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Wearable EEG framework with time-aligned audio segmentation for quantifying countable mental energy

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Abstract. *In this paper authors extend research based on countable mental energy (CME), so that it will becmome all-day use by fusing continuous audio lifelogging (dictaphone) with EEG from Muse S Athena. The day is segmented into actions A_i via speech-to-text with diarization. For each segment an EEG-derived effort level L(t) is computed, a per-segment energy rate w_i, a flow factor φ_i from intra-segment stability, and an energy-reserve multiplier m(E) that captures fatigue non-linearities. Closed-form formulas linking spectral EEG features are given to w_i, derive the final CME expression, and a minimal architecture for time-alignment, preprocessing, and analysis is provided, along with a numeric toy example.*
Keywords: *EEG framework, human–computer interaction, audio processing, dictaphone, countable mental energy (CME).*

Lifelogging and segmentation

The relevance of this research lies in the growing demand for objective and continuous assessment of cognitive and mental effort in real-world conditions, where wearable EEG systems offer a practical and non-invasive solution; by proposing a time-aligned audio segmentation framework for quantifying countable mental energy, the study bridges neuroscience and applied computing, enabling more accurate monitoring of workload, attention, and cognitive fatigue in daily activities, which is crucial for advancing human–computer interaction, adaptive learning systems, and mental health support technologies.

The initial main idea was to record the whole day using continuous audio devices such as dictaphone which data will be transcribed and timestamped. Then each action A_i will be defined in the time intervals $[t_i^{start}, t_i^{end}]$ inferred from the transcript (topic/activity switches, pauses, voice notes "start email", "break", etc.). Each duration will be defined as $\Delta t_i = t_i^{end} - t_i^{start}$.

Now the goal is to define clock offset for the voice activity detection (VAD) and EEG.

$$\Delta\tau^* = \arg\max_{\Delta\tau}(x_a(t), x_e(t + \Delta\tau)),$$

where $x_a(t)$ is a VAD onset and $x_e(t + \Delta\tau)$ – EEG event marker. Then align all streams by shifting audio timestamps by $\Delta\tau^*$.

EEG effort signal *L(t)*

By activating raw data in Muse S Athena EEG into single, moment-to-moment score of "how hard the brain is working" [1]. We will operate on short overlapping sliding windows 2s, and 50% overlap and clean the data by applying basic filters: notch 50/60 Hz, band-pass 1-40 Hz, then extract 3 workload-sensitive bands:

- frontal theta $P_\theta(t)$: 4-7 Hz, linked to working memory and mental effort;
- posterior/occipital alpha $P_\alpha(t)$ [2]: 8-12 Hz, high alpha indicates idling/relaxed state;
- focus/engagement [3]: 13-30 Hz,

$$Engagement(t) = \frac{P_\beta(t)}{P_\theta(t) + P_\alpha(t)},$$

where *P* is a strength of EEG activity in a frequency range.

To compute effort level *L(t)*, we also have to compute *z*-score on each power band-pass with corresponding weights:

$$L(t) = \alpha_\theta * z\big(P_\theta(t)\big) - \alpha_\alpha * z\big(P_\alpha(t)\big) + \alpha_{eng} * z\big(Eng(t)\big)$$

and to retrieve per-segment average effort, from $[t_i^{start}, t_i^{end}]$:

$$\dot{L_i} = \frac{1}{\Delta t_i}\int_{t_i^{start}}^{t_i^{end}} L(t)\, dt.$$

Identifying energy rate from effort level

For now, we can set that effort level represents for each action *A* (e.g. 60 minutes of coding) we take the average effort during that segment $\dot{L_i}$, having w_i as the speed of "mental fuel tank" is changing per minute during that action:

$$w_i = -C\big(\dot{L_i} - L_0\big).$$

If the action feels harder than normal $\dot{L_i} > L_0$ then weight is negative, meaning this action is burning energy (a "taker") and otherwise $\dot{L_i} < L_0$ then weight is positive, meaning recharging actions (e.g. meditation, a "giver"). *C* is a scale parameter that sets the "energy units per minute" one step of effort above/below normal should cost or give back.

Computing countable mental energy (CME)

To calculate energy taken by the action during the time segment:

$$\Delta E_{A_i} = w_i * \Delta t_i.$$

During an action the brain activity can be in the deep flow state, steady focus often makes the same work feel cheaper. Capturing that by multiplying the segment's energy change by a flow factor $\varphi i \in (0, 1]$ (e.g., 0.2 in strong flow, 1.0 otherwise):

$$\Delta E_{A_i,effective} = \varphi_i * w_i * \Delta t_i.$$

And to compute countable mental energy there should be a sum of all energy segments:

$$CME = \sum_{i=1}^{N} \varphi_i * w_i * \Delta t_i = \sum_{i=1}^{N} \varphi_i * [-C(\dot{L_i} - L_0)] * \Delta t_i$$

Interpretation: CME < 0 = net drain (fatigue); ≈ 0 = balanced; > 0 = net recovery.

Let $C = 2, L_0 = 0$. The obtained research results are presented in Table 1.

Table 1. Calculation of countable mental energy (CME) across different activities based on effective energy expenditure and recovery rates

Action, A	*Δt*	$\dot{L_i}$	φ_i	w_i *(units/min)* = $-C(\dot{L_i} - L_0)$	$\Delta E_{A_i,effective}$
Coding deep focus	60 min	+0.70	0.60	-1.4	0.6 · (-1.4) · 60 = -50.4
Walk outside (rest)	20 min	-0.20	1.0	+0.4	1.0 · 0.4 · 20=+8.0
Email triage	30 min	+0.30	1.0	-0.6	1.0 · (-0.6) · 30=-18.0

CME = -50.4 + 8.0 − 18.0 = -60.4 units (net drain).

The obtained results demonstrate that intensive cognitive activity such as coding in deep focus leads to significant mental energy drain (–50.4 units), while restorative activities like walking outside provide moderate recovery (+8.0 units), and light tasks such as email triage result in additional minor drain (–18.0 units).

Overall, the total CME of –60.4 units indicates a pronounced net fatigue, highlighting the necessity of balancing cognitively demanding work with restorative actions to maintain sustainable mental performance.

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