Journal of Multi Disciplinary Engineering Technologies
Volume 19, Issue 01
DOI: https://doi.org/10.64992/jmdet.vol.19.issue.1.1

# Estimation of BCI Model Based on Non-linear Oscillator Using UKF-Based Training Method

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**Abstract**

This research focuses on developing a mathematical model to estimate neurological signal parameters for investigating brain dynamics. The proposed model leverages the nonlinear dynamics of oscillator models, assuming that an individual's brain state can be represented by an unknown parameter vector denoted as $\boldsymbol{\theta}$. To address the challenge of handling noisy training data, an Unscented Kalman Filter (UKF) is employed in a joint training process involving EEG and speech signals. This method allows for precise estimation of the parameters $\boldsymbol{\theta}$ and $\boldsymbol{\phi}$, which are associated with EEG and speech signals, respectively. The validation procedure includes comparing the estimated EEG with the actual EEG and accounting for noise in the speech signal. The Unscented Kalman filter helps enhance the accuracy of synthesizing EEG signals and contributes to the modeling efficiency and reliability. Overall, the incorporation of the UKF in the modeling process improves the ability to capture the intricate dynamics of EEG signal generation based on speech data.

**Keywords:** EEG (Electroencephalogram), Speech, BCIs (Brain Computer Interference), UKF (Unscented Kalman Filter), Non-linear Dynamics

## 1 Introduction

This study introduces a mathematical model that focuses on estimating parameters of neurological signals within the context of brain dynamics. It employs nonlinear oscillator dynamics, emphasizing the role of an unknown parameter vector. This vector plays a crucial part in the harmonic process responsible for generating EEG signals. The model explores the relationship between EEG and speech signals, establishing an equation that governs speech signals based on these parameters. Parameter estimation is conducted using the Unscented Kalman Filter (UKF) by analyzing combined EEG and speech signals from 'N' individuals during training. The model's effectiveness is evaluated by estimating EEG parameters from the speech signal of a new individual not included in the training process using a dedicated function, thereby validating the suggested approach. Using the Unscented Kalman Filter (UKF), this study illustrates the value of nonlinear modeling in auditory processing to synthesize EEG signals from speech inputs, which excels over the Extended Kalman

Filter (EKF) by more adeptly managing complex parameter couplings in dynamic speech models and reducing computational complexity. Mathematical modeling of speech dynamics is pivotal in the speech chain, enabling observation, hypothesis formulation, testing, and prediction, thereby driving the evolution of new theories and phenomena in scientific reports [1]. A mathematical model to estimate neurological signal parameters from EEG and speech data using nonlinear dynamics and an Extended Kalman Filter (EKF). It validates the model by synthesizing EEG from speech data of new individuals, demonstrating its effectiveness in predicting and classifying brain states [2].

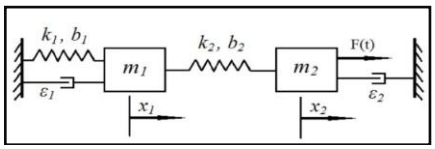


**Fig. 1**: Block diagram of Stochastic Coupled Duffing vander Pol Oscillator model fig[3]

Sample entropy improves the depiction of EEG signals by the stochastic non-linear oscillator model, effectively differentiating between healthy individuals and those with Alzheimer's across various eye conditions. Precise parameter and noise intensity selection enable accurate reflection of power spectral densities, highlighting its effectiveness in capturing non-linear signal details across diverse brain states[4]. An ODLM is designed to improve EEG-based speech recognition, which is essential for enhancing human-machine interactions and daily activities. By integrating the DBNN with the EOA, the ODLM method achieves superior results in speaker identification, surpassing conventional techniques like RNN-PSO, SVM, and ANN[3]. Investigates emotion analysis using EEG by employing non-linear characteristics and ensemble learning techniques. Extracting complex brain dynamics and non-linear features from EEG data enhances emotion classification accuracy. It also demonstrates the effectiveness of this approach in accurately identifying and analyzing emotions [5]. EEG/MEG studies demonstrate accessible directional and nondirectional kinematics, enhancing decoding accuracy in low-frequency signals through the use of an Unscented Kalman filter (UKF) [6]."De-noising of EEG for brainstem speech-evoked potentials in 10 subjects, employing methods such as the Yule-Walker Multiband Filter, various wavelet families, FAST Independent Component Analysis, and a hybrid algorithm."Daubechies and translation-invariant wavelets are favored, and CSTIICA shows potential for superior auditory artifact removal. It investigates multiple denoising approaches for EEG signals related to Brainstem Speech Evoked Potentials, assessing their ability to minimize noise and enhance metrics such as SNR and MSE. It emphasizes the enhanced denoising performance of the combined TI Wavelets and ICA (CSTIICA) technique over other methods [7]. Combining a new cross-correlation feature extractor with a Least Squares Support Vector Machine (LS-SVM) is a hybrid algorithm that improves the classification of motor imagery (MI) signals in brain-computer interfaces (BCIs). Comparative analyses reveal that LS-SVM performs better than both logistic regression and kernel logistic regression. Tested on BCI Competition III datasets, it outperforms eight recent algorithms, boasting accuracy improvement[8]. EEG signals to distinguish covert speech tasks, achieving accuracy in identifying speech from rest using an MLP artificial neural network. Discrimination between "yes" and "no" indicates covert speech's potential as an intuitive BCI activation task for communication[9]. An LSTM-based architecture attains a mean classification accuracy in determining correspondence between EEG and speech envelope, surpassing a CNN-based model and a linear model. A novel speech decoder architecture called the Very Large Augmented Auditory Inference (VLAAI) network. This neural network outperforms traditional models significantly by utilizing non-linear components to decode speech from EEG data, demonstrating enhanced performance and identifying influential elements[10]. It delves into human activity recognition by integrating current advancements such as unsupervised learning and transfer learning, and it highlights ongoing research areas needing further exploration

[11]. Motion Binary Patterns (MBPs), a novel spatiotemporal descriptor merging (VLBPs), Volume Local Binary Patterns and Optical Flow. Evaluated on KTH, Weizman, and IXMAS datasets with a Random Forest classifier, MBPs, and VLBPs achieve competitive accuracy in recognition of human actions surpassing cutting-edge techniques[12].

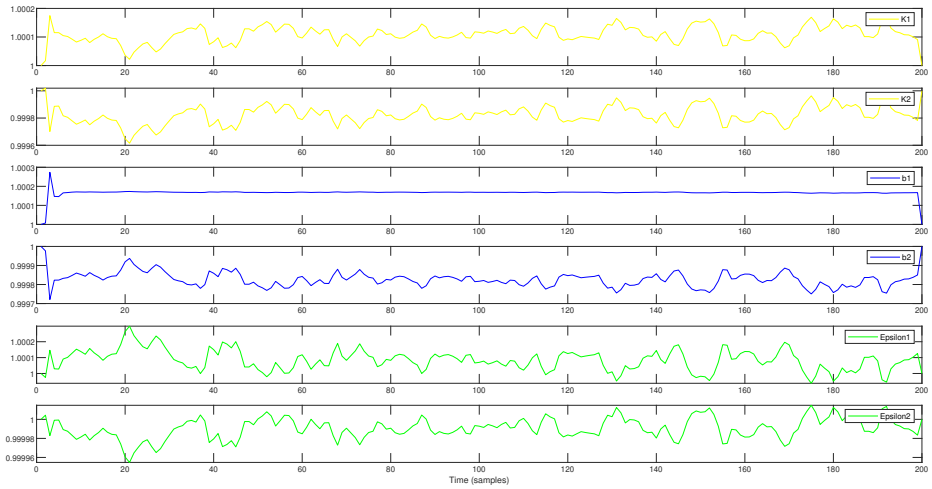


**Fig. 2**: EEG parameters generated by the oscillator model

It introduces the depth-based online system for Human Activity Recognition (HAR) system with novel multi-fused features, achieving superior recognition accuracy on IM-DailyDepthActivity, MSRAction3D, in comparison to cutting-edge techniques using MSR DailyActivity3D datasets [13] "A methodical strategy for continuous human activity recognition (HAR) employing the Microsoft Kinect, emphasizing a coarse-to-fine approach that addresses the constraints of isolated activities. It employs 3D skeleton trajectories alongside BLSTM-NN (Bidirectional Long Short-Term Memory Neural Network) and achieves rates of recognition with high chances of accuracies using length-modeling, respectively, surpassing previous techniques in continuous HAR[14]. Non-linear dynamic [15]models have proven effective in biomedical applications involving data from electrocardiograms (ECG), magnetoencephalograms (MEG), and electroencephalograms (EEG). Various techniques are employed to study brain dynamics, such as Computer Tomography and Electroencephalography (EEG). Of these, EEG is particularly advantageous as it provides real-time measurements, making it valuable for practical applications. The research identifies a gap in existing literature concerning the nonlinear characteristics of EEG signals that the transformation techniques cannot accommodate. This study has addressed this gap through the application of mathematical modeling using a nonlinear oscillator model and speech dynamics. This study enhances motor imagery-based brain-computer interfaces by introducing advanced filtering and channel selection methods that significantly improve feature extraction, demonstrated through superior performance on BCI competition datasets. The methodology utilizes a novel regression model to estimate EEG parameters from noisy speech signals using the Unscented Kalman Filter, enabling the prediction of brain states and integration into a speech model dependent on EEG parameters. The Unscented Kalman Filter (UKF) enhances neurological signal parameter estimation by adeptly handling nonlinearities, ensuring accurate, robust predictions, and improving the classification of brain dynamics through effective EEG and speech signals correlation. Some of the research highlights are

1. The study investigates the modeling of EEG and speech signals through stochastic differential equations, with a specific emphasis on scenarios where parameters are unknown.
2. The Unscented Kalman Filter (UKF) plays a crucial role in estimating these parameters within both EEG and speech models.
3. A Linear Regression for Estimating Speech Parameters from EEG and establishing a strong Correlation between Speech and EEG Parameters.
4. Mathematically model the EEG parameters using speech signal.

There are seven sections in this paper. The introductory remarks are found in Section 1. Section 2 explores the dynamics of speech and the analysis of EEG signals. Section 3 details the method for parameter estimation using the UKF algorithm. Section 4 is dedicated to the simulation and implementation aspects. The results are discussed in Section 5. In Section 6, conclusions are presented. Finally, Section 7 addresses the declaration.

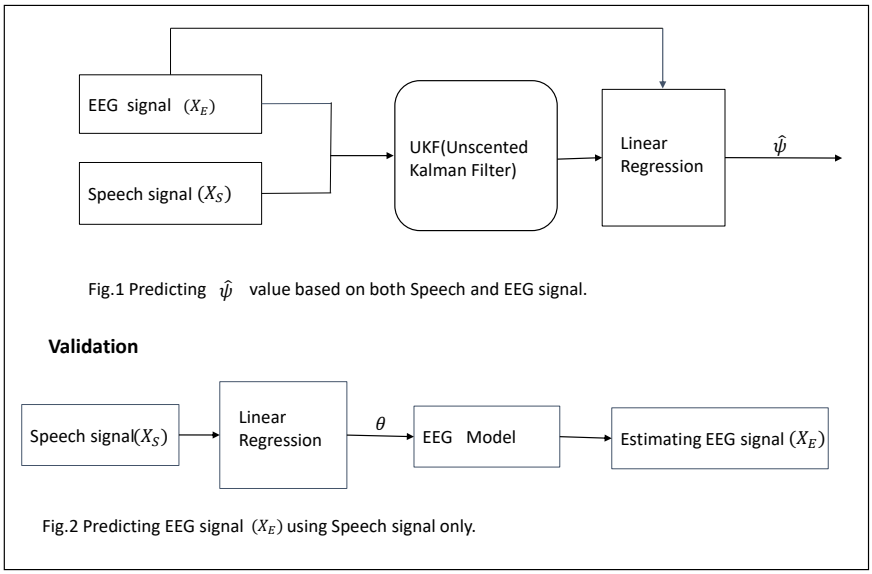


**Fig. 3**: A block diagram for the Estimation of an EEG signal from a Speech signal

## 2 Speech Dynamics and EEG

A non-linear oscillator model is used for the generation of EEG signal given by the following system of equations:

$$\frac{d^2x_1}{dt^2} + (k_1 + k_2)x_1 - k_2x_2 + b_1x_1^3 + b_2(x_1 - x_2)^3 - \epsilon_1\frac{dx_1}{dt}(1 - x_1^2) = 0 \tag{1}$$

$$\frac{d^2x_2}{dt^2} - k_2x_1 + k_2x_2 - b_2(x_1 - x_2)^3 - \epsilon_2\frac{dx_2}{dt}(1 - x_2^2) = \mu\frac{dw}{dt} \tag{2}$$

The parameters $k_1$, $k_2$, $b_1$, $b_2$, $\epsilon_1$, and $\epsilon_2$ are considered as the EEG parameters denoted as '$\theta$'. Using non-linear differential equations and perturbation theory enables the linearization of the model. The first-order dynamical model governing the generation of speech signals encompasses a

differential equation elucidating the temporal evolution of the speech signal.

$$X_S(t+1) = r_{s1}X_S(t) + r_{s2} + W_S(t+1) \tag{3}$$

where $r_{s1}$ and $r_{s2}$ are speech parameters is used to form a '$\phi$' vector. $\phi = [r_{s1}, r_{s2}]^T$ are that the speech parameters.

# 3 Parameter Estimation of EEG Signals applied to Speech model with the Unscented Kalman Filter (UKF) Algorithm

The equation for updating the EEG parameters is

$$\theta(t+1) = \theta(t) + W_\theta(t+1) \tag{4}$$

This implies that the EEG parameters are almost constant over time, except for noise. A dynamic equation describing the evolution of the speech signal at the time $(t+1)$ is obtained by assuming the EEG parameter to be linearly correlated with the speech parameter i.e.

$$\phi = \psi_0^T\theta + \psi_1 + \psi_2^T\theta + \psi_3 \tag{5}$$

$$S(t+1) = (\psi_0^T\theta(t) + \psi_1)S(t) + \psi_2^T\theta(t) + \psi_3 + W_s(t+1) \tag{6}$$

The measurement model relates to the observed measurement $z(t)$ to the Speech signal $S(t)$

$$z(t) = S(t) + V_s(t) \tag{7}$$

The measurement algebra up to time $t$ is $Z_t = \zeta(S) : S \leq t$. The combined state vector representation is

$$\zeta(t) = \begin{bmatrix} S(t) \\ \theta(t) \end{bmatrix} \tag{8}$$

The covariance matrix representing the uncertainty in the state estimation at the time $t$

$$P(t|t) = \begin{bmatrix} P_{ss}(t|t) & P_{s\theta}(t|t) \\ P_{\theta s}(t|t) & P_{\theta\theta}(t|t) \end{bmatrix} \tag{9}$$

The prediction covariance matrix indicates the predicted uncertainty in the state at the time

$$P(t+1|t) = \begin{bmatrix} P_{ss}(t+1|t) & P_{s\theta}(t+1|t) \\ P_{\theta s}(t+1|t) & P_{\theta\theta}(t+1|t) \end{bmatrix} \tag{10}$$

$$\sqrt{P(t|t)} = Q(t|t) \tag{11}$$

$$\sqrt{P(t+1|t)} = Q(t+1|t) \tag{12}$$

The UKF estimate state estimate updates are as follows:

$$\hat{S}(t+1|t) = \frac{1}{K}\sum_{m=1}^{K}[(\psi_0^T(\hat{\theta}(t|t) + Q_{\theta s}(t|t)\eta_{sm} + Q_{\theta\theta}(t|t)\eta_{\theta m}) + \psi_1) \\ (\hat{S}(t|t) + Q_{ss}(t|t)\eta_{sm} + Q_{s\theta}(t|t)\eta_{\theta m})]$$

$$+\frac{1}{K}\sum_{m=1}^{K}[\psi_2^T(\hat{\theta}(t|t)+Q_{\theta s}(t|t)\eta sm+Q_{\theta\theta}(t|t)\eta_{\theta m})+\psi_3]$$

$$e(t|t)=\begin{bmatrix}\hat{S}(t|t)\\ \hat{\theta}(t|t)\end{bmatrix}-\begin{bmatrix}S(t)\\ \theta(t)\end{bmatrix}=\begin{bmatrix}\eta_s(t|t)\\ \eta_\theta(t|t)\end{bmatrix} \tag{13}$$

Note that this formula is based on the following approximation of the covariance mean

$$|E[f(S(t)),\theta(t)|Z_t]=|E[f(\hat{S}(t|t))+\eta_s(t|t),\hat{\theta}(t|t)+\eta_\theta(t|t)] \tag{14}$$

$$=|E[f(\hat{S}(t|t),\hat{\theta}(t|t))^T+\eta_{(t|t)}] \tag{15}$$

$$=\frac{1}{K}\sum_{m=1}^{K}f(\hat{S}(t|t),\hat{\theta}(t|t))^T+\sqrt{P(t+1|t)}\eta_m \tag{16}$$

where

$$\{\eta_m\}_{m=1}^{K}$$

are iid standard Gaussian vector and $\eta_m=\begin{bmatrix}\eta_{sm}\\ \eta_{\theta m}\end{bmatrix}$

$$\sqrt{P(t+1|t)}\eta_m=Q(t|t)\eta_m=\begin{bmatrix}Q_{ss}(t|t) & Q_{s\theta}(t|t)\\ Q_{\theta s}(t|t) & Q_{\theta\theta}(t|t)\end{bmatrix}\begin{bmatrix}\eta_{sm}\\ \eta_{\theta m}\end{bmatrix} \tag{17}$$

i.e. the residual components are

$$e_s(t|t)=Q_{ss}(t|t)\eta_{sm}+Q_{s\theta}(t|t)\eta_{\theta m} \tag{18}$$

$$e_\theta(t|t)=Q_{\theta s}(t|t)\eta_{sm}+Q_{\theta\theta}(t|t)\eta_{\theta m}\leq m\leq K \tag{19}$$

The state estimate and prediction error covariance

$$\begin{bmatrix}\hat{S}(t+1|t+1)\\ \hat{\theta}(t+1|t+1)\end{bmatrix}=\hat{\zeta}(t+1|t+1) \tag{20}$$

$$=|E[\zeta(t+1)|Z_t,z(t+1)] \tag{21}$$

$$=E[\zeta(t+1)|Z_t]-Cov(\zeta(t+1),z(t+1)|Z_t)Cov(z(t+1)|Z_t)^{-1}(Z(t+1)$$
$$-E[(Z(t+1)|Z_t))]$$

$$=\hat{\zeta}(t+1|t)-C_1C_2(Z(t+1)-\hat{\zeta}(t+1|t)) \tag{22}$$

where

$$C_1=Cov(\zeta(t+1),z(t+1)|Z_t)=\frac{1}{K}\sum_{m=1}^{K}[Q(t+1|t)\chi_m\chi_{sm}^T\theta(t+1|t)_{ss}] \tag{23}$$

where $\chi_m$,$m=1,2,...K$ are again iid Gaussian random vectors. The measurement equation in matrix form is given by

$$\zeta(t+1)=H*\zeta(t+1)+V(t+1) \tag{24}$$

and $H=[I:0]$ and the covariance conditional measurement is defined by

$$C_2=Cov(\zeta(t+1)|Z_t)_{R_{vs}}=Cov(S(t+1)|Z_t)_{R_{vs}}+P_{ss}(t+1|t)) \tag{25}$$

where the prediction error covariance matrix

$$P(t+1|t)=\begin{bmatrix}P_{ss}(t+1|t) & P_{s\theta}(t+1|t)\\ P_{\theta s}(t+1|t) & P_{\theta\theta}(t+1|t)\end{bmatrix} \tag{26}$$

where UKF approximation is

$$P(t+1|t) = Cov[\zeta(t+1)|Z_t] \tag{27}$$

$$P(t+1|t) = Cov[\begin{bmatrix} S(t) \\ \theta(t) \end{bmatrix} + \begin{bmatrix} \psi_0^T\theta(t) + \psi_1 \\ \psi_2^T\theta(t) + \psi_3 \end{bmatrix} + \begin{bmatrix} W_s(t+1) \\ W_\theta(t+1) \end{bmatrix} |Z_t] \tag{28}$$

$$= Cov[\begin{bmatrix} S(t+1) \\ \theta(t+1) \end{bmatrix} |Z_t] \tag{29}$$

so that

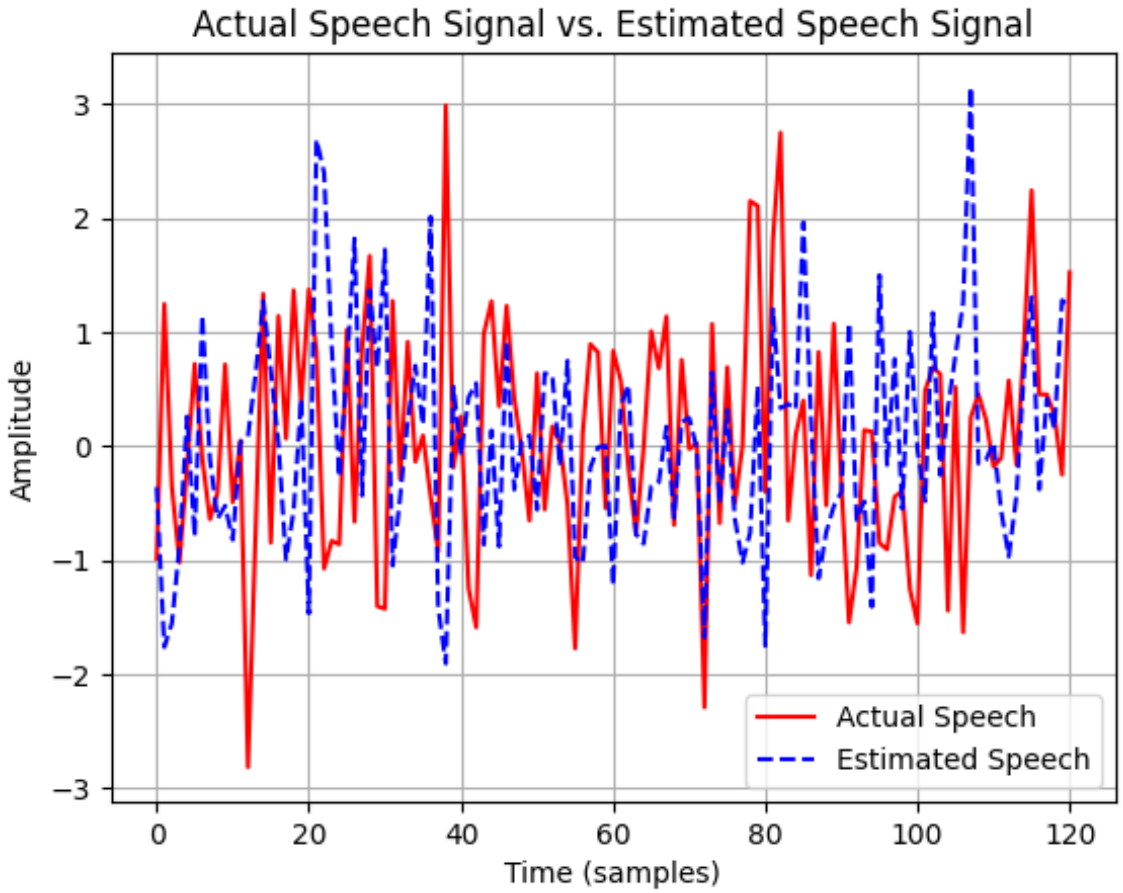


**Fig. 4**: Plot between the Actual Speech signal and Estimated speech signal

$$= \frac{1}{K}\sum_{m=1}^{K}\Big[(\psi_0^T(\hat{\theta}(t|t) + Q_{\theta s}(t|t)\eta_{sm} + Q_{\theta\theta}(t|t)\eta_{\theta m} + \psi_1)(\hat{S}(t|t) + Q_{ss}(t|t)\eta_{sm} + Q_{s\theta}(t|t)\eta_{\theta m}) + \psi_2^T(\hat{\theta}(t|t) + Q_{\theta s}(t|t)\eta_{sm} + Q_{\theta\theta}(t|t)\eta_{\theta m}) + \psi_3)\Big][n]^T - \hat{S}(t+1|t)\hat{S}(t+1|t)^T$$

$$\zeta(t+1) = \begin{bmatrix} S(t+1) \\ \theta(t+1) \end{bmatrix} \tag{30}$$

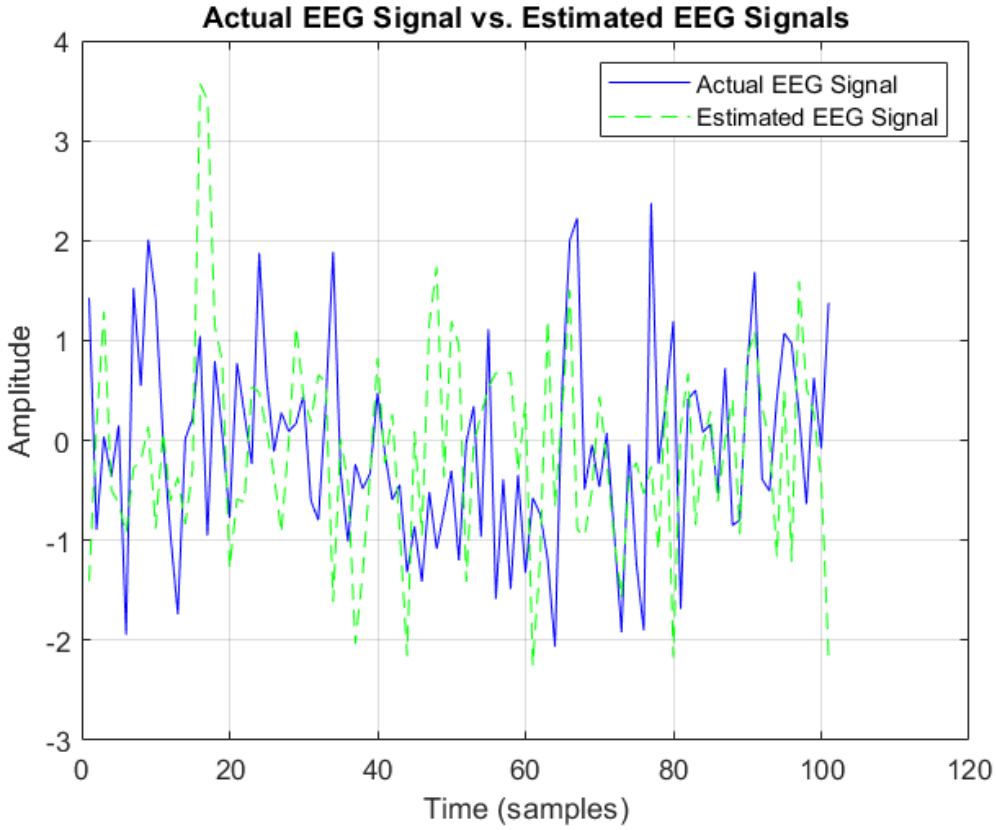


**Fig. 5**: Estimated EEG and Actual EEG

$$= \begin{bmatrix} (\psi_0^T\theta(t)+\psi_1)S(t)+\psi_2^T\theta(t)+\psi_3 \\ \theta(t) \end{bmatrix} + \begin{bmatrix} W_s(t+1) \\ W_\theta(t+1) \end{bmatrix} \tag{31}$$

$$P(t+1|t) = \frac{1}{K}\sum_{m=1}^{K} \begin{bmatrix} (\psi_0^T\hat{\theta}(t|t)+Q_{\theta s}(t|t)\eta_{sm}+Q_{\theta\theta}(t|t)\eta_{\theta m}+\psi_1) \\ (\hat{S}(t|t)+Q_{ss}(t|t)\eta_{sm}+Q_{s\theta}(t|t)\eta_{\theta m}) \\ +\psi_2^T(\hat{\theta}(t|t)+Q_{\theta s}(t|t)\eta_{sm}+Q_{\theta\theta}(t|t))\eta_{sm}+\psi_3 \\ \hat{\theta(t)}(t|t)+Q_{\theta s}(t|t)\eta_{sm}+Q_{\theta\theta}(t|t)\eta_{\theta m}[n]^T \end{bmatrix}$$
$$- \begin{bmatrix} (\psi_0^T\hat{\theta}(t|t)+\psi_2)\hat{S}(t|t)+\psi_2^T\hat{\theta}(t|t)+\psi_3 \\ \hat{\theta}(t|t) \end{bmatrix}[n]^T + R_w$$

where

$$R_w = \begin{bmatrix} R_{ws} & R_{w\theta} \\ R_{\theta w} & R_{\theta W} \end{bmatrix} \tag{32}$$

$$Cov(\zeta(t+1)|Z_t) = Cov(S(t+1)+V_s(t+1)|Z_t) \tag{33}$$

$$= R_{vs} + Cov(S(t+1)|Z_t) \tag{34}$$

$$= R_{vs} + Cov(\hat{S}(t+1|t)+e_s(t+1|t)|Z_t) \tag{35}$$

$$= R_{ws} + Cov(e_s(t+1|t)|Z_t) \tag{36}$$

$$= R_{vs} + P_s(t+1|t) \tag{37}$$

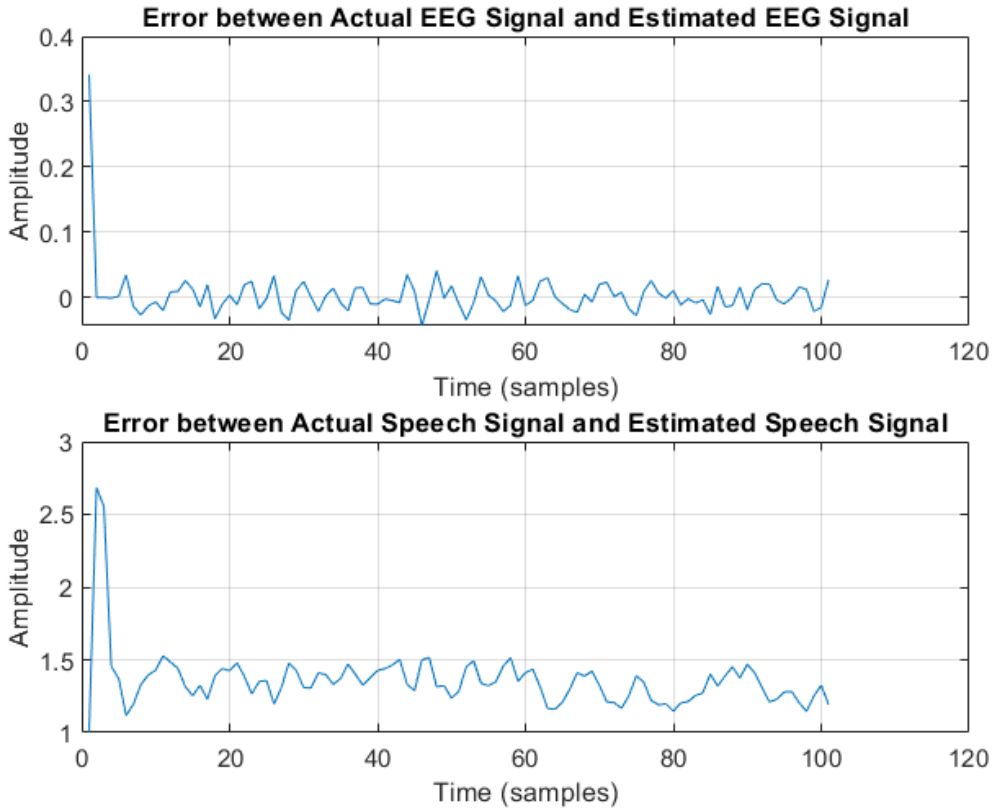


**Fig. 6**: Error plots

The new measurement of time $(t+1)$ is

$$P(t+1|t+1) = Cov(\zeta(t+1)|Z_{t+1}) \tag{38}$$

$$= Cov(\zeta(t+1)|Z_t, z(t+1)) \tag{39}$$

$$= \mathrm{Cov}(\zeta(t+1) \mid Z_t) - \mathrm{Cov}(\zeta(t+1), z(t+1) \mid Z_t)\,\mathrm{Cov}(z(t+1) \mid Z_t)^{-1}\,\mathrm{Cov}(z(t+1), \zeta(t+1) \mid Z_t) \tag{40}$$

The estimation of an error covariance update is given by

$$Cov(\zeta(t+1), z(t+1)|Z_t) = Cov(\begin{bmatrix} S(t+1) \\ \theta(t+1) \end{bmatrix}, S(t+1) + V_s(t+1)|Z_t) \tag{41}$$

$$= Cov(\begin{bmatrix} S(t+1) \\ \theta(t+1) \end{bmatrix}, S(t+1)|Z_t) \tag{42}$$

$$= Cov(\begin{bmatrix} \hat{S}(t+1|t) \\ \hat{\theta}(t+1|t) \end{bmatrix} + \begin{bmatrix} e_s(t+1|t) \\ e_\theta(t+1|t) \end{bmatrix}, S(t+1)|Z_t) \tag{43}$$

$$= Cov(\begin{bmatrix} e_s(t+1|t) \\ e_\theta(t+1|t) \end{bmatrix}, e_s(t+1|t)|Z_t) \tag{44}$$

$$= \begin{bmatrix} Pss(t+1|t) \\ P_{\theta s}(t+1|t) \end{bmatrix} \tag{45}$$

Note that

$$P(t+1|t) = \begin{bmatrix} Pss(t+1|t) & Ps\theta(t+1|t) \\ P_{\theta s}(t+1|t) & P_{\theta\theta}(t+1|t) \end{bmatrix} \tag{46}$$

with

$$P_{\theta s}(t+1|t) = P_{s\theta}(t+1|t)^T$$

The algorithm begins by initializing the state vector $\zeta(0) = [S(0), \theta(0)]^\top$ along with the initial covariance matrix $P(0|0)$, also defines the process and measurement noise parameters. From this state and covariance, sigma points are generated to capture the uncertainty in the system. These sigma points are then propagated through the speech–EEG model defined in equations (4) and (5) to obtain the predicted state. Using the measurement model described in equation (6), the predicted measurement $\hat{z}(t)$ is derived from the predicted speech state. The Kalman gain is subsequently computed from the cross-covariance between state and measurement, as well as the measurement covariance. With the actual speech measurement $z(t)$ the state estimate $\hat{\zeta}(t)$ and the covariance are updated. Finally, the updated EEG parameters $\hat{\theta}(t)$ are utilized within the nonlinear oscillator model defined by equations (1) and (2) to synthesize the EEG signal.

# 4 Simulation and Implementation

In this research, we model electroencephalogram (EEG) signals using linear differential equations with an unknown EEG parameter $\theta$, which plays a crucial role in signal estimation. Similarly, speech signals are modeled using a combination of linear and polynomial dynamics to capture unknown speech characteristics for the same subjects. We hypothesize a potential correlation between an individual's speech and EEG signals. To investigate this, we develop a linear model that maps EEG parameters to speech attributes, with the model parameters determined through a training process involving $'K = 120'$ simulated individuals. EEG signals were sampled at 512 Hz and speech signals at 16 kHz, with each trial lasting 5 seconds. The Unscented Kalman Filter (UKF) was used to estimate the EEG parameters $\hat{\theta}$ from the generated speech parameters. For model validation, we predict the EEG parameter for a new individual by using the speech parameters derived from their speech signal. We then use an affine linear regression to correlate the predicted EEG parameters with the actual speech parameters for each subject. This method enables us to calculate the EEG parameter for an individual, which helps in generating their EEG signal with our pre-existing model. This synthesized signal is then matched with known EEG signals. Fig. 2 represents the parameters of EEG generated by the oscillator model and Fig. 6 represents the error plots between the Actual EEG signal and estimated EEG signal and also the error plot between the Actual speech signal and the estimated speech signal.

# 5 Results

In this study, we model EEG signals using linear differential equations with unknown parameters, denoted by $\theta$, which serve as classification features. Speech signals from the same subjects are modeled using a linear–polynomial (L/P) framework that incorporates unknown parameters as well. We hypothesize that the speech parameters are correlated with the EEG parameters, enabling the formulation of a linear function that maps speech parameters to EEG parameters. For parameter estimation, we employ the Unscented Kalman Filter (UKF), which is more effective at handling the nonlinearities inherent in this data compared to the Extended Kalman Filter (EKF) used in prior work. From the $K = 120$ simulated individuals are generated, and their EEG and speech parameters are estimated using the respective models. During validation, the EEG parameters of a new simulated individual are estimated solely from their speech signal, using the UKF to process the measured speech parameters through the speech model. An affine linear regression model is then applied to map each individual's speech parameters to their EEG parameters. Figure 4 presents the plot of actual versus estimated EEG signals, while Figure 5 shows the plot of actual versus

estimated speech signals. These estimates are compared against the ground-truth simulated EEG classes to accurately reconstruct the individual's EEG signal using the EEG model. The proposed UKF-based framework outperforms the conventional EKF, achieving low RMSE 0.055, very low NSR and high correlation for EEG estimation, clearly demonstrating its superior accuracy and robustness in modeling EEG signals.

# 6 Conclusion

This work presented a UKF-based framework for estimating EEG parameters from speech-derived features, using a coupled nonlinear oscillator EEG model and a polynomial speech dynamics model. The proposed method was validated in a fully controlled simulation environment, in which both EEG and speech signals were synthetically generated with physiologically realistic parameter variations and subjected to additive noise. The results demonstrated accurate recovery of EEG parameters and effective reconstruction of EEG and speech signals, as evidenced by low noise-to-signal ratio values. The exclusive use of synthesized data in this study enabled precise control over parameters, noise, and variability, thereby isolating algorithm performance from real-world artifacts. Future work will focus on applying the method to experimentally recorded EEG and speech data to evaluate its performance under realistic conditions and to compare it with established methods.

# Declarations


- The authors received no specific funding for this study.
- The authors declare that they have no conflicts of interest to report regarding the present study.
- No Human subject or animals are involved in the research.
- All authors have mutually consented to participate.
- All the authors have consented the Journal to publish this paper.
- Authors declare that all the data being used in the design and production cum layout of the manuscript is declared in the manuscript.


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