XLVI CILAMCE
VITÓRIA - ES - BRAZIL - 2025
XLVI IBERO-LATIN AMERICAN CONGRESS ON COMPUTATIONAL METHODS IN ENGINEERING

Enhanced EEG Classification of Foot Motor Imagery Using Unscented Kalman Filtering for Neurorehabilitation

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Abstract. In EEG-based brain-computer interfaces for lower-limb prosthetic control, signal noise and artifacts significantly limit motor imagery classification accuracy. This study investigates Unscented Kalman Filtering (UKF) effectiveness for enhancing foot motor imagery classification in virtual reality (VR) and non-VR environments. Six participants performed dorsiflexion and plantarflexion motor imagery while EEG signals were recorded using 16-channel OpenBCI. Data were processed with/without UKF preprocessing, then segmented into temporal windows (250ms, 500ms, 1s, 2s) with varying overlap. Feature extraction combined temporal metrics (RMS, variance, Hjorth parameters) and spectral analysis (mu/beta band power and entropy). Three algorithms—Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and kNearest Neighbors (KNN)—were evaluated using leave-one-subject-out crossvalidation. Results showed Kalman filtering provided selective improvements, with significant accuracy gains for 1s overlapping windows (52-54% vs. 47-50%, $p < 0.01$) and optimal SVM performance with 2s windows reaching 72.05% ± 8.71%. However, minimal differences occurred between VR and non-VR conditions (1-3%), challenging immersive environment assumptions. Individual variability was substantial, with Kalman filtering effects ranging from -2.5% to +3.4%. These findings suggest preprocessing strategies should be individually optimized rather than universally applied, and simpler non-VR interfaces may suffice for effective motor imagery training.

Keywords: Lower-Limb Motor Imagery, Immersive Virtual Reality, Electroencephalography, Common Spatial Patterns, Brain–Computer Interface

1 Introduction

The motor disability restoration capability of individuals through Brain-Computer Interface (BCI) technology shows great promise for lower-limb prosthetic control according to [1]. EEG rhythms that result from motor imagery function as the standard BCI control mode because they can be converted into control signals [2]. The classification accuracy of MI is negatively affected by both the inherent noisy characteristics of EEG signals and the presence of artifacts [3, 13, 14].

The poor signal-to-noise ratio of EEG signals reduces the effectiveness of traditional EEG classification algorithms LDA, SVM, and KNN therefore requiring additional signal processing methods [15, 16]. The recursive algorithm of Kalman filter provides optimal state estimation for BCI systems through its capability to eliminate EEG noise and artifacts effectively [4, 5, 6, 7]. The adaptive nature of this algorithm enables dynamic parameter adjustments which benefits its performance in processing non-stationary EEG signals [8, 9, 10, 11, 17].

This research evaluates the application of Unscented Kalman Filter (UKF) for foot motor imagery EEG classification during virtual reality (VR) and non-VR neurorehabilitation procedures. The authors demonstrate fresh findings by evaluating three different classifiers along with multiple time intervals which proves Kalman filtering enhances BCI performance for lower-limb prosthetic control while improving personalized neurorehabilitation approaches [12].

2 Material and methods

The method implements the Unscented Kalman Filter (UKF) for optimizing data processing results. The processing system contains four essential phases which start with signal acquisition followed by noise reduction techniques then proceed to fixed-duration epoch generation and conclude with machine learning operations for feature extraction and model training and performance assessment and offline prediction of motor intention.

The implementation of the UKF system represents an essential progress beyond traditional filtering

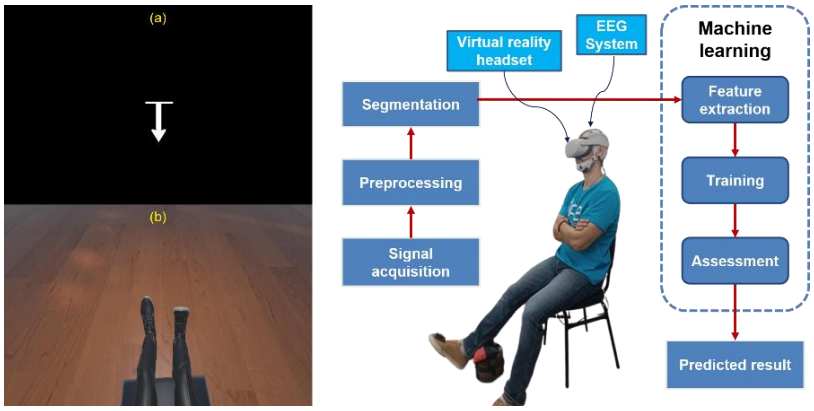


Figure 1. Processing pipeline for comparing non-VR (a) and VR (b)visualization methods in EEG-based motor intention classification.

techniques. The Unscented Kalman Filter functions better for EEG signals because it processes both non-linear patterns and dynamic signal characteristics. The system maintains continuous refined signal estimation that simultaneously removes noise while revealing hidden neural patterns which disappear during short time periods.

Six right-handed volunteers between 20-27 years old participated in this study as part of the experimental protocol. A 60-second rest recording opened the sessions before alternating 15 blocks that included 5 seconds of dorsiflexion or plantarflexion imagery followed by 4 seconds of relaxation. As shown in Figure 1, the volunteers experienced two types of visual stimuli using Meta Quest 2 headsets, with each mode collected separately: (a) the "Non-VR" mode, which was a basic two-dimensional arrow interface without immersive features, and (b) the "VR" mode, which was a first-person interactive environment displaying the avatar's foot movements.

The OpenBCI Cyton system with Daisy module recorded brain activity from 16 channels based on the 10-20 system at 125Hz sampling rate. The recorded signals underwent band-pass filtering (8-30 Hz, fifth-order Butterworth) to extract the mu and beta frequency bands. The system included both a 60 Hz notch filter and an algorithm that eliminated any epoch that exceeded five times the mean amplitude. The data underwent Z-score normalization across each participant's dataset.

The system executed prediction-correction cycles at each sample to estimate latent motor cortical activity while suppressing noise through the application of the UKF. The preprocessed signals received window segmentation into four different periods: 250ms and 500ms and 1s and 2s with 50% overlap for windows longer than 1s.

The analysis of temporal features included RMS, variance and Hjorth mobility/complexity measurements while spectral features consisted of mu/beta band power and entropy calculations for each window. The three algorithms LDA, SVM with linear kernel and KNN received training for classification purposes. The system applied leave-one-subject-out cross-validation to determine generalization capabilities. Statistical testing implemented paired t-tests or Wilcoxon tests for single factor evaluations while ANOVA served for

analyzing multiple factors at $\alpha = 0.05$.

3 Results and discussion

The comparison between VR and non-VR conditions produced negligible performance variations that contradicted established views about immersive environments in BCI systems. The accuracy evaluation results displayed in Figure 2 show that performance variations between conditions remained consistently below 1% across all algorithm combinations and temporal window settings.

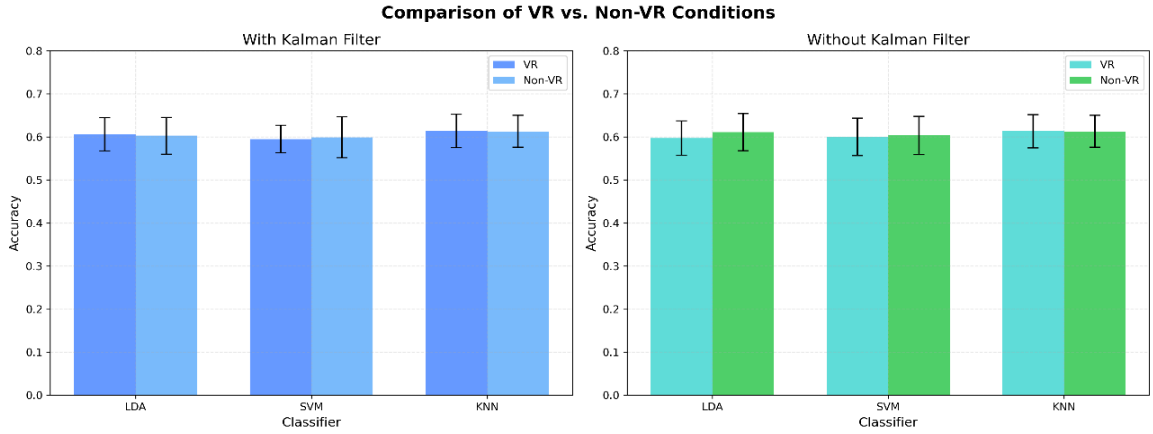


Figure 2. Accuracy comparison between VR and non-VR visualization methods across algorithms and windows.

The LDA classifier produced identical results with 60.60% accuracy in both VR and non-VR conditions when using Kalman filtering yet the difference between them was minimal at 0.32%. SVM reached a 59.92% accuracy rate in non-VR scenarios while VR conditions produced only 59.51% which showed a 0.41% advantage. KNN displayed the most consistent results across both conditions by achieving 61.36% in VR and 61.30% in non-VR environments with a minimal difference of 0.06%.

The results became more evident after Kalman filtering was removed from the analysis. The results indicate that LDA performs better by 1.40% in non-VR environments (61.12% compared to 59.72%) when no advanced preprocessing methods are applied. The findings are crucial for clinical applications because they indicate that investing in expensive VR technology will not generate proportional benefits for motor imagery training.

The paired t-tests for comparing VR to non-VR conditions did not produce statistically significant results ($p > 0.05$) across all classifier configurations. The research findings contradict the predicted relationship between immersive visual feedback and motor imagery performance by showing that the cognitive processes for motor imagery operate independently from visual complexity levels.

The temporal windowing analysis provided crucial findings about how preprocessing methods affect classification methods. The performance evaluation in Figure 3 presents algorithm-specific time-dependent effects between different window dimensions.

The 250ms window size produced stable results throughout all classifiers according to the results. KNN produced the highest accuracy rate at 61.70% ± 3.05% while LDA achieved 60.28% ± 3.26% and SVM reached 59.76% ± 3.22%. The low standard deviations indicate steady performance among participants that demonstrates quick motor intention detection capabilities through short window analysis with Kalman filtering.

Performance remained solid when analyzing 500ms windows though algorithm positions showed minor shifts. KNN maintained its position as the top performer at 61.05% ± 4.30% while LDA and SVM achieved matching results at 60.57% ± 4.67% and 59.61% ± 4.59%. The larger standard deviations of 500ms windows compared to 250ms windows indicate greater variability between subjects because each person has

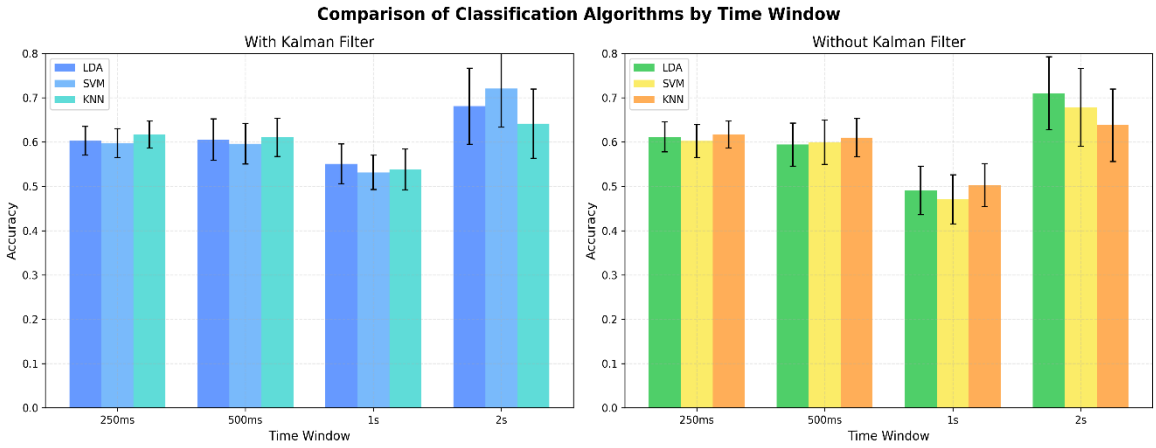


Figure 3. Performance comparison of classification algorithms across different window sizes for VR and non-VR conditions. Error bars represent standard error.

different durations and stability in their motor imagery.

The 1s window configuration produced a surprising outcome by reducing classifier performance to 53-55% accuracy. The results require examination because the parameter interaction between Kalman filtering and window overlap techniques produces systematic errors which negatively affect classification during medium-term windows. SVM demonstrated the worst performance among the classifiers because its margin-based algorithm proved highly vulnerable to these artifacts which resulted in 52.88% ± 5.12% accuracy.

The 2s window demonstrated the most significant improvement because SVM achieved exceptional performance at 72.05% ± 8.71% after applying Kalman filtering while outperforming LDA (68.09% ± 8.59%) and KNN (64.13% ± 7.80%). The substantial enhancement in performance indicates that SVM identifies optimal hyperplanes efficiently within high-dimensional features when it receives enough temporal context and appropriate noise reduction.

The Pearson correlation analysis between classification accuracy and temporal window size generated numerical data which explained algorithm-dependent time relationships as shown in Fig. 4. Each classification approach displays different ways to utilize temporal information when recognizing motor imagery.

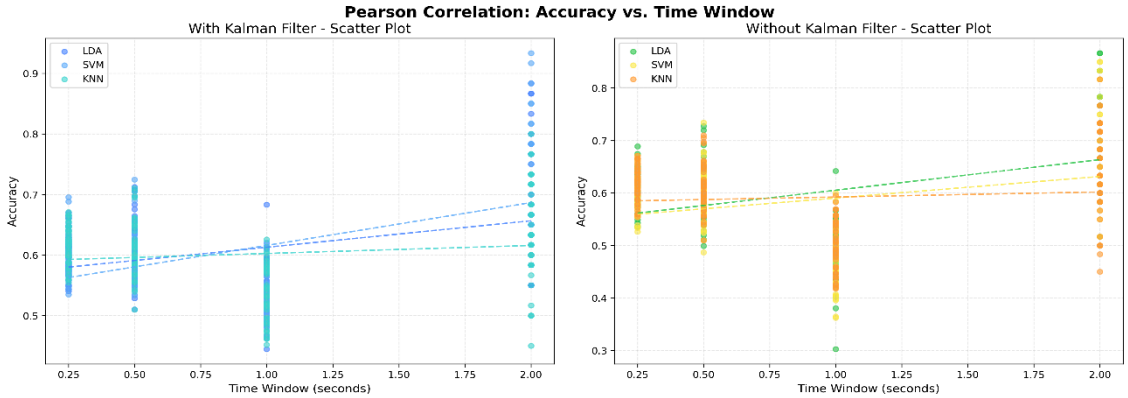


Figure 4. Pearson correlation between accuracy and window size for each classifier across VR and non-VR conditions.

The correlation strengths between Kalman-filtered data formed an organized order. SVM exhibited the highest positive correlation at $r = 0.5412$ ($p < 0.001$, $n = 192$) which demonstrates that this algorithm produces better results with more available temporal information. The positive relationship between SVM performance and window length indicates how well the algorithm benefits from the additional features available after effective noise reduction in longer windows.The linear discriminant analysis (LDA) demonstrated a moderate positive relationship with $r = 0.4046$ ($p < 0.001$, $n = 192$) which reflects how it uses time-dependent information yet performs less well than SVM. The moderate correlation indicates that LDA gains from longer windows yet its linear assumptions limit its ability to extract intricate temporal patterns in motor imagery data.

KNN showed distinct performance from other models through its weak non-significant correlation ($r = 0.1371$, $p = 0.058$, $n = 192$) indicating its instance-based classification performance remains independent from window size. This discovery implies KNN is the better choice for BCI systems needing stable performance despite changing temporal limitations because it works well for BCI systems that change their window dimensions to match signal strength or user state changes.

Individual participant analysis showed significant variability, questioning universal BCI solutions. The performance profiles of individual participants are shown in Figure 5 which demonstrates how different neural characteristics of each person and system parameters interact with each other.

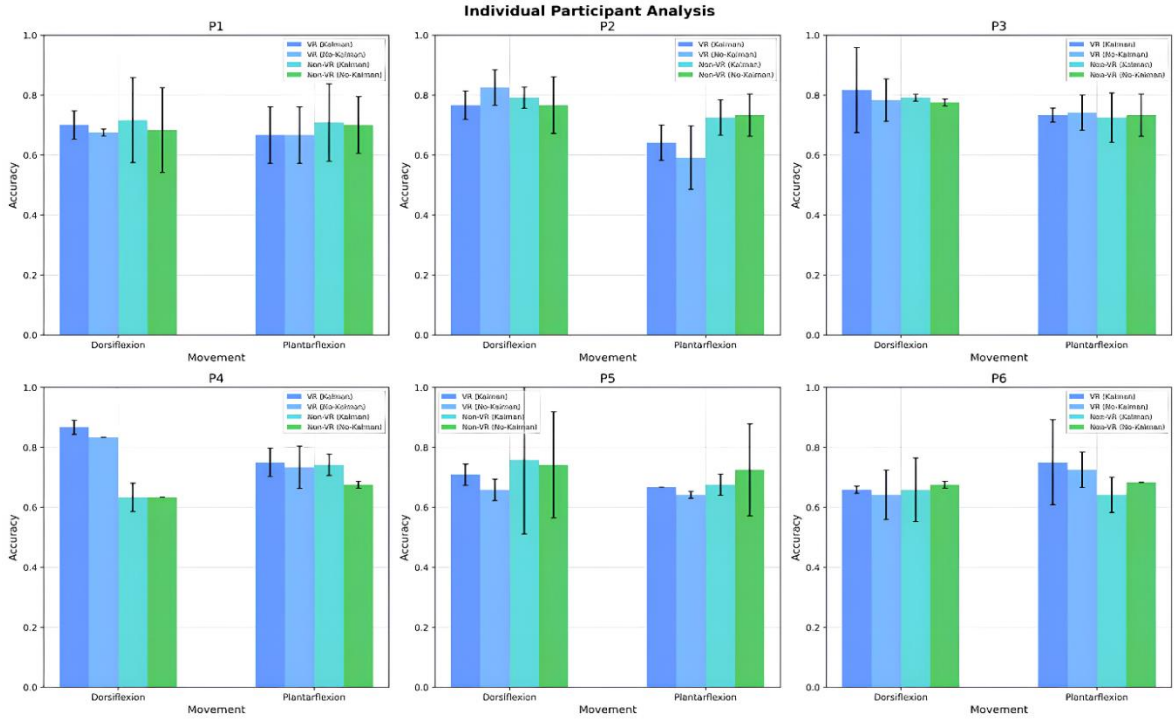


Figure 5. Individual participant performance comparing VR and non-VR visualization methods for each movement type in the 2s window.

We achieved best results by using a 2s window with SVM on filtered data while using a 2s overlap with LDA on non-filtered data. P1 showed moderate improvements with Kalman filtering. The accuracy of dorsiflexion movements rose from 67.50% to 70.00% in the VR environment and from 68.33% to 71.67% in the non-VR environment. The non-VR condition showed high variability which made filtering not entirely effective. Plantarflexion showed minimal filtering effects.

The results from P2 were unanticipated because filtering produced negative effects in certain assessment conditions. The application of filtering led to a decline in dorsiflexion accuracy to 76.67% in the VR environment from its original 82.50% accuracy which indicates that the signals were already clean and filtering created interference. The VR plantarflexion accuracy improved to 70.00% following filtering even though the movement type created complex effects on preprocessing.

P4 demonstrated outstanding baseline capabilities along with considerable advantages from filtering when specific circumstances applied. The filtering process improved the VR dorsiflexion accuracy to 86.66% which approached theoretical maximum performance. Non-VR dorsiflexion accuracy remained substantially lower at 63.33% which proved that visual feedback played a critical role in the process.

The filtering outcomes for P5 were inconsistent because it led to a 5% boost in VR dorsiflexion performance yet resulted in a 5% decrease for non-VR plantarflexion measurements thus showing task-dependent filtering outcomes. The filtering effects on P6 produced diverse results that sometimes benefited performance but at other times damaged it. The 4.16% decrease in non-VR plantarflexion accuracy demonstrates why proper validation becomes crucial.

The observed differences between filtering effects range from -5.83% to +6.67% which demonstrates the necessity of individualized calibration procedures. Adaptive systems require the ability to choose preprocessing

strategies dynamically because of the complex interactions between parameters. The study demonstrates that basic non-VR systems with appropriate filtering achieve performance levels matching advanced VR systems without their excessive cost or complexity.

4 Conclusion

This study demonstrates that Kalman filtering brings specific advantages to EEG-based motor intention classification yet the effectiveness depends on time window duration and personal characteristics. The accuracy increases substantially for 1s overlapping time windows (52-54% vs. 47-50%, $p < 0.01$), but short non-overlapping time windows (250-500ms) yield small improvements (<1%) and some configurations of 2s windows produce decreased performance. Real-time prosthetic systems require adaptive filtering approaches that must be tailored to each user because individual differences in accuracy range from -2.5% to +3.4%. The performance results between VR and non-VR environments show only 1-3% distinction which contests the idea that immersive environments are required for successful motor imagery training. The findings support the implementation of low-cost non-VR interfaces as an alternative to expensive immersive systems because they deliver equivalent performance results. SVM performance reached 72.05% ± 8.71% accuracy with 2s windows to establish a new benchmark for foot motor imagery classification accuracy and a strong positive correlation between SVM performance and temporal window size ($r = 0.5412$, $p < 0.001$) helps applications maximize accuracy at the expense of speed. Research will continue to conduct real-time tests on the UFES Leg robotic prosthesis while developing hybrid or adaptive filter methods to enhance performance through EEG signal quality and characteristics analysis [18].

Acknowledgements. This work was partially funded by grants from FAPES (Fundação de Amparo à Pesquisa do Espirito Santo, Grant: 946/2023, No. 2023-F0GWQ, Grant: 565/2023, No. 2023-BQK22), MCTI/FINEP (Financiadora de Estudos e Projetos) with resources from FNDCT (ref. 2784/20 and ref. 2790/20), National Council for Scientific and Technological Development (CNPq) (project 442445/2023-7 and project 402317/2023-8) and CAPES (Coordination for the Improvement of Higher Education Personnel, Financial Code 001). The author also acknowledges receipt of a master's scholarship from FAPES under Edital No. 13/2023 – PROCAP MESTRADO 2024 (Process No. 230/2024; Scholarship No. 2024-RDBHR), funded by FUNCITEC and awarded at the Federal University of Espírito Santo (UFES), effective June 1, 2024.

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