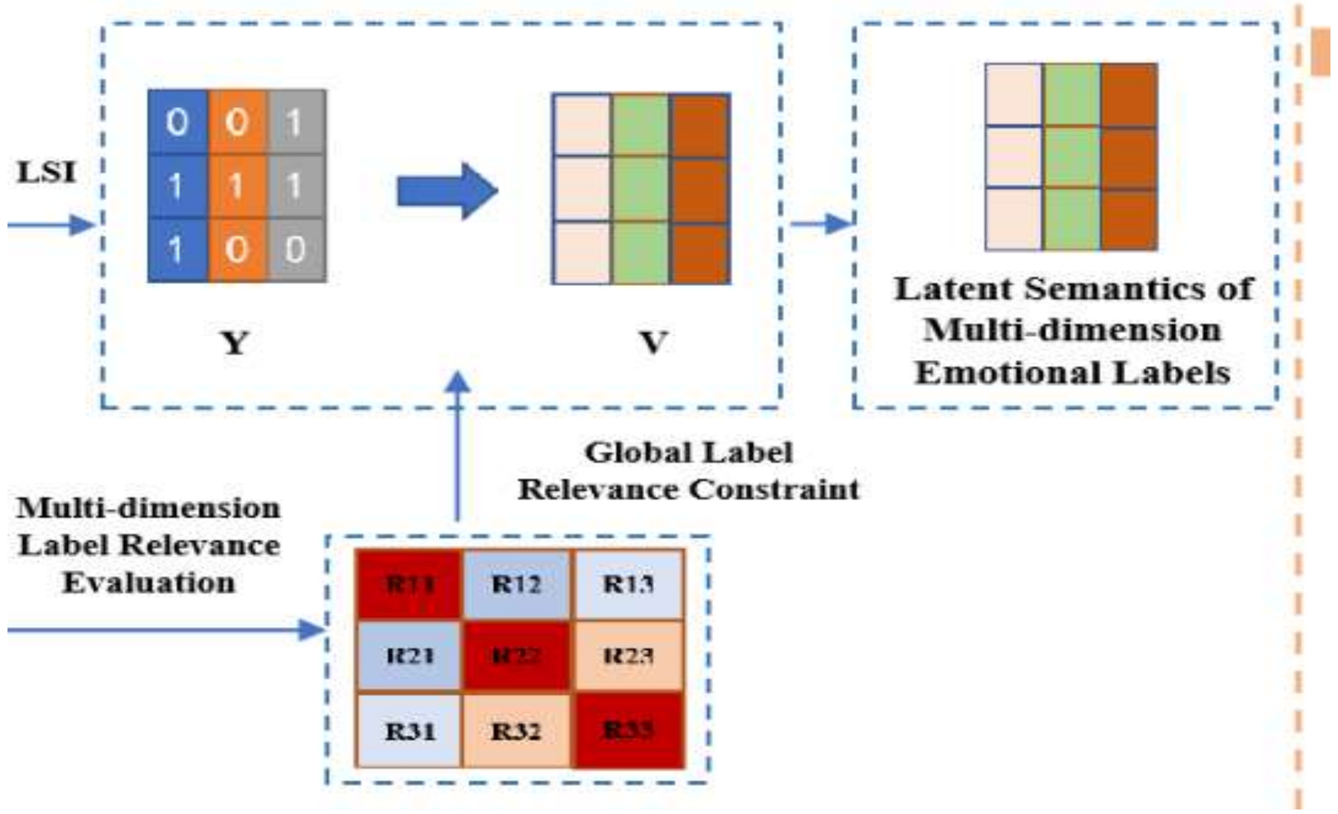
$$\Omega(\Theta) = \boldsymbol{\theta}^T A \boldsymbol{\theta} \quad \text{s.t. } \boldsymbol{\theta}^T \mathbf{1}_d = 1, \boldsymbol{\theta} \geq 0$$

- **Evaluating Global Feature Redundancy**

  A global feature redundancy matrix A assess the correlations among the EEG features. It is a matrix that represents the correlation between f_i and f_j through cosine similarity.

  The Ω(Θ) learns the weights of features and removes redundant features by controlling them so that redundant features do not have high weights.

III EFSMDER Framework



$$C(Y, V) = \|Y - V\|_F^2 + \beta \operatorname{tr}\left(RV^{T}V\right)$$

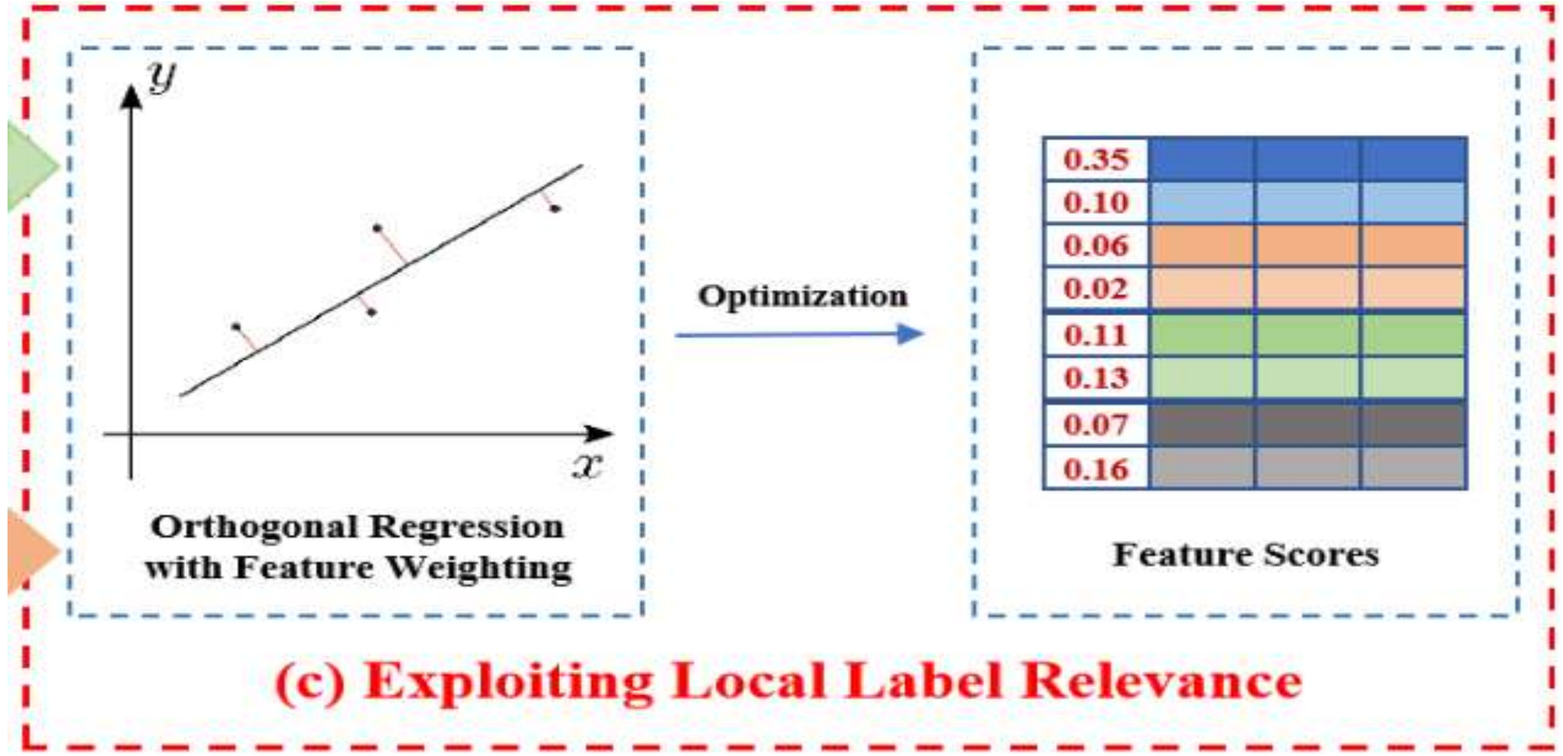
$$\sum_{i=1}^{k}\sum_{j=1}^{k} R_{ij}\, v_{.i}^{T} v_{.j}$$

- **Exploring Global Label Correlations**

  For similar labels, v_i and v_j are adjusted to become closer, while for dissimilar labels, they are adjusted to move farther apart.

  This process considers the global relationships to effectively reflect the correlations between emotion labels.

III EFSMDER Framework



$$F(X, W, \Theta, V) = \left\| X^T \Theta W + \mathbf{1}_n \boldsymbol{b}^T - V \right\|_F^2 + \eta tr\left(V^T L V\right)$$

$$\text{s.t. } W^T W = I_c, \boldsymbol{\theta}^T \mathbf{1}_d = 1, \boldsymbol{\theta} \geq 0 \qquad (2)$$

- **Exploting Local Label Relevance**

  By projecting the original data into a lower-dimensional space through W, the differences with V are minimized, thereby incorporating the information from (a) and (b).

  Additionally, the graph Laplacian matrix L ensures that local structures are preserved, achieved feature selection.

IV Experimental Setup

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- Trials were not segmented into several segments to increase the sample size for EEG feature extraction.

TABLE I
COMPARISONS AMONG THE THREE EEG DATABASES

Data set	DREAMER	DEAP	HDED
Channel no.	14	32	90
Subject no.	23	32	16
Video no.	18	40	12
Sample no.	414	1280	192
Stimulus materials	film clips	music videos	film clips

- A cross-subject experiment setting was conducted.
- To avoid possible bias, 50 independent realizations were conducted and then the average was regarded as the final emotion recognition results.

Ⅴ Performance comparison – single dimension

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TABLE III
THE COMPARISONS OF AVERAGE CLASSIFICATION ACCURACY (%) OF KNN ON 3 BENCHMARK DATASETS

Methods	Discrete Labels								
	DREAMER			DEAP			HDED		
	Valence	Arousal	Dominance	Valence	Arousal	Dominance	Valence	Arousal	Dominance
mRMR	60.16	73.87	77.74	61.48	64.77	64.64	86.87	63.97	68.45
ReliefF	63.71	72.34	77.42	58.26	63.02	64.24	58.10	68.97	68.79
CMIM	58.63	74.03	76.85	59.43	62.71	63.80	87.93	65.00	68.28
RFS	62.58	73.95	77.26	59.90	64.97	64.71	86.72	67.41	69.48
SDFS	61.13	73.71	78.06	56.72	62.42	62.42	82.93	66.72	68.45
ESFS	64.68	74.03	77.66	59.77	63.28	64.24	85.00	64.48	64.48
RPMFS	62.74	71.94	77.82	63.36	63.05	65.05	55.86	62.59	63.97
FSOR	62.18	71.77	77.50	60.08	64.11	65.18	86.72	64.31	66.72
SCMFS	60.48	70.97	76.77	62.24	63.52	65.49	58.28	57.93	65.17
GRRO	63.79	75.48	79.27	63.93	65.76	66.98	93.62	77.76	74.14
MDFS	65.81	75.81	79.35	63.91	65.47	66.54	93.79	79.31	73.97
MFS_MCDM	60.48	71.85	76.85	58.67	65.00	65.60	72.76	62.76	69.31
MGFS	61.94	73.06	77.66	61.85	64.32	64.87	92.24	76.21	70.86
GRMOR	61.77	75.16	79.44	63.83	65.13	65.55	90.34	69.83	72.07
EFSMDER	**69.68**	**78.37**	**83.89**	**67.08**	**66.35**	**69.40**	**95.69**	**81.03**	**76.17**

TABLE IV
THE COMPARISONS OF AVERAGE CLASSIFICATION ACCURACY (%) OF SVM ON 3 BENCHMARK DATASETS

Methods	Discrete Labels								
	DREAMER			DEAP			HDED		
	Valence	Arousal	Dominance	Valence	Arousal	Dominance	Valence	Arousal	Dominance
mRMR	61.13	74.52	76.37	56.38	62.34	61.85	71.72	56.72	62.59
ReliefF	60.16	71.37	77.18	54.87	60.52	60.10	69.66	60.86	59.66
CMIM	59.44	71.85	75.81	55.89	62.71	61.82	67.41	58.28	58.10
RFS	61.45	72.90	74.44	57.66	64.82	65.00	79.31	64.48	67.59
SDFS	60.89	72.82	74.92	54.79	62.24	62.01	79.48	62.41	59.31
ESFS	59.76	70.97	76.29	57.89	63.10	63.83	71.03	57.41	59.48
RPMFS	58.55	73.71	76.77	57.99	62.66	62.68	65.17	61.21	64.31
FSOR	60.48	71.94	76.21	60.21	62.50	62.55	73.97	62.41	60.17
SCMFS	60.56	72.58	76.61	56.80	63.44	64.66	61.55	53.10	56.72
GRRO	63.15	74.19	78.79	60.78	63.82	65.76	83.45	68.62	69.48
MDFS	63.31	73.79	79.84	62.42	64.49	66.07	83.79	71.38	70.34
MFS_MCDM	57.34	70.08	77.42	59.38	62.86	64.14	70.69	68.28	64.14
MGFS	58.95	71.69	75.65	59.79	63.72	63.54	81.38	62.24	62.59
GRMOR	62.18	73.31	78.39	60.94	64.38	65.47	78.62	67.76	68.62
EFSMDER	**66.35**	**76.48**	**82.16**	**65.35**	**66.03**	**68.89**	**86.72**	**73.62**	**73.44**

TABLE V
ACCURACY (%) COMPARISON WITH EXISTING WORKS ON THE DEAP DATASET

Studies	Valence	Arousal
Lew et al. [44]	56.78	56.60
Pandey et al. [45]	62.50	61.25
Rayatdoost et al. [46]	59.22	55.70
Pandey et al. [47]	61.50	58.50
Li et al. [48]	64.20	58.40
Miguel et al. [49]	64.00	59.00
Li et al. [50]	62.66	-
She et al. [51]	65.59	-
He et al. [52]	64.33	63.25
Our work	**67.08**	**66.35**

Ⅴ Performance comparison– multi dimension

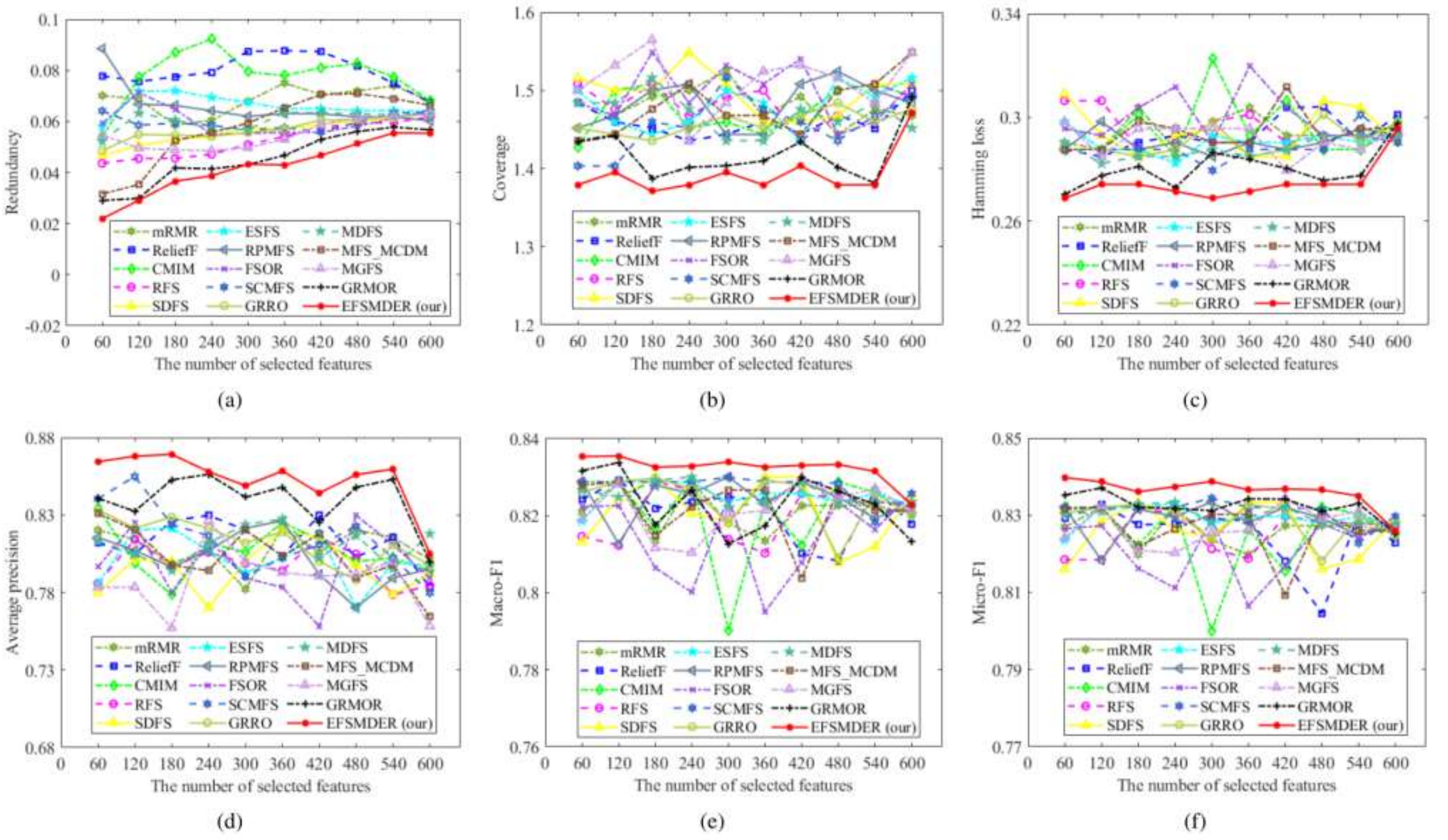

Fig. 2. Multi-dimension emotion classification performance with different number of selected features on the DREAMER data set: (a) Redundancy; (b) Coverage; (c) Hamming loss; (d) Average precision; (e) Macro-F1; (f) Micro-F1.

TABLE VI
THE COMPARISONS OF AVERAGE CLASSIFICATION ACCURACY (%) OF ML-KNN ON 3 BENCHMARK DATASETS

Methods	Multi-dimension Labels		
	DREAMER	DEAP	HDED
mRMR	82.02	82.05	90.17
ReliefF	81.19	79.64	74.36
CMIM	83.45	80.28	92.95
RFS	78.57	82.39	87.18
SDFS	77.98	79.11	91.03
ESFS	78.57	79.90	93.16
RPMFS	81.55	82.54	71.15
FSOR	79.64	79.98	93.59
SCMFS	84.05	82.16	91.45
GRRO	83.33	80.92	90.81
MDFS	81.31	83.26	95.73
MFS_MCDM	83.10	79.75	80.77
MGFS	78.33	82.88	88.03
GRMOR	81.07	81.86	92.31
EFSMDER	**86.43**	**84.80**	**97.86**

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VI Result

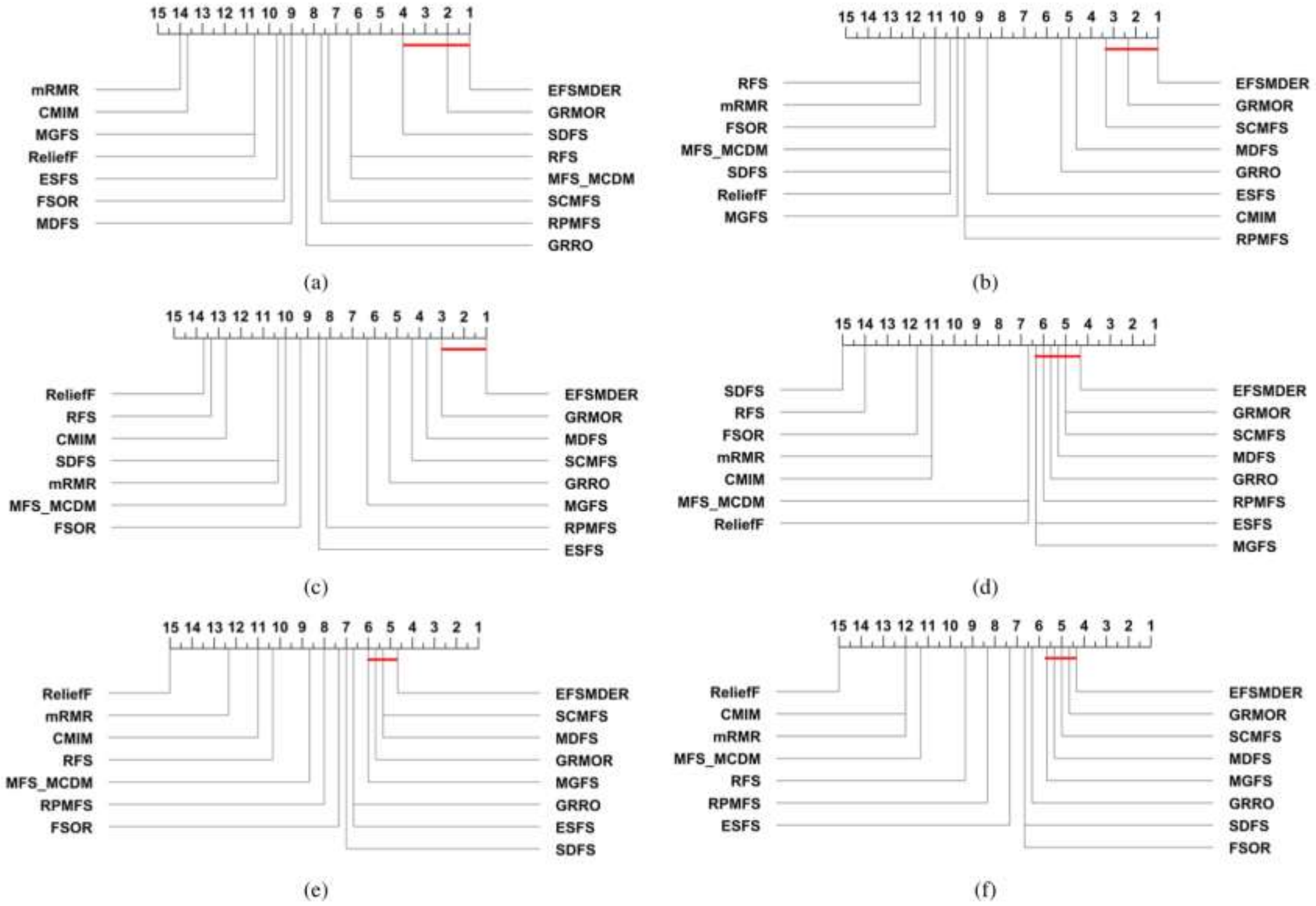


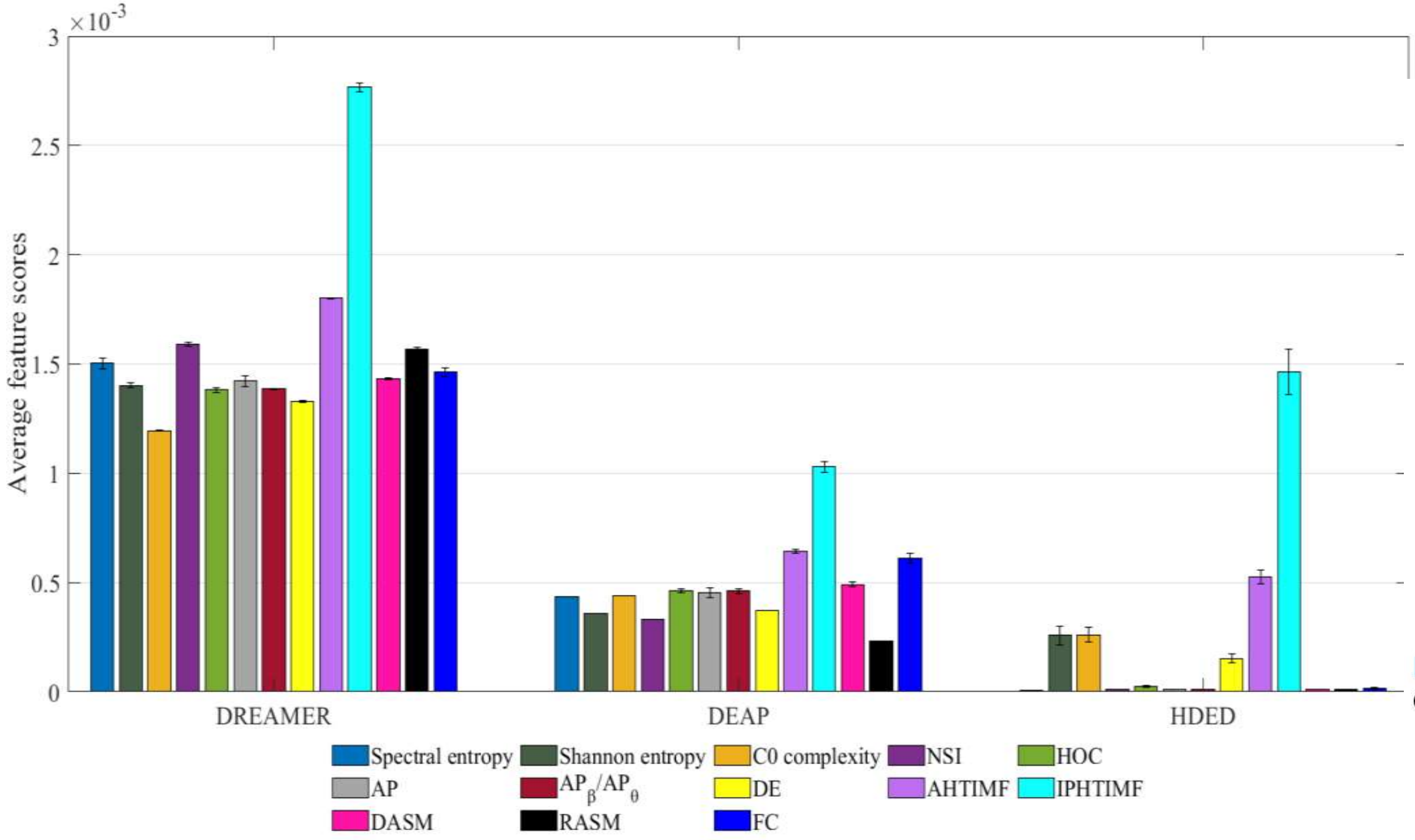
Fig. 5. The Nemenyi test results ($CD = 12.3830$, significance level $\alpha = 0.05$): (a) Redundancy; (b) Coverage; (c) Hamming loss; (d) Average precision; (e) Macro-F1; (f) Micro-F1.

(1) Multi-dimension emotional labels help in uncovering latent semantic information.

(2) Important to remove redundant information.

(3) Global improves feature selection.

VII Discussion



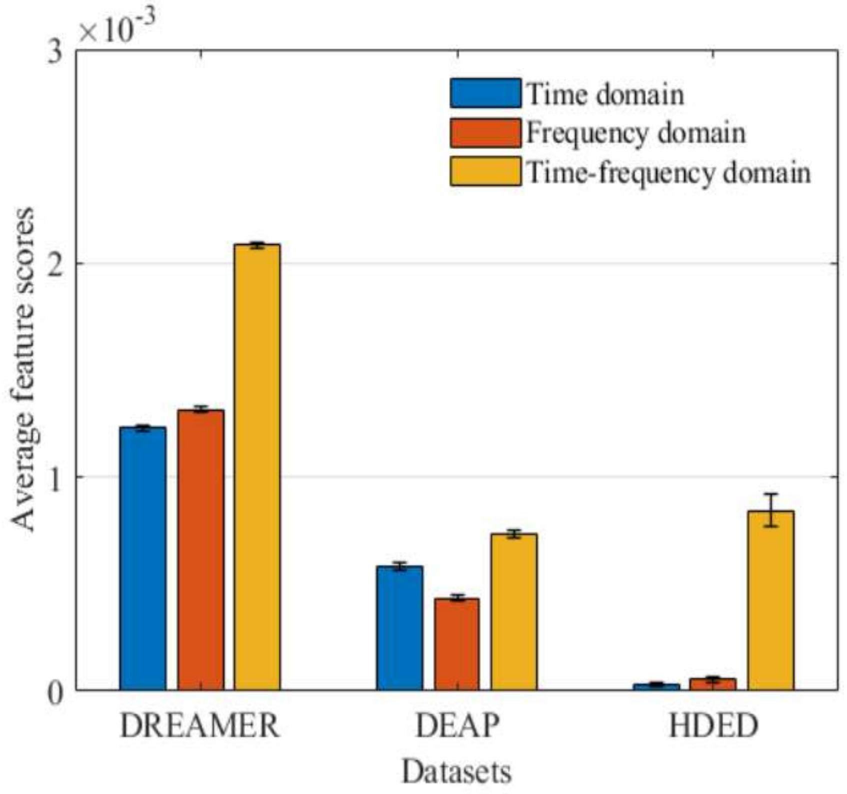


Fig. 9. Average feature scores of EEG features extracted from the time domain, frequency domain, and time-frequency domain.

THANK YOU

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