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Automated Feature Identification and Classification Using Automated Feature Weighted Self Organizing Map (FWSOM)

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Abstract. This paper investigates the application of a novel method for classification called Feature Weighted Self Organizing Map (FWSOM) that analyses the topology information of a converged standard Self Organizing Map (SOM) to automatically guide the selection of important inputs during training for improved classification of data with redundant inputs, examined against two traditional approaches namely neural networks and Support Vector Machines (SVM) for the classification of EEG data as presented in previous work. In particular, the novel method looks to identify the features that are important for classification automatically, and in this way the important features can be used to improve the diagnostic ability of any of the above methods. The paper presents the results and shows how the automated identification of the important features successfully identified the important features in the dataset and how this results in an improvement of the classification results for all methods apart from linear discriminatory methods which cannot separate the underlying nonlinear relationship in the data. The FWSOM in addition to achieving higher classification accuracy has given insights into what features are important in the classification of each class (left and right-hand movements), and these are corroborated by already published work in this area.

1. Introduction

Previous work on the classification of EEG data as described in [1] show that machine learning methods can be used to achieve classification accuracies of up to 97.1%. The work highlighted the difficulty of achieving better classification, and also highlighted that linear classification models performed poorly due to the nonlinear nature of the underlying data. The results from this work [1] show that the performance of the various classification algorithms can vary considerably depending on which features are used for the classification. Whilst for small numbers of features (such as in this work which had 4 features) this is possible and it is not an issue to exhaustively compare each and every combination of features as inputs, for larger datasets this clearly becomes impractical and is therefore otherwise accomplished either by hand or not at all.

In addition, work by [2-4] shows that irrelevant features can result in low classification results. A novel method presented in this paper looks to automatically identify the irrelevant features so that classification performance can be improved. The same EEG data from [1] is used which is publically available data from Physionet [5]. Using this data we are able to compare with this earlier study and highlight that the proposed method is able to improve the classification performance by correctly identifying the relevant inputs and discarding automatically the irrelevant inputs.

2. Methodology



The EEG data will be analysed and classified using a self-organizing map, by SVM linear and cubic methods, and the FWSOM method which are described in the following sections.

2.1. Self-Organizing Map (SOM)

The Self-Organising Map (SOM) is an unsupervised neural network clustering algorithm, referred as Kohonen's SOM [6]. A SOM aims to map data patterns onto n-dimensional grids of neurons; this is inspired by the tendency of the biological neurons that have similar functions stored in the same region of the brain. The SOM's mapping preserves a topological relation by maintaining neighbourhood relations such that patterns that are close in the input space are mapped to units that are close in the output space, and vice-versa.

2.2. Support Vector Machines (SVMs)

SVM is a well-known regression and classification learning algorithm [7, 8]. The basic aim of SVM is finding optimal hyperplanes (which could be linear or nonlinear) that segregate multiple groups.

2.3. Feature Weighted Self Organizing Map (FWSOM)

The FWSOM approach is a novel approach that looks to automatically identify what features are important in a given dataset so that the classification accuracy can be improved.

In the proposed approach, information from what a standard SOM has learnt during training is used to identify what the SOM has seen as important for making decisions and to guide subsequent steps of the training, and to generate individual weightings at a node level which will reduce the importance of inputs that are considered to be irrelevant for that node. It is expected that samples from a given class may spread over multiple nodes (i.e. will not be mapped to a single node) due to any irrelevant features in the dataset. When there are irrelevant inputs in the dataset the SOM will see samples from the same class as different due to these irrelevant inputs.

The analysis of input relevance begins after the SOM is trained. The distances between all nodes in relation to each individual class is calculated in order to identify what is important and irrelevant in the mapping of each class.

For each class, we defined a winner node $N_{winnerC_k}$ as the node with highest number of samples from a given class C_k , neighbouring nodes N_{NeighC_k} as all other nodes with samples from the class mapped, and the distant nodes N_{DistC_k} as other nodes with no samples from the class mapped.

A similarity matrix is calculated as the distance between the mean of the input samples μx_{ck}^d from the class in neighbouring nodes N_{NeighC_k} to corresponding $N_{winnerC_k}$ weight values as (Eqn 1) below;

$$Sim_{Ck}^d = \left\| \mu x_{ck}^d - w_{N_{winnerC_k}}^d \right\| \quad (1)$$

Where d is the input dimension of a given sample x belonging to class ck and w is the weight value of the winner node $N_{winnerC_k}$.

The distance values in the similarity matrix for important inputs for defining the class is expected to be low since it is assumed that these inputs will share similar values for the same class. The distance for the irrelevant inputs is expected to be high since it is assumed that these inputs will have different values in the SOM for the nodes to which the class samples are mapped, and are the reason why the class samples are mapped to different nodes rather than a single node. This process clearly makes the assumption that the class has a single underlying set of features that define the class, and so these assumptions will not be correct when a class is made up of a number of different feature relationships.

In addition, a dissimilarity matrix (Eqn 2) describing the features that can be identified as being different from the current class and all other classes is computed as the distance between the mean of the class samples in the winner node $\mu x_{N_{winnerC_k}}^d$ to the weight values of N_{DistC_k} as;

$$Diss_{Ck}^d = \left\| w_{N_{DistC_k}}^d - \mu x_{N_{winnerC_k}}^d \right\| \quad (2)$$

This calculation uses the assumption that the SOM did not map the samples from a given class to these other distant nodes due to the inputs that the SOM sees as different, and therefore the distance values in the dissimilarity matrix for these inputs will be high.

For each class, important inputs are identified as inputs with > 0 percentage change from variance of similarity matrix $SIMC_k$ to the variance of dissimilarity matrix $DISC_k$ as in Eqn 3 below;

$$CkInputs_{roc} = \left(\frac{DISC_k - SIMC_k}{SIMC_k} \right) * 100 \quad (3)$$

3. Experimental Design

3.1. EEG Dataset

EEG signals record the differences of the voltage from two locations on the scalp over time. The EEG signals have an amplitude in the range of 1-100 μv with frequency in the range of 0.5 to 10 Hz [9]. The data recorded and contributed by Physionet using the BCI2000 instrumentation system described in [5] is used.

3.2. Feature Extraction

Frequency bands α and β are chosen for the frequency domain feature extraction because of their ability to distinguish movements in the active state. The delta band is also chosen since research [10] supports that existence of Delta rhythm in the motor cortex within the pre-movement stages (Movement-Related Cortical Potential (MRCP)). The EEG data is transformed by extracting Alpha, Beta and Delta band features for 8 electrodes for 6 subjects. For each of the left hand and right-hand tasks separately. The selected electrodes are (C3,C4, Cz, Fc3, Fcz, Fc4, C1, C2). The choice of fewer electrodes is also quite practical and allows the proposed method to be easily incorporated within a portable Wireless EEG system for use in prosthetics applications for example. These electrodes were selected in corroboration with the literature and they include the C3, C4 and Cz electrodes (located on the top of the head) for which distinguishable difference in the Power Spectral Density (PSD) can be observed [11]. Three frequency domain features are extracted from the raw EEG data for each selected electrode by applying Fourier Transform [12]; converting from the time domain to frequency domain characteristics.

3.3. Training and Validation Parameters

The Datasets were separated into training and test sets with the 5-fold cross validation method, accuracy was measured using the confusion matrix [13].

4. Classification Accuracy Results

The table as shown in Table 1 gives the results of classification using the various methods using all inputs, and then also the results using only those inputs identified by the FWSOM process

The FWSOM method returns the identification of irrelevant inputs, and this allows the classification methods to be tested once more with a reduced feature set. These results are also shown in Table 1 for each method, with the relevant features identified by the FWSOM when trained with a 10x10 lattice being used. From an initial input feature set of 24 the FWSOM reduces this to 12 features for alpha band, 73 to 33 for beta band and 20 to 6 for delta band.

The FWSOM has identified the instantaneous power spectrum of the frequency bands at various EEG sampling points as important features for separating the two groups. The location of where the power spectrum sample point features are important is different for the different frequency bands and across the 8 subjects investigated in this paper. The FWSOM has also identified that relative power and peak power features are consistently less important in the classification compared to the instantaneous power spectrum feature. This result is corroborated with those obtained in [11, 14] where it was found that the peak power feature is not a disguisable feature for classification when multiple frequency bands are used and that high and low values of relative power across frequency bands might not be able to be clear distinguisher for EEG data. These results, therefore, show that the FWSOM method has correctly identified the important inputs for this particular dataset.

After application of the FWSOM method, the results of the SVM cubic method have improved, showing that the SVM method is indeed affected by the poor choice of features for training and can struggle to ignore the effect of irrelevant inputs. Interestingly, the SVM linear method shows virtually no change with one result even giving a worse result.

It can be seen that the standard SOM using all inputs gives a poor performance for the small 2x2 lattice size although this does improve when a larger SOM is used of 10x10 lattice. The results also improve when the inputs identified by the FWSOM only are used for training, but 100% diagnosis can still not be achieved.

The results presented in the FWSOM column show that 100% classification performance can be achieved through the use of the feature weighting element that allows the samples to be differentiated from each other based on their class membership more easily as seen in figures 1 to 6.

Table 1. Classification Accuracy Results

EEG Band	Method									
	SVM (Linear)		SVM (Cubic)		SOM (2x2 Lattice)		SOM (10x10 Lattice)		FWSOM (2x2 Lattice)	FWSOM (10x10 Lattice)
	all Inputs	10x10 FWSOM Inputs	all Inputs	10x10 FWSOM Inputs	all Input	10x10 FWSOM Inputs	All Input	10x10 FWSOM Inputs	2x2 FWSOM Inputs	10x10 FWSOM Inputs
α	63%	63%	83%	88%	53%	63%	78%	88%	66%	100%
β	79%	78%	88%	90%	66%	68%	73%	84%	60%	100%
δ	53%	53%	72%	80%	60%	40%	76%	82%	53%	100%

The figures (1-6) show the hits for nodes in the 10x10 lattice from a standard SOM and then for the FWSOM following the process that calculates weights for each node and remaps the samples against these nodes for each of the EEG band datasets. The figures show pie charts for each node that a sample maps to. Therefore, not all nodes are shown in the figures when no samples map to them. The colours of the pie chart relate to the class of the samples that map to it, and are % at a node level.

These graphical representations of the results show clearly that the samples from class 1 (red node) can be represented by a single node, whereas the 2nd class (blue node) require a large number of nodes to allow the variability in this class to be properly represented.

It is clear from the results of the standard SOM shown in the figures that this variability results in the classes being mixed throughout the nodes making classification difficult, and hints at the effect that the irrelevant features are having on the spread of data throughout the SOM. This is likely to be similar to the SVM methods and explains why these methods are also finding classification difficult.

The results of the two different sizes of SOM also indicate that this is an important factor in the analysis process. If the SOM size is too small then the variability in the dataset will not be properly mapped resulting in the ineffective application of the FWSOM method.

Figures (7-12) show bar charts of the equation given in Eqn 3, and illustrate the important indexes for each class found by the FWSOM process (those with a value >0) and the irrelevant indexes for each class (those with a value <0). The analysis for this dataset shows clear differences in the values for the majority of features allowing straightforward identification of both relevant and irrelevant features.

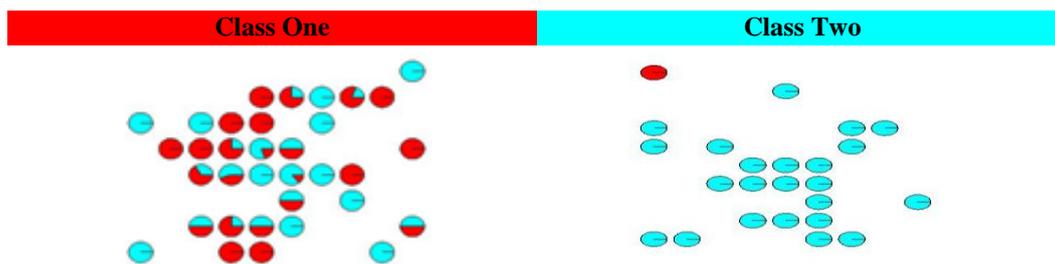


Figure 1. Standard SOM's Samples Hits - alphaBand

Figure 2. FWSOM's Samples Hits - alphaBand

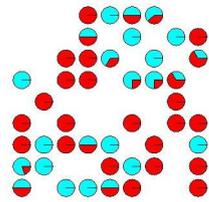


Figure 3. Standard SOM's Samples Hits - betaBand

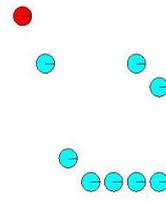


Figure 4. FWSOM's Samples Hits - betaBand

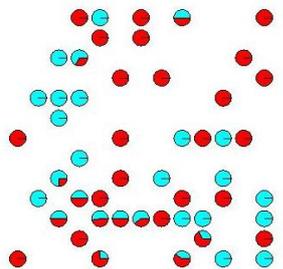


Figure 5. Standard SOM's Samples Hits - deltaBand

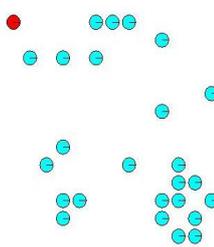


Figure 6. FWSOM's Samples Hits - deltaBand

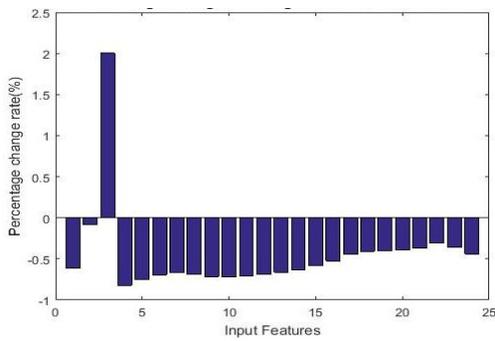


Figure 7. FWSOM's relevant inputs for class 1 - alphaBand

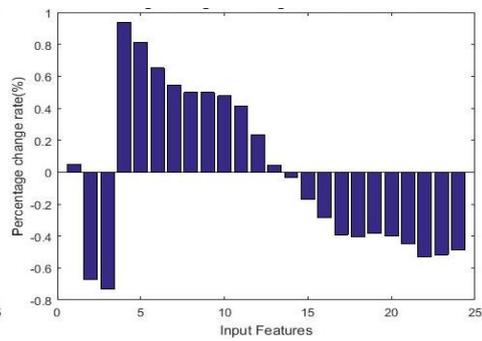


Figure 8. FWSOM's relevant inputs for class 2 - alphaBand

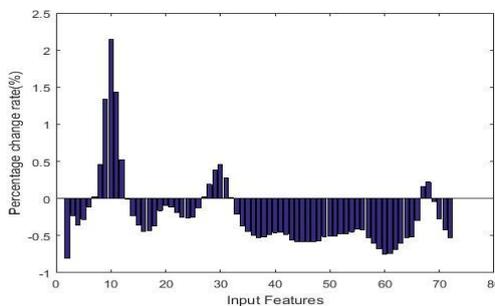


Figure 9. FWSOM's relevant inputs for class 2 - betaBand

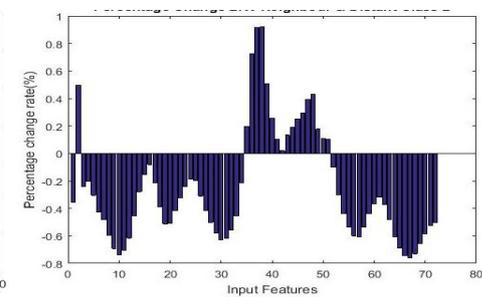


Figure 10. FWSOM's relevant inputs for class 2 - betaBand

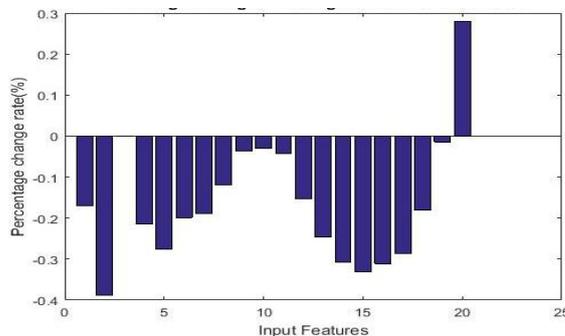


Figure 11: FWSOM's relevant inputs for class 1 - deltaBand

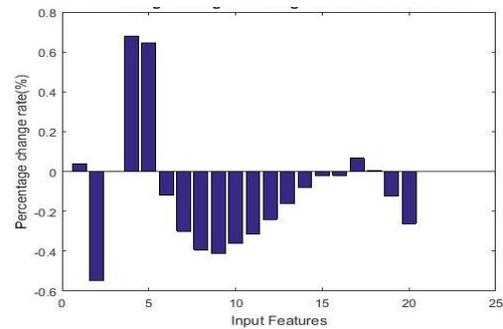


Figure 12: FWSOM's relevant inputs for class 2 - deltaBand

5. Conclusion

The Temporal nature of the EEG data makes it difficult for classifiers especially linear to separate the groups distinctly without pre-processing, transformation and extraction of features that are well known to clearly distinguish different mental tasks (which is quite difficult to achieve in practice). We have demonstrated how the powerful topology property of the SOM in conjunction with a novel feature weighting method can be used to improve the classification of this data.

The FWSOM in addition to achieving higher classification accuracy has given insights into what features are important in the classification of each class (left and right-hand movements), and these are corroborated by already published work in this area. The exact location of each of the input features identified by the FWSOM method as important is an interesting area to explore in future work extension of this paper.

The results also show that the identified features as relevant can also be used to improve the classification performance of other classification methods, which highlights again the importance of the features used during the SOM training process. The application of the FWSOM method has the potential to help identify relevant features in any given dataset and to give much improved classification accuracy over other methods.

Future work will focus on the usage of growing SOM methods so that a defined SOM lattice size is not required, a relaxing of the assumption for a class to be defined by a single relationship, and also improvements to the calculation of relevant and irrelevant inputs.

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