REAL-TIME PROCESSING FOR CONSUMER BCI

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MAIN MARKETED APPLICATIONS FOR CONSUMER BCI

1. Self-monitoring & Mental Health
2. Gaming..with gaming being much more challenging:
   - movement artifacts during gaming (muscle activity, head movement)
   - gamers expect plug-and-play
   - false-positive commands ruin gaming experience

Emotiv EPOC X

OpenBCI Galea

CONSUMER BCI BOTTLENECKS

Channels & Electrodes:
- 2-16 channels (vs. 64-256+ Channels in Research BCI) → less spatial resolution
- dry electrodes (vs. gel prep in Research BCI) → session / day-to-day electrode drifts
- user self-application → placement errors

Connectivity & Latency:
- Bluetooth LE: connection-interval bound latency (e.g. 7.5 – 30 ms) + protocol overhead (~2-5ms)
- Proprietary USB receivers: buffer-bound latency (16 ms default, can be tuned to 1 – 2 ms to reduce jitter)

EEG SIGNAL UTILIZATION STRATEGIES

Established BCI Paradigms:
- Motor Imagery = imagined movement without actual execution, sensorimotor rhythms (8-30Hz) modulation over motor cortex
- P300/ERP = oddball paradigm utilizing rare target detection, characterized by P300 component ~300ms post-stimulus over parietal regions
- SSVEP = visual cortex response to flickering stimuli, steady-state potentials at stimulus frequency (6 – 75 Hz, strongest 10 – 20 Hz)
- ErrP = neural response to perceived errors, marked by negativity (ERN ~80 – 150 ms) and positivity (Pe ~200 – 400 ms)

Other Approaches:
- Neurofeedback: Meditation/Relaxation, Workload, Attention monitoring
- User-specific patterns for gaming (Train-your-own-command)

Traditional approaches use fixed signal processing rules (e.g., predefined frequency bands, static spatial filters). This poster focuses on some Machine Learning and Deep Learning methods that enable adaptive feature extraction and real-time classification for BCI devices

BASELINE ML APPROACH

Riemannian minimum distance to mean (MDM) Classifier

IDEA: As cortical function emerges from interacting networks, class-relevant information often manifests as cross-channel dependence, that can be effectively captured by computing covariance matrices across EEG channels.

WHY RIEMANNIAN? Since covariance matrices are symmetric positive definite (SPD), they lie on a curved Riemannian manifold. Standard Euclidean operations ignore this curved geometry, whereas Riemannian metrics naturally preserve the manifold's intrinsic structure through geodesic-based distances.

PIPELINE:
Step 1: Preprocessing (notch + paradigm-specific band-pass filter)

Step 2: Feature extraction (per trial / sliding window)
- Estimate covariance matrix for each trial/ window
- If samples ≲ channels, apply shrinkage regularization to ensure positive-definiteness (e.g. OAS)

Step 3: Training (class prototypes)
For each class, compute the Riemannian mean (Karcher / Fréchet mean) of its training covariances; store it as the prototype

Step 4: Classification.
For each test sample, compute its Riemannian distance to all class prototypes (e.g. Affine-Invariant, Log-Euclidean) and assign the label of the closest prototype.

WHY GOOD FOR REAL TIME ON DEVICE PROCESSING?
Simple training: ~10-50 iterations to compute Riemannian mean
Inference: direct geodesic distance calculation, no iterative optimization
Low memory: only class prototypes stored
Parameter-free: deterministic, less overfitting with limited consumer data
Cross-Subject: needs subject-specific calibration or domain adaptation

DEEP LEARNING APPROACH: EEGNet

Although ML pipelines currently outperform DL in consumer BCI scenarios characterized by limited data, DL approaches provide noteworthy advantages – for example, end-to-end nonlinear feature discovery and superior multimodal fusion capabilities, enabling seamless integration of EEG with other biosignals (EMG, EOG, fNIRS).

EEGNet, an example of one DL architectures, is presented below.

Block	Layer	# filters	size	# params	Output	Activation
1	Input				(C, T)	
	Reshape				(1, C, T)	
	Conv2D	F_1	(1, 64)	$64 * F_1$	(F_1, C, T)	Linear
	BatchNorm			$2 * F_1$	(F_1, C, T)	
	DepthwiseConv2D	D * F_1	(C, 1)	$C * D * F_1$	(D * F_1, 1, T)	Linear
	BatchNorm			$2 * D * F_1$	(D * F_1, 1, T)	
	Activation				(D * F_1, 1, T)	ELU
	AveragePool2D		(1, 4)		(D * F_1, 1, T // 4)	
	Dropout*				(D * F_1, 1, T // 4)	
2	SeparableConv2D	F_2	(1, 16)	$16 * D * F_1 + F_2 * (D * F_1)$	(F_2, 1, T // 4)	Linear
	BatchNorm			$2 * F_2$	(F_2, 1, T // 4)	
	Activation				(F_2, 1, T // 4)	ELU
	AveragePool2D		(1, 8)		(F_2, 1, T // 32)	
	Dropout*				(F_2, 1, T // 32)	
	Flatten				(F_2 * (T // 32))	
Classifier	Dense	N * (F_2 * T // 32)			N	Softmax

*Conv2D → learns frequency-specific features (temporal filters)
*Depthwise Conv2D → learns spatial activation patterns across electrodes (spatial filters)
*Separable Conv2D → integrates temporal + spatial features (combined representations)
*ELU (Exponential Linear Unit) activation → stabilizes learning by preserving small negative activations (better suited for oscillatory EEG signals than ReLU)

WHY SUITABLE FOR REAL TIME PROCESSING?
Compact model: ~10^3 parameters vs. 10^6+ in standard CNNs → latency in the ms-range; memory footprint in KB, enabling deployment on embedded systems

CONCLUSIONS

Current BCIs show impressive capabilities in research and therapeutic applications, yet consumer BCIs are not market-ready – today`s systems lack plug-and-play simplicity and robustness. But breakthroughs in intelligent signal processing suggest that someday in the future, BCIs may evolve into standard wearable devices, seamlessly integrated into daily life..

REFERENCES

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