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Evaluation of Electroencephalography Signals in Alzheimer's Disease Using Coherence Analysis and Persistent Homology

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Abstract

Objective: This study aimed to use a new approach, namely persistent homology, to analyse electroencephalogram (EEG) coherence and identify the alterations in brain connectivity in patients with Alzheimer's disease (AD).

Materials and Methods: We applied persistent homology to the distance maps that we created using the EEG coherence values from five different frequency bands in order to determine if there are disruptions specific to these bands in patients diagnosed with AD.

Results: Our findings revealed that the features extracted using persistent homology were significantly different in two bands (delta and theta) between AD patients and subjects in the healthy control (HC) group. Furthermore, the machine learning algorithms using these topological features achieved accurate classification results. This suggests that persistent homology may be a useful adjunct in the diagnosis of AD.

Conclusion: We have demonstrated the potential of persistent homology in identifying AD-related changes in brain connectivity, which are the most clearly present in the theta and delta bands. Larger datasets should be used in future research to determine the clinical relevancy of this method.

Keywords Alzheimer's disease · EEG · Coherence · Persistent homology

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INTRODUCTION

Dementia has become one of the leading causes of death in recent years, and with a rapidly ageing global population, its prevalence is expected to rise (1). Alzheimer's disease (AD) accounts for the majority of dementia cases and it is characterised by progressive memory loss (2).

Memory impairment is usually the first symptom of AD and it typically begins after the age of 65 years. Disease progression is accompanied by executive dysfunction, impairment in judgement, loss of insight, visuospatial problems, language deficits and other neurological and psychiatric symptoms (3). Currently, no cure is available for AD, but there are treatment options intended to mitigate certain symptoms of the disease.

Histopathological examination is required to establish a definitive diagnosis of AD, but it is usually not used in clinical practice (4). Clinicians generally use neuropsychological tests, neuroimaging techniques, and molecular biomarkers when diagnosing patients with AD. Although it is not used in the routine evaluation, several studies suggest that electroencephalogram (EEG) might add confidence to the diagnosis and, as a non-invasive and relatively cheap technique, it could prove to be a valuable tool in discovering potential biomarkers for the disease (5, 6).

Because the visual assessment of EEG signals is somewhat subjective, various quantitative analyzing techniques have been used to evaluate the EEG data to help with the diagnosis of neurological disorders including AD (7-10). The analysis of quantitative EEG in Alzheimer's disease typically involves the extraction of features such as absolute power, relative power, coherence, sample entropy, and Lempel-Ziv complexity using signal processing techniques including the fast fourier transform (FFT), Welch's method, coherence analysis, and wavelet transform. These features are subsequently used in classification tasks employing traditional machine learning algorithms, such as support vector machine (SVM), random forest (RF), and k-nearest neighbours (kNN)- as well as advanced deep learning approaches, including convolutional neural networks (CNN), recurrent neural networks (RNN), and autoencoders (11). A consistent finding in numerous quantitative EEG studies is an increase in the slow frequency band (delta and theta) power, a decrease in the fast frequency band (alpha and beta) power and a reduction in the alpha band coherence in AD. (10, 12, 13). These findings were shown to be correlated with the disease severity (14), Mini-Mental State Examination (MMSE) scores (15), and different cognitive functions (16).

Functional connectivity analysis is one of the most commonly used quantitative EEG analysis methods. It measures coherence, which indicates the level of correlation between two signals in the frequency domain, providing insights into their functional connectivity (17). While traditional coherence analysis examines the pairwise relationships between electrodes, topological data analysis (TDA) enables the investigation of relationships beyond simple pairwise interactions, extending to structures such as triangles, tetrahedra, and higher-dimensional formations (18). A comparison of the two methods is shown in Table 1. One of the principal methods of TDA is persistent homology. It examines the evolution of the topological features across multiple scales (18). It extends classical homology by not only identifying the presence of features such as connected components, loops, and voids but also quantifying their persistence across different levels of detail. This makes persistent homology particularly effective for understanding the structure of data embedded in high-dimensional spaces.

Table 1. A comparison of the traditional coherence analysis and topological data analysis

Traditional Coherence Analysis	Topological Data Analysis
Based on Fourier transforms, spectral analysis, and correlation	Based on the algebraic topology and computational geometry
Limited to pairwise, linear interactions	Captures non-linear, higher-order structures and multiscale patterns in the data
Requires a fixed or manually chosen threshold	No need for an arbitrarily chosen threshold
Gives coherence values ranging from 0 to 1 between the channel pairs	Provides persistence diagrams showing the birth and death of topological features
Easy to interpret	Interpretation requires training

TDA has been used to extract topological features from EEG signals for various clinical applications such as detection of delirium (19), attention deficit hyperactivity disorder (ADHD) classification (20), identification of EEG characteristics in children with sleep apnoea (21), and discrimination of epileptic from the non-epileptic EEG signals (22). In recent years, it has been suggested that TDA, especially persistent homology, may prove to be useful in the diagnosis of AD (23). In our study, we used persistent homology with a coherence-derived distance metric to compute H_1 persistence to differentiate between the AD and HC groups. Given that AD is often associated with reduced coherence in certain frequency bands and brain regions, using a tool from TDA, we were able to evaluate the functional connectivity without being limited to pairwise interactions and arbitrarily determined thresholds, as is often the case with the traditional coherence-based methods. Choosing persistent homology over traditional coherence in our analysis allowed us to represent high-dimensional EEG data with compact

yet informative topological features that we then used for classification. The features extracted via persistent homology, which exhibited notable differences in the slower brain waves, were subsequently employed as input to various machine learning algorithms. These algorithms achieved accurate classification results, demonstrating the effectiveness of the topological features in distinguishing between the AD and HC groups.

MATERIALS AND METHODS

Dataset

We used the dataset provided by Miltiadous et al. (24). There were eyes-closed resting-state EEG recordings of 65 participants in this dataset. The demographic and clinical features of the participants are presented in Table 2.

The duration of each recording was approximately 13.5 min for the AD group (min=5.1, max=21.3) and 13.8 min for the HC group (min=12.5, max=16.5) and the total duration of the recordings was 485.5 min for the AD group and 402 min for the HC group.

The EEG signals recorded from the 19 channels were pre-processed following the steps described in Miltiadous et al. (24). The first step of the pre-processing was re-referencing the signals to the average of A1-A2. Subsequently, a Butterworth band-pass filter (0.5–45 Hz) was applied to achieve noise reduction. The ASR routine was then used for automatic artefact rejection. Independent component analysis (ICA) decomposed the signals into 19 components, with the eye and jaw artefacts automatically removed. The baseline correction was applied to reduce the high-frequency artefacts as the last step. We used these pre-processed EEG data in our analysis.

Coherence Analysis

As the first step in the coherence analysis, FFT was used to transform the signals into the frequency domain, and subsequently these signals were divided into five widely studied frequency bands: Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–25 Hz), and Gamma (25–45 Hz) bands. Coherence, more specifically, magnitude-squared coherence, was computed for each frequency band according to the following formula:

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)} \quad (1)$$

where $C_{xy}(f)$ is the coherence value between the x and y signals at an f frequency, $P_{xy}(f)$ is the cross-spectrum, which represents the shared power between x and y at an f frequency, $P_{xx}(f)$ is the power spectrum density for the x signal, and $P_{yy}(f)$ is the power spectrum density for the y signal.

The coherence values range between 0 and 1. The closer a value is to 1, stronger the synchronisation is, which means that the two signals are associated with the same functional activity. In contrast, values near 0 imply the absence of functional connectivity between the corresponding brain regions. For this analysis, coherence was evaluated in the sensor space, reflecting functional connectivity patterns based on the spatial arrangement of the EEG electrodes.

The EEG signals were first epoched into 2-s windows with 50% (1-s) overlap, following a standard segmentation strategy for the time-frequency analysis. Within each epoch, the magnitude-squared coherence between the electrode pairs was estimated using the Welch method with a Hann window of 2 s. All recordings exceeded 5 min in length, ensuring sufficient overlapping segments for stable coherence estimation across participants.

The computed coherence values were then used to construct distance maps, where the distance between two electrodes was defined as follows:

$$Distance = 1 - Coherence \quad (2)$$

These distance maps are used as inputs for persistent homology, which will be explained in the following subsection, to characterise EEG channel interactions across each frequency band at varying scales.

Persistent Homology

Persistent homology was applied to the distance maps obtained from the coherence analysis, capturing higher-order connectivity patterns beyond the pairwise relationships between the EEG channels. These maps represent the functional connectivity, where each value indicates the relationship between the electrode pairs.

To analyse the topology of the distance maps, a mathematical structure called a simplicial complex was constructed. Simplicial complexes are composed of basic building blocks known as simplices (e.g., vertices, edges, triangles, and higher-dimensional analogs). The most widely used method for constructing simplicial complexes from point clouds is the Vietoris-Rips filtration, which operates as follows:

Table 2. Demographic and clinical features of the participants

	AD Group	HC Group
Number of individuals	36	29
Age, year, mean ± SD	66.4 ± 7.9	67.9 ± 5.4
Gender (Male/Female)	12/24	18/11
MMSE score, mean ± SD	17.75 ± 4.5	30.0 ± 0.0

AD: Alzheimer's disease, HC: Healthy control, MMSE: Mini Mental State Examination, SD: Standard deviation.

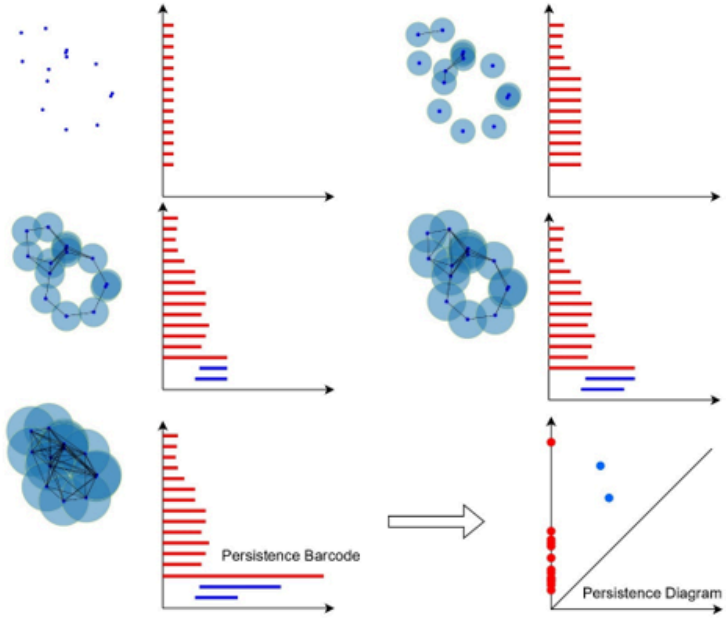


Figure 1. Persistent homology on a 2D point cloud

- Points are connected by edges if their pairwise distance is within a threshold a (the scale parameter).
- Higher-dimensional simplices, such as triangles and tetrahedra, are added based on the connections of the lower-dimensional simplices.

Increases in the scale parameter a are accompanied by the addition of new simplices to the complex, resulting in a nested sequence of simplicial complexes ($S_{a1} \subseteq S_{a2}$ for $a_1 < a_2$). Persistent homology captures the appearance of topological features (e.g., connected components, loops) at specific scales, referred to as their "birth," and their disappearance at another scale, termed "death." The persistence of a feature is defined as the difference between its death and birth scales, representing its lifespan across varying resolutions.

These topological features are categorised based on their dimension: H_0 (zero-dimensional homology) represents connected components, H_1 (one-dimensional homology) stands for loops or holes, and H_2 (two-dimensional homology) captures enclosed voids. This pattern extends to higher dimensions, where H_n describes the n-dimensional cavities within the data.

Features with high persistence are interpreted as robust and meaningful structures in the data, whereas those with low persistence are often attributed to noise or sampling artefacts. This process is illustrated in Figure 1, which shows a sequence of the Vietoris–Rips complexes constructed at increasing scale values. As the scale increases, topological features such as connected components and loops emerge, merge, or vanish. These changes are visualised using barcode diagrams, where red bars represent H_0 features and blue bars represent H_1 features. The corresponding persistence diagram summarises all features by plotting their birth and death scales. Features that persist over a wide range of scales appear farther from the diagonal and are considered topologically significant.

Wasserstein Distance

The Wasserstein distance is a metric that quantifies the cost of transforming one distribution into another. If the two distributions are similar, the cost will be lower. Therefore, it is a widely used metric for comparing persistence diagrams.

Given the two distributions P and Q, the Wasserstein distance is defined as

$$W(P,Q) = \inf_{\gamma \in \Gamma(P,Q)} \sum_{(p,q)\in\gamma} |p-q|_p, \qquad (3)$$

where:

- (P, Q): The set of all possible matchings between points in the persistence diagrams P and Q, including points matched to the diagonal.

  p: The p-norm distance between points p ∈ P and q ∈ Q.

In this study, we chose p=2, where the distance metric simplifies to the Euclidean distance. If p is set to ∞, the distance corresponds to the *bottleneck distance*, which captures the maximum difference between the matched points. The flexibility in choosing p allows for different

interpretations of the similarity between the persistence diagrams.

Figure 2 shows the difference in the persistence diagrams between the AD and HC groups based on the Wasserstein distance (p=2).

Statistical Analysis

To compare the persistence values extracted from the persistence diagrams between the AD and HC groups, we used Welch's t-test for five EEG frequency bands. The test was conducted on three persistence features: the mean of the birth scales, the mean of the death scales, and the mean of the persistence values (death – birth scales). Welch's t-test was chosen as it does not assume equal variances between the two groups. For each comparison, we reported the t-statistic (t), indicating the magnitude and direction of the difference, and the p-value, determining whether the difference had statistical significance (p<0.0001).

Classification

In this study, machine learning algorithms were employed for classification using the persistence features extracted via persistent homology. These were multilayer perceptron (MLP), SVM, kNN (k=7) and logistic regression. The performance of these algorithms was evaluated on the basis of accuracy (overall correctness), sensitivity (true positive rate), specificity (true negative rate), and F1 score (balance between precision and recall) using K-fold cross-validation.

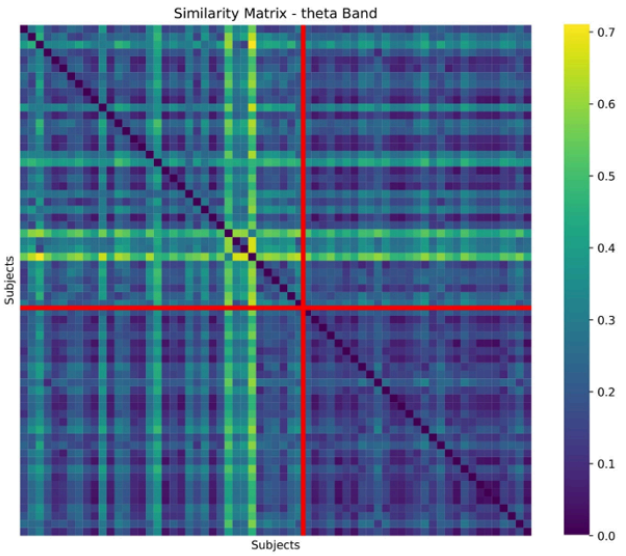


Figure 2. Wasserstein distance matrix of H_1 persistence features from theta band coherence

Table 3. Mean Wasserstein distances of H_1 persistence within and between the AD and HC groups across frequency bands

Band	Mean within the AD Group	Mean within the HC Group	Mean between Groups
Delta	0.0712	0.0201	0.0479
Theta	0.2632	0.1423	0.2182
Alpha	0.3322	0.3853	0.3742
Beta	0.2225	0.3187	0.2902
Gamma	0.1446	0.1842	0.1711

AD: Alzheimer's disease, HC: Healthy control.

RESULTS

The heatmap in Figure 2 shows that the persistence diagrams of the HC group (lower right section) are highly similar based on the Wasserstein distance, indicating consistent H_1 persistence within the group. This suggests that persistence diagrams capture the key differences between groups.

Moreover, we found that in the delta and theta bands, the mean H_1 birth, death, and persistence features differed significantly between the HC and AD groups, as shown in Table 3.

The AD group exhibited higher birth, death, and persistence values in the delta and theta bands compared with the HC group (p<0.0001). In contrast, the alpha and beta bands showed reduced birth and death values in the AD group. The persistence features in these bands are less affected. There were no significant differences detected in the gamma band. These findings reveal that the most significant changes in brain activity in AD occur in the slower brain waves.

Table 4 shows the statistical analysis of the persistence features across the EEG frequency bands for the AD and HC groups. In the delta and theta bands, birth, death, and persistence values were significantly higher in the AD group (p<0.0001). In the alpha and beta bands, birth and death values were lower in AD patients. In the gamma band, no significant differences were observed. This implies that high-frequency brain activity is less affected.

The results of the machine learning algorithms using topological features extracted via persistent homology as input, along with a comparison of their performance to that of algorithms using features derived from relative band power for distinguishing AD from HC, are presented in Table 5. The best performing relative band power-based model, i.e., LightGBM achieved an accuracy of 76.43% and an F1 score of 76.12% (24), and several classifiers trained on topological features exceeded these results. Notably, both the k-Nearest Neighbours (kNN) and Support Vector Machine (SVM with linear kernel) classifiers trained on topological features

Table 4. Statistical analysis of the persistence features across the frequency bands

Frequency Band	Feature	Mean Values		T-test Results	
		AD Group	HC Group	T-statistic	p value
Delta	Birth	0.0668	0.0343	6.0027	<0.0001
	Death	0.0819	0.0399	6.2044	<0.0001
	Persistence	0.0151	0.0056	5.1096	<0.0001
Theta	Birth	0.2022	0.1339	8.7890	<0.0001
	Death	0.2497	0.1495	9.1735	<0.0001
	Persistence	0.0475	0.0256	5.6515	<0.0001
Alpha	Birth	0.3157	0.3730	−3.9829	0.0001
	Death	0.3804	0.4491	−4.0787	0.0001
	Persistence	0.0647	0.0761	−1.8391	0.0666
Beta	Birth	0.3877	0.4182	−1.7555	0.0801
	Death	0.4453	0.4919	−2.3635	0.0187
	Persistence	0.0576	0.0737	−2.3972	0.0171
Gamma	Birth	0.4378	0.4514	−0.5464	0.5853
	Death	0.4870	0.4957	−0.3268	0.7441
	Persistence	0.0492	0.0443	0.9613	0.3373

AD: Alzheimer's disease, HC: Healthy control.

reached an accuracy of 81.50%, with the SVM also yielding the highest F1 score of 79.50%.

DISCUSSION

Our results show that the delta and theta waves exhibit increased persistence, which may be indicative of pathological overactivity (25). Higher persistence values indicate altered slow wave activity, which is associated with cognitive decline. This increased persistence may be interpreted as a sign of abnormal neural synchronization or potential compensatory mechanisms. Alpha and beta waves show reduced persistence, indicating decreased neural complexity and desynchronization, which may reflect an impairment in cognitive performance (26). Thus, by capturing these differences, persistence homology may present a new way to understand the effects of AD on brain dynamics. These results show that the altered slow-wave activity and disrupted neural synchronization seen in AD patients can be identified using the persistence features in the theta and delta bands.

While previous literature has primarily identified a decrease in pairwise coherence in the alpha band (5), our study highlighted the theta band when examining beyond pairwise relations, such as H_1 persistence, revealing distinct features that differentiate AD patients. The extracted topological features from the theta band showed significant alterations in functional connectivity among patients with AD.

EEG connectivity measures demonstrate higher diagnostic accuracy compared with traditional EEG power analysis and conventional AD biomarkers (27). While traditional coherence analysis has been extensively used in EEG research, it primarily captures pairwise relationships and does not account for higher-dimensional structures. In contrast, TDA, particularly persistent homology, provides a more comprehensive understanding of EEG connectivity by identifying complex topological patterns that coherence analysis alone cannot detect.

The use of persistent homology has enabled the identification of distinctive features in EEG data. TDA-based methods have shown potential for enhancing EEG-based diagnostic techniques, particularly in differentiating AD from normal brain activity. It is effective in the early detection of the disease and characterisation of disease severity (28, 29). Our results show that machine learning algorithms utilising topological features as input demonstrated superior performance in distinguishing between the AD and HC groups compared to those employing features derived from relative band power.

Table 5. Classification performance using different feature extraction and classification methods for distinguishing AD patients from HC subjects.

Feature Type	Classification Method	Accuracy %	Sensitivity %	Specificity %	F1 Score %
Relative Band Power	LightGBM	76.43	76.01	76.16	76.12
	SVM	73.14	71.89	75.98	73.74
	kNN (k=7)	71.23	69.67	74.19	72.81
	MLP	73.12	73.00	74.63	74.82
Topological	MLP	79.40	71.40	89.30	78.80
	Logistic Regression	80.00	74.30	86.00	78.90
	kNN (k=7)	81.50	68.90	96.00	78.20
	SVM (linear kernel)	81.50	71.40	92.70	79.50

SVM: Support vector machine, kNN: k-Nearest neighbours, MLP: Multilayer perceptron.

However, while topological analysis successfully uncovers high-dimensional relationships, it still lacks the capability to precisely localise the specific brain regions where these loops form. Further advancements in methodological frameworks may help address this limitation, thereby refining the interpretability of topological features in clinical applications.

CONCLUSION

In this study, coherence analysis and persistent homology methods were used to differentiate between patients diagnosed with AD and healthy individuals based on EEG data. By examining the topology of coherence in the electrode space, we demonstrated that meaningful features could be extracted. Unlike traditional metrics, our approach analyses the overall topological structure rather than individual pairwise relationships, revealing significant associations with the disease.

Our findings suggest that the TDA methods provide a promising approach for EEG-based Alzheimer's diagnosis. Future research can further explore the applicability of this methodology by evaluating it on different EEG frequency bands and larger datasets, potentially enhancing its clinical relevance.

Ethics Committee Approval	In our study we have made use of a freely available open access database. I accept and declare that no violation of ethical rules was made in the preparation and publication process of the study.
Peer-review	Externally peer-reviewed.
Author Contributions	Conception/Design of Study – M.B., O.B.E., C.K., A.U.; Data Acquisition – M.B., O.B.E., C.K., A.U.; Data Analysis/Interpretation – M.B., O.B.E., C.K., A.U.; Drafting Manuscript M.B., O.B.E., C.K., A.U.; Critical Revision of Manuscript – M.B., O.B.E., C.K., A.U.; Final Approval and Accountability – M.B., O.B.E., C.K., A.U.
Conflict of Interest	The authors declare no conflict of interest.
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