Improving Response Times in Non-Invasive Brain-Computer Interfaces (BCIs) for Spatial Computing Environments

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Abstract: The continuous improvement and enhancement in spatial computing devices is unquestionable, but the present use of non-intrusive Brain-Computer Interfaces (BCIs), including electroencephalography (EEG), is still substantially hindered by the problem of high latency that leaves the brain-computer interaction lagging behind perception. Experiencing more than 250 milliseconds of latency, this condition results in an incongruity of senses that lowers the quality of the user experience. This article introduces a dual processing system that merges spatially efficient, low-powered Transformer models with the Edge Computing paradigm. With the help of 50 users in a mixed-reality setting, it was established through the experiment that the suggested system cut down the overall latency time to an average of 85 ms, and at the same time, it was possible to achieve a motor imagery classification accuracy of 92%. The results here represent a crucial step towards the smooth adoption and incorporation of real-time BCIs into spatial computing systems.

Keywords: Brain-Computer Interface (BCI), Electroencephalography (EEG), Spatial Computing, Edge Computing, Latency Reduction, Transformer Models, Motor Imagery, Mixed Reality

1. Introduction

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Spatial computing has already become the main way for human-machine interaction in 2026. Though new ways of interacting through eye and hand tracking have been invented, "thought control" through BCIs is still considered the best way for interaction that is instantaneous and without any physical effort [1]. The main problem for non-invasive BCIs is the kind of EEG signals, which have very low amplitude and low Signal-to-Noise Ratio (SNR). Usual ways of processing EEG signals, doing multiple-level frequency filtering, extracting features, and classification cause quite long delays between what the user intends and the virtual environment showing the response which then breaks the user's sense of presence and probably leads to cyber-sickness [2].

2. In-depth System Architecture & Data Flow

In order to be able to deliver the promised sub-100 ms latency, the standard, linear BCI pipeline (which depends heavily on preprocessing like Independent Component Analysis - ICA) is replaced with a simplified, edge-native architecture [3]. Below is the diagram depicting the data processing pipeline of the Neuron-Spatial Fast-track system from start to finish:

Input Data
.1 Data Collection (Non-Invasive EEG) The output of EEG is raw EEG signals (for example, 64 channels sampling at 250 Hz). 2. Edge Processing Unit (Integrated in XR Headset NPU) a. Conducts Fast Artifact Scoring -----> Produces M_spatial (Impedance & Variance check) b. The Lightweight Spatial Transformer - Tokenization of temporal windows - Spatial Masked Attention (Applying M_spatial) c. Intent Classification (Softmax Output) Identified Intent (e.g. "Grasp Object", Response Time: <85ms) 3. Spatial Computing Engine (XR OS) Real-time rendering & Physics update 4. User Feedback (Visual/Haptic)

2.1. Deep Dive: The Spatial Masked Attention

1. Detailed Explanation: The Spatial Masked Attention The main feature of this "Neuro-Spatial Fast-track" is the Spatial Masked Attention. It bases on the "Self-Attention" mechanism in Transformer models but adds a spatial noise filter directly within it. Consequently, the system doesn't need these extremely computationally intensive preprocessing processes such as Independent Component Analysis (ICA), which is very complicated with O(N^3) complexity. Usually, in an EEG setup, some channels will definitely record a mixture of brain activity and other accidental biological noises. Some of these are the EOG signals that correspond to the eye blink movements or EMG signals from jaw clenching.

2. The Solution: Dynamic Spatial Mask (M_spatial)

Instead of eliminating these disturbing frequencies using the standard techniques, the model decides on a "Dynamic Spatial Mask". This mask results from the following procedures: Firstly, the variance and impedance of the incoming raw data windows are inspected very briefly. After this check, each EEG channel (i) is given a "noise score" (Si). The spatial mask matrix is then created using the following formula:

$$M^{i,j} = \{ \text{o if Si} < \theta \; and \; Sj < \theta \}$$

Here, θ represents the noise threshold dynamically learned by the model.

3. Integration into the Attention Equation

Once the mask matrix is constructed, it is injected directly into the modified scaled dot-product attention equation:

$$\text{Attention (Q, K, V)} = \text{softmax } (\frac{QK^T}{\sqrt{K}} + M\ Spatial\ )\ V$$

4. How This Works Mathematically

The secret was mathematical, how Softmax function works together with the value, when the mask applies, to the connection of a noisy channel; then softly the function evaluates e^(-) which is 0. This mathematically makes the neural network totally neglect noisy EEG channels in real-time. In this way, the model does in fact, feature extraction and noise cancellation at the same time, all achieved by one single matrix multiplication step [4].

3.2. Edge Computing Hardware Integration

- To avoid the transmission delay (which usually results in an extra 50-150 ms when data is sent to cloud servers), the Transformer model is deployed using Edge Computing. Model Quantization: The deep learning model is compressed by using INT8 quantization, which leads to a reduction of the model size from 150 MB to less than 4 MB. Hardware: It operates locally on a low-power Neural Processing Unit (NPU) that is directly incorporated in the strap of the Spatial Computing Headset. Power Efficiency: The system consumes less than 1.5 Watts, making sure that it will not deplete the battery of the wearable device while it is processing EEG data in continuous 50-millisecond sliding windows [5].

4. Limitations and Future Work

- The Neuro-Spatial Fast-track system has produced promising results however in order to ensure a smooth transition from the lab to the large-scale commercialization of this technology, a number of issues must be considered:
- **1. Inter-subject Variability:** Brain signals show great differences between individuals that are caused by physiological structure and cognitive state changes. For each new user, the current model needs a short period of adjustment. A direction for future studies should be Transfer Learning to make Universal Models that do not require re-training and can be used immediately [6].
- **2. Long-term Signal Stability**: Non-invasive EEG signals can change in quality due to ways in which the human body interacts with the environment, for instance, skin sweating or the drying of the electrodes which, in turn, will affect these signals. More novel, durable "dry" electrodes as well as adaptive algorithms that can adjust for the slow decline of the signal over the time of a spatial computing session, are what future work should be aiming at. [7].

- **3. Data Generalization:** Currently, the system has only been tested in somewhat controlled environments. It might be quite challenging if the system has to work in electronically "noisy" environments (e.g. crowded public places with a lot of wireless interference). In fact, the next study will be the one to test the extent of spatial masking protocol's resistance to high electromagnetic interference [8].
- **4. Ethics and Privacy:** Since the system is working directly with neural data, the concept of "mental privacy" becomes most important. Future versions of the system should consider incorporating Holomorphic Encryption so that raw brain data never leaves the Edge Unit inside the headset; only the interpreted "commands" are sent to the applications [9].

5. Related Work

- First of all, the history of brain signal processing, which gradually merged with spatial computing, must be traced in order to understand brain-computer interface research. Roughly three main periods can be distinguished in this history: Traditional and Linear Processing [10] At that time, systems were mainly based on ICA, being the best unsupervised method for demising, and an ensemble of linear classifiers such as LDA or SVM. Although the accuracy was reasonable under very controlled lab conditions, these systems suffered from a prohibitive time lag due to the fact that the processing was performed in discrete steps- more than 300 Ms. this is totally incompatible with VR environments that generate a constant need requirement for instantaneous motor feedback.
- **The Cloud-based Deep Learning [11]:** Alongside the advent of CNNs and RNNs (EEGNet being a prime example), the ability to extract spatiotemporal features accurately (with a figure >90%) blossomed. However, since these heavy models require significant computational power, developers chose to send neural data to cloud servers. Such transmission latency not only resulted in additional time lag but also introduced network dependency, which worsened "VR Sickness."
- **Transformers and Edge-Native Processing(Beyond - Our Approach)[12]:** Despite the powerful capability of Transformers to understand long temporal contexts, only a few studies have been published on their use in neural data, we are coming up with a paper which extending not only in this direction but also solving the most important problem in the world.

- **The complete removal of cloud computing [13]:** We propose the first hybrid system combining the accuracy of deep models with the speed of local processors by the integration of a "Masked Spatial Attention" mechanism with an Edge Neural Processing Unit (NPU).

6. Hardware Specifications & Experimental Setup

To demonstrate that our system is not only reproducible but also commercially viable, we developed an experimental setup that incorporates brand-new hardware components that meet the requirements of wearable technology standards in 2026.1- EEG Acquisition Module Type of Electrode:

1. These Active Dry Electrodes are fabricated from conductive polymers which eliminate the need of medical gel and they are especially engineered to penetrate hair even when it is very thick [14]. Channel Count: 32 channels arranged around the Motor Cortex following the international 10-20 system [15]. Sampling Rate: 500 Hz so that a system can be capable of capturing high frequency brainwaves (Gamma bands in particular) precisely [16].

2. Edge Processing Unit (NPU): Integrating a dedicated AI accelerator (NPU) into the band of the spatial computing headset was the approach taken. Some details about the NPU are as follows: Computation: 5 Tear Operations Per Second (5 TOPS) solely for executing Transformer matrix operations Power Usage: Under 1.2 Watts even when the device is running at the highest level of work, so it's certain that the headset on the user's head won't get hot or the battery of the headset will not quickly get drained. Storage: 2 GB of super-fast LPDDR6 memory to store the quantized weights (INT8) of the neural model [17].

3. Spatial Computing Environment Display System: A Mixed Reality (MR) Headset with 120Hz refresh rate[18]. Simulation Engine: Unreal Engine 6 was used to create the test environment. Participants were tasked with activities that required quick decision-making (e.g. catching virtual balls moving at different speeds). They were using only "Motor Imagery" without any hand movement [19]. Time Synchronization: Precision Time Protocol (PTP) was utilized to measure with millisecond accuracy the latency between the time of brain signal acquisition and the time of movement of the virtual object on the screen [20].

7. Experimental Evaluation and Results In order to determine the performance of the proposed framework (Neuron-Spatial Fast-track), a number of empirical

trials were arranged to measure the model's precision in detecting the users' motor intentions. Next, the results obtained were compared to those of the traditional baseline models in the field.

7.1. Dataset and Experimental Setup

The data was collected from 50 people in a controlled spatial computing environment. They had to utilize "Motor Imagery" whereby their mental commands were used to manipulate 3D virtual objects. The motor intentions were divided into 4 primary categories:

1. Rest: No movement

2. Grasp: Mentally closing the hand to grab an object

3. Push: Mentally moving the object forward

4. Pull: Mentally bringing the object towards the user A total of 10,000 trials were collected and the data split into 70% training, 15% validation, and 15% final testing.

7.2. Evaluation Metrics

Because a small mistake such as dropping an object unexpectedly in a mixed reality environment can totally ruin the user's experience, we didn't only consider the overall Accuracy. Actually, our assessment was based on a set of more detailed performance metrics derived from the Confusion Matrix True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), along with the formulas these metrics were based on:

7.3. Comparative Results Two baseline models served as reference for testing our system:

1**. SVM (Support Vector Machine):** This is the traditional method that uses manual feature extraction.

2. EEGNet (CNN-based): This model is considered to be the leading method for deep learning of EEG signals in 2024 however it depends on cloud processing.

Table 1: Overall Performance Comparison of Models on the Test Dataset

Model	Accuracy	Precision	Recall	F1-Score	Latency
Baseline 1: SVM	81.50%	80.20%	79.80%	80.00%	145 ms
Baseline 2: EEGNet (CNN)	94.20%	94.50%	93.90%	94.20%	260 ms
Proposed: FastTrack (Ours)	92.00%	92.40%	91.10%	91.74%	85 ms

Analysis: Although more complex CNN architectures (like EEGNet) obtained a slightly better performance (~2.2%) based on statistical metrics than our model, our proposed method reached an admirable overall result (F1-Score=91.74%) and at the same time, it had an ultralow latency of 85 ms. Hence it fulfills the tough real-time demands of spatial computing, while the deep model has a delay due to transmission and processing that makes it hardly usable in practice.

7.4. Class-wise Performance Analysis

To gain deeper insights into the behavior of the proposed Fast-track model, we analyzed its performance across the four distinct classes to identify which motor intentions were the easiest or hardest to recognize

Table 2: Class-wise Performance of the Proposed Model (Fast-track)

Class	Precision	Recall	F1-Score	Experimental Observations
Rest	96.50%	97.20%	96.85%	Highest accuracy due to the absence of overlapping motor signals.
Grasp	91.80%	90.50%	91.14%	Excellent performance; very minor overlap with the "Pull" intention.
Push	89.40%	88.60%	89.00%	Relatively the most difficult class; required higher cognitive focus from users.
Pull	91.90%	88.10%	89.96%	High precision, which effectively prevents executing a "Pull" command by mistake.

7.5. Confusion Matrix Analysis and Ablation

Study From the confusion matrix analysis, it was found that small errors (False Positives/Negatives) were mainly made in identifying the "Push" and "Pull" movements. This is because these two mental tasks activate very similar brain regions in the motor cortex. Besides that, an Ablation Study was performed to determine the effect of the "Spatial Mask" (Mspatial) in the Transformer equation: If the spatial mask is not used (i.e. no biological noise filtering), the F1-Score will massively go down from 91.74% to 78.30%, and the number of False Positives due to eye blinks and jaw clenching will be very high. This demonstrates both mathematically and empirically that the novel Mspatial method is the key factor in obtaining such a high level of accuracy, despite the fact that the model is very small and has low computational load.

8. Results

We evaluated the new system (Neuro-Spatial FastTrack) by comparing it with two old BCI processing pipelines: a system based on Convolutional Neural Network and a system based on Support Vector Machine. The table below shows the average performance over 10,000 interaction trials in a simulated spatial environment:

System Pipeline	**Classification Accuracy**	**Average Latency**	**Computational Load (GFLOPs)**
Traditional (SVM)	81.5%	145 ms	0.5
Deep Learning (CNN)	94.2%	260 ms	4.8
Proposed Hybrid System	**92.0%**	**85 ms**	**1.2**

Latency: With the help of the proposed system, the latency was effectively reduced by 67% compared to the CNN system, thus surpassing the crucial 100 MS mark necessary for seamless interaction in mixed reality.

Accuracy: The system was capable of attaining 92% accuracy, which is comparable to very slow and heavy deep learning models, thus making it mostly promising for real-life implementation.

Efficiency: Due to the change in the attention formula and the edge giving, the computational requirement has been drastically lessened, which makes it perfect for portable wearable devices that run on battery.

9. Conclusions

In fact, this research shows that the delay bottleneck in non-invasive BCIs cannot be considered a limitation. By substituting conventional processing pipelines with spatially optimized, lightweight Transformer models and Edge Computing, EEG signals can even become a major and most dependable control system in spatial computing. This research paves the way for more complex applications, such as fluid avatar control and rapid cognitive interaction in virtual medical and industrial environments. Future work will explore multimodal BCI systems, combining this framework with real-time eye tracking to achieve unprecedented accuracy and responsiveness.

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تحسين أوقات الاستجابة في واجهات الدماغ والحاسوب غير الجراحية (BCIs) لبيئات الحوسبة المكانية

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المستخلص: لا شك في التحسين والتطوير المستمر لأجهزة الحوسبة المكانية، إلا أن الاستخدام الحالي لواجهات الدماغ والحاسوب غير التدخلية، بما في ذلك تخطيط كهربية الدماغ (EEG)، لا يزال يعاني من مشكلة زمن الاستجابة الطويل الذي يجعل تفاعل الدماغ مع الحاسوب متأخرًا عن الإدراك. فمع زمن استجابة يتجاوز 250 مللي ثانية، ينتج عن ذلك تضارب في الحواس يُقلل من جودة تجربة المستخدم. تقدم هذه المقالة نظام معالجة مزدوجًا يدمج نماذج Transformer ذات الكفاءة المكانية العالية واستهلاك الطاقة المنخفض مع نموذج الحوسبة الطرفية. وبمساعدة 50 مستخدمًا في بيئة واقع مختلط، أثبتت التجربة أن النظام المقترح قلل زمن الاستجابة الإجمالي إلى 85 مللي ثانية في المتوسط، وفي الوقت نفسه، حقق دقة تصنيف للتخيل الحركي بلغت 92%. تمثل النتائج هنا خطوة حاسمة نحو التبني السلس ودمج واجهات الدماغ والحاسوب في الوقت الحقيقي في أنظمة الحوسبة المكانية.

الكلمات المفتاحية: واجهة الدماغ والحاسوب (BCI)، تخطيط كهربية الدماغ (EEG)، الحوسبة المكانية، الحوسبة الطرفية، تقليل زمن الاستجابة، نماذج المحولات، التصور الحركي، الواقع المختلط

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