Time Series Classification of Electroencephalography Data

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Abstract. Electroencephalography (EEG) is a non-invasive technique used to record the electrical activity of the brain using electrodes placed on the scalp. EEG data is commonly used for classification problems. However, many of the current classification techniques are dataset specific and cannot be applied to EEG data problems as a whole. We propose the use of multivariate time series classification (MTSC) algorithms as an alternative. Our experiments show comparable accuracy to results from standard approaches on EEG datasets on the UCR time series classification archive without needing to perform any dataset-specific feature selection. We also demonstrate MTSC on a new problem, classifying those with the medical condition Fibromyalgia Syndrome (FMS) against those without. We utilise a short-time Fast-Fourier transform method to extract each individual EEG frequency band, finding that the theta and alpha bands may contain discriminatory data between those with FMS compared to those without.

Keywords: Time series classification · EEG · Fibromyalgia

1 Introduction

The use of electroencephalography (EEG) for brain activity monitoring has become increasingly popular due to its high temporal resolution, non-invasive nature and low cost. With this has come an increased interest in the use of machine learning algorithms to assist in tasks involving EEG data, such as classification. However much of the focus has been on the processing and feature extraction steps, with standard classifiers being applied to derived features: a recent report found that 40% of studies use support vector machine or nearest-neighbour models [24]. Other popular methods include deep learning or linear models such as ridge classification. Whilst these models often perform well when applied to EEG tasks, they are often used without any adaption and require dataset specific features to be used. EEG datasets are multivariate time series recorded at fixed frequencies and often used in classification tasks. There has recently been a boom in publication of classification algorithms designed to be applied directly to time series from any problem domain [1,22]. Time series classification (TSC) aims to classify datasets consisting of instances of one or more dimensions containing evenly spaced time-points, and can be applied to a wide variety of fields. For example, they have been successfully applied to human activity recognition, audio classification [12] and the analysis of spectrographs [17].

TSC internalise and automate the process of feature extraction, and are based on different types of discriminatory patterns such as repeating patterns or common segments. The most accurate approaches combine multiple representations in an ensemble to avoid a weakness of any individual method. Our aim is to investigate whether applying these time series specific algorithms can improve EEG classification over standard approaches. Our contributions are to assess a range of TSC algorithms on some archive EEG problems, identify the most promising approaches then conduct a case study to demonstrate how TSC could help differentiate individuals with a chronic pain medical diagnosis (Fibromyalgia Syndrome) based on their EEG characteristics.

The remainder of the paper is as follows. Section 2 provides background information into EEG analysis and TSC. Section 3 describes nine EEG classification datasets in the time series archive[1] and Sect. 4 evaluates how TSC models perform compared to existing results on these datasets. Section 5 contains a case study into a specific EEG dataset, looking at if TSC methods can find discriminatory data between subject with and without the Fibromyalgia Syndrome (FMS), a medical diagnosis characterised by chronic widespread pain. Finally, Sect. 6 provides a summary of the results found and suggests some future areas of research for further improvement.

1.1 List of Commonly Used Acronyms

EEG: Electroencephalography, a way to measure brain activity by recording electrical signals produced by neurons.
MEG: Magnetoencephalography, similar to EEG but using magnetic fields rather than electrical activity.
(M)TSC: (Multivariate) Time Series Classification, a form of classification where the input data takes the form of a number of evenly spaced data points.
BCI: Brain Computer Interfacing, ways to map brain activity to an external device, commonly using EEG.
FMS: Fibromyalgia Syndrome, a medical condition characterised by a general feeling of generalised chronic pain.

2 Background

2.1 Electroencephalography

EEG is a technique used to measure the brain's electrical activity. It uses electrodes placed on the scalp to measure changes in voltage over time produced by cells of the brain (neurons). EEG data is commonly used in medicine for diagnosis assistance, computer science for human-computer interaction and psychology to further understand disorders such as Narcolepsy [28] or Insomnia [32].

[1] https://tsc.com.

Due to the relatively low cost of equipment, ease of use, non-invasive recording method and speed, EEG has become one of the most popular and well used brain imaging methods. Electrodes at different points on the scalp measure different sections of the brain which are responsible for different areas of information processing. EEG data is usually recorded at a high frequency with EEG devices commonly recording at 1000 or more observations per second, allowing for good temporal resolution.

EEG data can be broken down into distinct frequency bands, representing clearly defined frequencies of neural oscillation. Usable information in EEG usually falls between the range of 1 and 50 Hz where 1 Hz represents one oscillation per second, and can be broken up into each band using spectral analysis (including use of Fourier Transforms). Each band related to different levels of brain activity with the import important bands being context-specific for any given study. The frequency ranges for these bands is provided in 1, and a example of splitting an EEG signal into each band in 1.

Table 1. EEG band to frequency range

Band	Delta	Theta	Alpha	Beta	Gamma
Frequency range(Hz)	0.5–4	4–8	8–12	12–30	30+

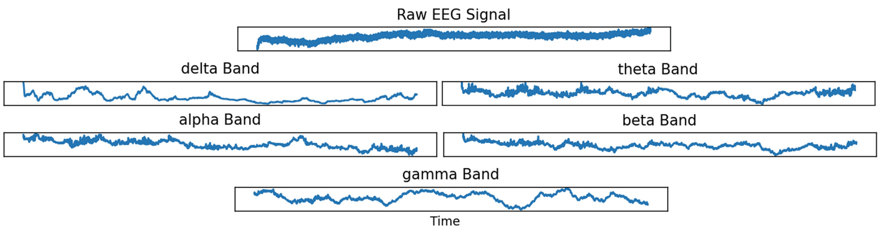

Fig. 1. An example of splitting an EEG signal from one channel into individual frequency bands

Magnetoencephalography (MEG) is another method of measuring brain activity similar to EEG, but measuring changes in magnetic fields rather than the electrical current in the brain directly. MEG has better spatial resolution, meaning it can localise more effectively, as the magnetic fields are less affected by the skull [7]. However, MEG requires a considerable equipment infrastructure, making it less mobile and more expensive. Therefore, EEG tends to be more commonly used.

One of the main uses of EEG is within the clinical setting to support diagnosis of various neurological disorders including epilepsy. Within the context of epilepsy diagnosis [23], EEG data is collected whilst a patient is exposed to specific sensory stimuli (such as flashing lights) or during an active seizure to look for 'epileptiform' features that are indicative of abnormal electrical activity.

Another use for EEG is to understand how the brain works and reacts to different environments. For example, much of our current understanding on how rapid eye movement (REM) sleep works has come from studies using EEG. EEG is also used to further our understanding of human emotions and behaviours [27].

A growing area of use for EEG is within the brain-computer interface (BCI), allowing the brain to communicate with an external device such as a prosthetic limb or computer. EEG provides a simple, non-invasive method for measuring brain activity in real-time, making it perfectly suited to mobile BCIs. One example of an EEG-based BCI [15] demonstrated that EEG data could be used to control a robotic quad copter in a 3D environment.

2.2 Time Series Classification

Time series classification (TSC) is a special case of traditional classification where each instance is a time series target variable pair [1]. For multivariate TSC (MTSC), each observation of the time series is a vector. For EEG data, an observation at a given time point represents a vector of values for each channel. Alternatively, a multivariate time series can be considered as a set of two or more time series aligned in time, one for each channel. A number of different approaches have been proposed for the MTSC task.

Distance based methods utilise distance functions to calculate similarity between two time series, then use a classification method such as nearest neighbour. One of the more popular distance calculations is Dynamic Time Warping (DTW), which allows for a level of warping to occur between the two series to adapt to any offset. Multivariate DTW can either be dependent (distance calculation is pointwise over channels) or independent (distance found for each channel then summed).

Convolution based approaches utilise convolutional kernels to create features to be used for classification. The most popular is ROCKET [8], which uses a large number of randomly generated kernels to find many different feature representations before applying a ridge regression classifier. ROCKET's strength comes from its speed, achieving high accuracy at a significantly reduced computation time. There have also been extensions to ROCKET, such as multi-ROCKET [30], which adds three additional features per kernel, mini-ROCKET [9], which optimises the convolutions used, and the Arsenal [22], an ensemble of ROCKET classifiers.

Deep learning based methods are ever increasing in popularity, and are becoming more viable for TSC. InceptionTime [11] is generally considered the best performing deep learning algorithm. The original InceptionTime uses an ensemble of five Inception networks, an adaption of a residual neural network (ResNet), although this number can be changed.

Feature based classifiers are simple pipeline approaches that extract global summary features then apply a standard classifier. The FreshPRINCE classifier [20], which combines the TSFresh transform [6] with a rotation forest [25], was found to be the most effective combination of transform and classifier.

Dictionary based methods, such as the Temporal Dictionary Ensemble (TDE) [19], adapt bag-of-words approaches used in computer vision. Histograms are formed based on the number of occurrences of discretised sub-sequences, or words.

Shapelet based methods are based on the presence or absence of a pattern, or shapelet. For the Shapelet Transform Classifier [4], large numbers of short subseries are selected from the training data and their discriminatory power is estimated. The best shapelets are retained and used to transform the data from the time domain to vector based distance to shapelet features.

Interval based classifiers are ensemble approaches that combine summary features from random intervals. DrCIF [21] derives Catch22 features [18] over different random intervals for each base classifier.

Hybrid approaches combine classifiers built on different representations. The HIVE-COTEv2 (HC2) [22] classifier combines classifiers from the shapelet, dictionary, interval and convolution domain in a heterogenious meta ensemble. HC2 is currently state of the art for MTSC.

3 Existing EEG Datasets

3.1 MTSC Archive EEG Classification Problems

There are currently nine EEG datasets in the TSML archive of TSC datasets[2]. Five of the nine datasets were used in BCI competitions, while the other four were collected from published research. A breakdown of the data characteristics of the nine datasets is shown in Table 2.

Eyes Open Shut [26] problem is a 2 class dataset on detecting whether a subject has open or shut eyes. One subject was recorded with both open and shut eyes for 117 s at 128 Hz, using 14 channels. In the original paper each time point was treated as a separate instance, equalling 128*117, or 14976 instances with 14 attributes. Their experiments found the best classification accuracy came from instance-based methods such as kstar, with a best accuracy of around 98%. However, their experiments contained biases through their use of k-fold cross validation without considering the temporal ordering of the data, so results may not be directly comparable. In the archive this dataset has been transformed into a time series format by first removing any outliers ($x > 5000$ or $x < 3000$), then segmenting the data into 1 s intervals of 128 observations each. 19 cases were also removed for containing both open and shut eyes. Finally a test train split was created, with test containing the last 21 observations.

Face Detection[3] involved 16 subjects being shown either a face or a scrambled face, with EEG data recorded. Each trial was recorded for 1.5 s from 306 channels, then down-sampled to 250 Hz and high-pass filtered at 1 Hz. Subjects 1 to 10 were used to form the training data, while 11 to 16 formed the test dataset.

[2] https://www.timeseriesclassification.com.
[3] https://www.kaggle.com/c/decoding-the-human-brain/data.

Finger Movements [3] dataset was collected by getting one subject to sit in a standard typing position, then press keys in a self chosen order. The goal is to predict if the next key pressed was with the subjects left or right hand. The data was recorded in three 6 min sessions on the same day with breaks. The data was initially recorded at 1000 Hz on 28 channels for 0.5 s, using a band pass filter at 0.05 and 200 Hz to remove outliers. The data was then downsampled to 100 Hz, so each instance contains 50 observations. In a classification competition using this dataset, an error rate of 16% was achieved by extracting features using common spatial subspace decomposition and Fisher discriminant before classifying using a neural network.

Hand Movement Direction[4] dataset was gathered by having 2 subjects move a joystick either up, down, left or right of their choosing. From this a 4 class problem was created. For each trial the subject was given 0.75 s to move the joystick and reach a target, then hold in position for 1 s. The data was recorded with 10 channels at 625 Hz and band pass filtered at 0.5 and 100 Hz, then re-sampled at 400 Hz. In a competition, the highest accuracy found was 46.9% by first extracting various features, using a genetic algorithm to select relevant features, then classifying using a linear SVM and LDA.

Motor Imagery [16] dataset is from an electrocorticography (ECoG) experiment where a single patient was tasked with imagining moving either their left small finger or tongue. An ECoG is placed directly on the brain rather than externally. Each recording lasted 3 s, starting 0.5 s after a visual cue has ended, at 1000 HzHz, and with 64 dimensions recorded. The training data was recorded on one day, then the test data a week later. The best classification result was 91% accuracy by combining various feature extraction methods such as CSSD and Fisher discriminant analysis, before using a linear SVM classifier.

Self Regulation SCP 1 and 2 [2] datasets are a pair of EEG datasets based on the use of EEG data to provide a method of communication for people paralysed with Amyotrophic Lateral Sclerosis (ALS) The patients were trained to voluntarily produce positive and negative changes in their Slow Cortical Potential (SCP), which was then used to move a cursor up and down on a screen, whilst receiving feedback. SCP 1 was recorded with a healthy patient over 2 d. Each trial was 6 s long and a total of 268 trials were performed. The data was sampled at 256 Hz from 6 channels with 2 classes, either positive or negative. SCP 2 performed the same experiment, but on a subject with ALS. For this experiment, 380 trials, 200 train and 180 test, were performed in total on the same day, each of length 8 s with 4.5 s used. Both of the datasets were used in a BCI classification competition. For SCP 1 the lowest error rate found was 11.3% by first extracting features using spectral analysis, then feeding into a linear classifier. For SCP 2 the lowest error rate was 45.6% using continuous wavelet transform and a linear discriminant analysis classifier. However, this dataset was found to contain very little data relevant to the classification problem.

Blink[5] dataset was formed by getting multiple subjects to blink in two second intervals, as either short or long blinks. The data as recorded at 255 Hz with

[4] http://bbci.de/competition/iv/.

4 channels. In the original dataset the trials were formed into 20 sets of 50 instances, 10 for each class. For the version used in the archive these sets have been joined together, then split into train and test portions.

MindReading [14] involves classifying 5 different visual stimulus shown to a participant using MEG data. The data was originally recorded at 330 Hz with 306 channels before being down-sampled to 200 Hz. Other processing steps include low-pass filtering at 50 Hz, removing noise caused by head movements and removing likely artefacts by applying trend removal. Finally, the data was segmented into 1 s intervals. This dataset was then given to 9 different research groups to partake in a competition to find the best accuracy, which was 68% using a logistic regression with the LASSO regression method.

Table 2. Description of EEG datasets in the tsml archive

Dataset	Classes	Channels	Series Length	Train Size	Test Size	Sample rate (Hz)
Blink	2	4	510	500	450	255
EyesOpenShut	2	14	128	56	42	128
FingerMovements	2	28	400	316	100	100
HandMovementDirection	4	10	400	160	74	400
MindReading	5	204	200	727	653	200
MotorImagery	2	64	3000	278	100	1000
SelfRegulationSCP1	2	6	896	268	293	256
SelfRegulationSCP2	2	7	1152	200	180	256

4 Results

Our experimental goal is to assess how useful TSC algorithms are for EEG classification with no hand crafting of features and no preprocessing beyond that done automatically by band pass filtering. We perform a series of experiments using the TSML archive data using a range of different TSC models. Due to its high number of channels and number of time-points the FaceDetection dataset was excluded leaving 8 datasets. 11 of the most popular and high performing classifiers were used in the experiments. In each experiment the model was trained on a training portion of the dataset, then performance measured against an unseen test set. Experiments were performed using the aeon time series machine learning toolkit[5]. This was repeated on 30 resamples of each experiment to get an average accuracy. These average accuracy scored are shown in Table 3.

Overall, ROCKET based classifiers performed the best, being the best performing classifiers for 5 of the 8 datasets used in the experiment. MiniROCKET has the best average rank (4.25), and the top three ranked classifiers are all ROCKET based. However, for the majority of the datasets there is not a large difference between the best and worst classifiers in terms of accuracy. These

[5] https://github.com/aeon-toolkit/aeon.

results can also be compared to results found in the competitions using these datasets, or the papers they originated from. Whilst direct comparison is not valid due to differences in experimental methodology, it does provide a good indication as to how well time series classifiers can perform compared to conventional approaches. These comparisons are shown in Table 4.

Table 3. Accuracy scores for 11 classifiers on 8 EEG/MEG datasets. The best result for each dataset has been underlined.

	Mini-ROCKET	ROCKET	Arsenal	HIVE-COTE 2	FreshPRINCE	Multi-ROCKET	DrCIF	InceptionTime	TDE	1NN-DTW	STC-2Hour
Blink	0.998	1.000	1.000	1.000	0.997	0.998	0.999	0.991	1.000	0.946	0.998
EyesOpenShut	0.570	0.514	0.512	0.496	0.540	0.551	0.528	0.695	0.489	0.664	0.490
FingerMovements	0.581	0.576	0.577	0.550	0.553	0.557	0.548	0.564	0.530	0.546	0.541
HandMovement	0.399	0.450	0.436	0.419	0.383	0.354	0.467	0.426	0.351	0.303	0.375
MindReading	0.737	0.675	0.678	0.685	0.697	0.726	0.571	0.211	0.332	0.606	0.538
MotorImagery	0.528	0.519	0.518	0.535	0.541	0.522	0.518	0.513	0.542	0.518	0.529
SelfRegulationSCP1	0.907	0.867	0.868	0.883	0.898	0.911	0.873	0.847	0.838	0.819	0.854
SelfRegulationSCP2	0.514	0.536	0.546	0.532	0.517	0.516	0.503	0.521	0.521	0.542	0.512
Average Rank	4.25	4.625	4.75	4.9375	5.25	5.375	6.5	6.875	7.5	7.8125	8.125

Table 4. Comparison between best existing accuracy and best from our experiments

Dataset	Existing results	Our best result	Our worst result
Blink	0.980	1.00	0.991
EyesOpenShut	0.980	0.695	0.489
FingerMovements	0.840	0.581	0.541
HandMovementDirection	0.469	0.467	0.350
MindReading	0.680	0.737	0.212
MotorImagery	0.910	0.542	0.513
SelfRegulationSCP1	0.887	0.911	0.838
SelfRegulationSCP2	0.544	0.546	0.500

For 5 of the 8 datasets used, the results found from our experiments are comparable to the best results found in competitions or papers, with time series classifiers performing better for Blink, MindReading and both SelfRegulation datasets. This is with no bespoke processing: we have simply given the EEG to the classifiers in the format provided. This suggests that at the very least, TSC can provide a useful benchmark for more bespoke, problem specific, classification approaches. They are no panacea though: TSC algorithms performed worse on the datasets, EyesOpenShut, FingerMovements, and MotorImagery.

For the EyesOpenShut dataset this difference could be explained by the biases in experimental set up in generating the original results. Poor performance on the other two is harder to explain. It is probable that the hand crafted approaches for these problems are genuinely discovering discriminatory features the generic approaches cannot automatically discover. In these situations, TSC algorithms offer the opportunity of providing a strong lower bound for performance.

5 VIPA Dataset Case Study

The VIPA study is an EEG dataset from an experiment designed to investigate EEG characteristics in patients with chronic pain. The investigation involved looking at how chronic pain may influence EEG data, and if virtual reality could be utilised in chronic pain treatment. Participants with the Fibromyalgia Syndrome (FMS) were asked to complete various tasks in a virtual reality environment whilst recording EEG data, with their clinical and feasibility outcome variables being recorded before and after each task. A secondary control experiment was completed on subjects without FMS (healthy controls).

For subjects with and without FMS, eyes-closed resting state data was collected at baseline (before any tasks were undertaken). The resulting dataset consisted of 27 individuals with FMS and 14 healthy controls. The data consisted of 64 EEG channels and 3 non-EEG channels (accelerometers), with 58091 time-points recorded at 500 Hz, representing slightly more than 116 s. As each recording lasted slightly different amounts of time, each was truncated to the shortest signal so that all 41 were of equal length.

We have defined a classification problem within this dataset related to the diagnosis of FMS, but this is not the ultimate use case we envisage will be important for classifiers built on FMS EEG data. We are interested in exploring whether we can give insight into the best way to treat FMS using, for example, emerging digital tools such as virtual reality. There is conflicting evidence regarding EEG-based 'biomarkers' in FMS with studies outlining the importance of the theta [10], alpha [31] and beta [13] bands. These studies mainly focus on the frequency domain alone and average data from across the entire electrode array over the total recording time. There is a lack of research investigating changes in EEG microstates and looking more carefully at changes in oscillatory information over time. We hypothesise that achieving improved classification of FMS patients based on alterations in particular frequency bands will support the ability to more closely define these alterations, leading to biomarkers of the future. Ultimately, our follow-on work will explore these potential biomarkers.

We construct classifiers on the full data, and for each individual band. Each channel is transformed independently into a bandwidth using standard methodology. A short-time fast Fourier transform (STFT) [29] method was used to extract individual bands. A one second overlapping sliding window was passed over the raw EEG signal, applying a Fourier transform and extracting an approximation of the absolute power for each band in each window using Simpson's rule. From this, five new multivariate time series can be extracted, each showing how the band differs over time.

Table 5. Accuracy comparing raw data to individual frequency bands

Experiment	Mini-ROCKET	ROCKET	Arsenal
Raw data	0.512	0.584	0.584
Delta	0.512	0.61	0.756
Theta	0.707	0.634	0.634
Alpha	0.707	0.634	0.683
Beta	0.634	0.61	0.659
Gamma	0.61	0.683	0.634
Ensemble	0.610	0.634	0.683

Due to the small number of subjects for each class, and to avoid any bias, a leave one subject out strategy was employed in each experiment. All but one subject were used to train the model, then the remaining subject was used as a test case. This was then repeated for each subject in the study, training a new model in each cross validation. The predicted class is then compared against the true class, and an overall accuracy calculated. This was done for the raw EEG data, each band, and an ensemble of all five bands, where the predicted class is the average prediction for each band. We have done no other pre-processing, such as artefact removal or data validation.

Based on the results presented in Sect. 4 and the relatively large size of the data set, the three top ranked ROCKET classifiers were selected for experiments. The accuracy scores over all subjects are displayed in Table 5. Given the very small sample size and the absence of any preprocessing, we believe these results are promising. Firstly, higher accuracy is generally observed when using any of the 5 frequency bands compared to the raw data. It can also been seen that, aside from the likely outlier for Arsenal with the delta band, accuracy was highest when using the theta and alpha bands. This suggests that important information for EEG classification can be found within the frequency domain, and that time-frequency analysis would likely be the best approach for EEG analysis. It offers some supporting evidence to the importance of alpha [31] and theta [10] bands being discriminatory for FMS. A contingency table for mini-ROCKET on the theta and alpha bands are shown in Tables 6a and 6b. False negatives are more common than false positives, and this could be due to the imbalance in the data towards individuals with FMS.

Table 6. Contingency tables for two EEG bands

(a) mini-ROCKET theta band

	True pos	True negative
Predicted positive	23	8
Predicted negative	4	6

(b) mini-ROCKET alpha band

	True pos	True negative
Predicted positive	22	7
Predicted negative	5	7

We also formed a naive ensemble over all five bands. Whilst it still performed better than classifiers built on the raw data, it was also notably worse than all the individual bands except for mini-ROCKET with delta. This implies that only a minority of bands contain useful information for FMS classification, and so a weighting system would be required to find which bands are most useful.

6 Conclusion

The aim of this study was to show whether time series classification models can usefully be applied to EEG problems. We have shown that not only can these models work well for EEG data, but can do so without needing any dataset-specific feature selection. The experiments on the datasets in the UCR time series archive showed that for 5 of the 8 datasets used, TSC models matched or exceeded results found in competitions involving these datasets. ROCKET based classifiers performed particularly well on these datasets. However, for 2 datasets our results were significantly worse than other studies, indicating that a generalised approach may still need some considerations before becoming viable for all EEG problems. We have also demonstrated the use of TSC models on a new EEG problem, discriminating individuals with a diagnosis of Fibromyalgia. Our findings show that time-frequency analysis increases accuracy over the time domain alone, with the alpha and theta bands the most discriminatory in FMS.

Whilst the results of the experiments performed do show that time series classifiers have potential, more testing on a larger variety of EEG datasets would need to be performed before any full conclusions can be drawn. This approach also has a significant drawback from an increased training time due to the size of raw EEG data. However, we believe that this could be avoided through the use of channel selection algorithms and automated processing techniques.

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