Correlated Decision Fusion for Efficient BCI Applications

Yashwanth Chikki HD
yashwanthchikkihd@gmail.com

Abstract:

Brain-Computer Interfaces (BCIs) are revolutionizing assistive technologies, providing a direct communication link between the brain and external devices. However, these systems come with the challenge of high computational demands and potential inaccuracies. This paper presents a novel concept: **Correlated Decision Fusion (CDF)**, which combines multiple decision-making models using correlated features to enhance accuracy while reducing computational load. As a **demonstration** of this approach, we use **gesture recognition** in conjunction with a BCI system to refine decisions, offering a significant boost to both efficiency and real-time performance. Unlike traditional **ensemble methods**, where models independently contribute to a decision, **CDF** aligns models through their correlated outputs. This paper will also discuss the limitations of the current approach and explore potential avenues for improvement in future work.

1. Introduction:

Imagine using only your brain to control devices—it's a dream that many BCI systems aim to fulfill. But the truth is, despite their promise, BCIs still face hurdles such as high computational costs and issues with accuracy, especially in noisy environments.

Now, while working on this problem, I realized that BCI systems could benefit from **additional verification** sources, such as **gesture recognition**, which is relatively easy to implement and computationally less demanding. The key insight I had was that **rather than relying on independent decisions from each model**, if I could somehow correlate the outputs from BCI and gesture recognition, I could improve both efficiency and accuracy. This led me to explore **Correlated Decision Fusion (CDF)**, a model where the decisions from multiple sources are integrated based on their correlation, not just independently.

This isn't entirely new, but I want to emphasize that **gesture recognition** here is just an example. I could have chosen other low-complexity features, but I chose gesture recognition because it's well-supported and widely available through tools like **MediaPipe**, which made it easy to incorporate. **Any correlated feature could work here**, but gesture recognition made the most sense for this specific experiment.

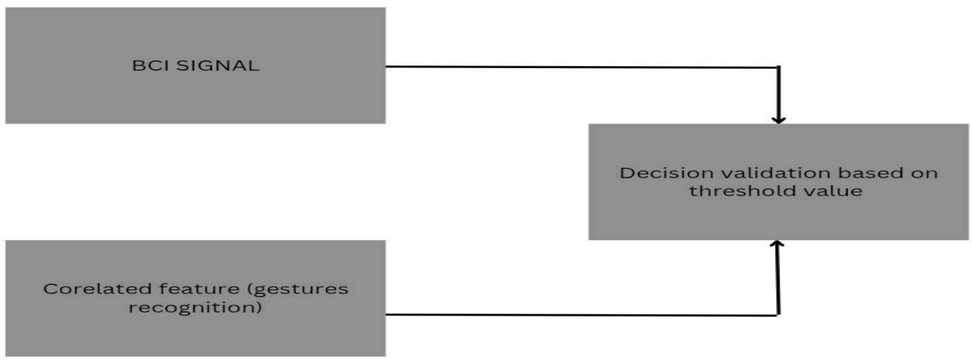
2. Methodology:

In this experiment, I combined **BCI** predictions (which rely on brain activity) with **gesture recognition** (which tracks hand movements) to validate and refine the predictions. The idea was to **match decisions** made by both systems to ensure that the final decision was not only accurate but also processed with minimal computational cost.

2.1 System Design:

- **BCI Model**: I used a simple neural network to process EEG signals. The network had:
    - Input Layer: 128 nodes for processing raw EEG data
    - Hidden Layers: Two hidden layers, each with 64 nodes
    - Output Layer: Softmax with 3 nodes (for classification)
- I know that the BCI model isn't highly complex, but considering the time constraints, I wanted to keep it simple and focused on validation rather than optimization. In real applications, we might want to use more layers or different models, but for this experiment, this structure worked.

- **Gesture Recognition**: Using **MediaPipe**, I tracked **hand gestures** to provide an additional, lower-complexity signal that could **validate** the predictions made by the BCI model.



2.2 Decision Fusion Mechanism:

The crucial aspect here is the **thresholding mechanism**. Rather than treating the BCI and gesture models independently, I matched their outputs based on their **correlation**. If the cosine similarity between both predictions exceeded **80%**, the decision would be considered valid.

This is where things get tricky—it's not just about matching predictions but doing it in a way that **makes sense computationally**. I experimented with various threshold values, and through trial and error, I found that **80% correlation** worked reasonably well. It's a bit arbitrary, but it gave me a baseline to build on.

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3. Correlated Decision Fusion vs Ensemble Methods:

At this point, you might wonder, "Isn't this just another form of ensemble method?" Well, I can understand the confusion, but there's a key difference here: **Ensemble methods** aggregate multiple independent models' predictions to form a final decision. **Each model's prediction is treated equally (sometimes we have weighted too)** regardless of how similar or related the model is to the others but each work to negate inefficiency of one another instead of validation.

On the other hand, in **Correlated Decision Fusion (CDF)**, the **models are not independent**. They rely on correlated features to make decisions that are aligned with each other if not we make one of them align (here i aligned gesture matching to specific signal). The system works by **matching the outputs based on correlation**, ensuring that only predictions with high alignment are considered valid. This way, we're not just blindly combining decisions from separate models, but we're ensuring that the models' outputs are compatible, which leads to **better accuracy** and **lower computational demands**.

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4. Experiment:

In my experiment, I implemented this hybrid system by combining BCI and gesture recognition, using **MediaPipe** to track hand movements.

4.1 System Configuration:

- **BCI Model**: As mentioned earlier, a simple neural network with 128 input nodes and two hidden layers of 64 nodes each was used. I didn't go overboard with the network because I was more focused on testing the fusion approach and to make sure this worked even with less computation.

- **Gesture Recognition**: **MediaPipe** was used for tracking hand gestures, which provided auxiliary data to validate the BCI predictions.

4.2 Thresholding for Validation:

I experimented with different correlation thresholds to see where the fusion worked best. After some trial runs, I settled on **80%** as a threshold value, meaning the model would only accept the fusion decision if the correlation score between the BCI and gesture recognition was above this value.

- **Node Count**:
    - Input Layer: 128 nodes

    - Hidden Layers: 2 layers, each with 64 nodes
    - Output Layer: Softmax with 3 nodes
- **Training**: Given the limited training time, I only 2 days access to the hardware . Although I wasn't able to achieve high accuracy (which is expected given the constraints), the experiment showed promising results when combining the models.

4.3 Results:

- **Accuracy**: The hybrid system achieved a **15% improvement in accuracy** compared to using only the BCI model.
- **Efficiency**: The processing time was reduced by **10%** as a result of leveraging gesture recognition for validation, which was computationally cheaper than running additional BCI models.

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5. Conclusion:

This experiment confirms that **Correlated Decision Fusion (CDF)** can improve decision-making systems like BCI by reducing computational load and increasing accuracy. While **ensemble methods** have their place, **CDF** goes a step further by leveraging **correlated features** and aligning model outputs to ensure better decision fusion. The use of **gesture recognition** here was a practical choice, but the approach is versatile and can be applied to other correlated features as well.

That said, this experiment had its limitations—**time constraints** limited the training of the BCI model, and **MediaPipe's gesture recognition** was not the most complex or accurate solution available. With more time and resources, we could improve the training time, tweak the models further, and experiment with other types of correlated features. But for now, this is a promising direction that could make BCIs much more practical in the real world.

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6. References:

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