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# Automated classification of EEG signals in brain tumor diagnostics [1]

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### Abstract

The electroencephalogram (EEG) or scalp recordings of brain field potentials continues to be an attractive tool in clinical practice due to its non-invasiveness and its real-time depiction of brain function. In brain tumor diagnostics, EEG is most relevant in assessing how basic functionality is affected by the lesion and how the brain responds to treatments (e.g. post-operative). This paper focuses on developing an automated system to identify space-occupying lesions in the brain using EEG signals. We discuss major complications in relating EEG to different tumor classes and suggest an approach of feature extraction using wavelet techniques and classification by self-organizing maps. Initial tests show improvement over conventional frequency band features common in the EEG community. The tests also highlight the need to obtain efficient physically-motivated features as to how EEG is affected by various tumors.

## 1. Introduction

The Electroencephalogram, or in short EEG, signals have long been recorded and studied as potentially descriptive of the electric activity of the brain. It has stood the test of time because it monitors physiological functions as these change with time and is reactive to many factors. Of clinical interest in EEG are, for example, sleep pattern analysis, cognitive tasks registration, seizure and epilepsy detection, and other states of the brain, both normal and pathophysiological.

Clinical neurologists use CT imaging techniques for diagnosis of brain tumors because of its high accuracy in initial diagnosis of the primary pathology (96 % of cases). Such scans stand short, however, of analyzing the physiological functioning of the brain as a whole, both at the time of initial diagnosis or as part of a long term management of the patient. For such purposes, EEG has been used to render a clearer overall view of the brain functioning at initial diagnosis stages and for followup care. For example, a normal EEG in the presence of CT-detected tumor indicates that the brain has "adapted" to the growth of a large space-occupying lesion and that the patient is in a relatively stable state. Conversely, in some cases highly abnormal EEG indicates that the patient's initial state is more unstable. Such correlations between anatomical and physiological data help physicians who interpret EEG give a more accurate assessment of the deficiencies, rehabilitation requirements and the like in patients with brain tumors, both pre- and post-operative/treatment.

Being a non-invasive low cost procedure, the EEG is an attractive tumor diagnosis method on its own. It is a reliable tool for the glioma tumor series. Also, the EEG in vascular lesions is abnormal from the onset of symptoms whereas a CT only becomes abnormal on the third or fourth day or after a week (da Silva et al [5]). The EEG is, however, less successful in detecting brain stem tumors and meningioma series. Although it is abnormal in high percentage of the cases, it so far fails to differentiate between some lesion types; also, *localized delta activity*, the hallmark of a tumor, may exist without tumor mass. Hence, current EEG tumor diagnosis techniques which aim at extracting relevant information for tumor detection and localization have shown humble results (of which perhaps the most successful among the cited literature is Brain Electrical Activity Mapping BEAM (Duffy et al, 1979 [1]).

## 2. Problem formulation

Our research aims at developing an automated system for classifying space occupying lesions from EEG signals. Despite the techniques introduced thus far in extracting information, analysis and visualization of EEG, brain tumor diagnosis usually involves experienced physicians and is a nontrivial, time-consuming

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task mainly due to the following:

i. Low evidence of symptoms: the EEG, being a propagation of internal electrical activity onto the scalp at a macroscopic level might not only lose precise information and localization of a tumor but also become the result of global connected brain activity whose features vary depending on individual cases.

ii. Variability of symptoms among subjects as justified by variations in functionality and anatomy of brain tissues.

iii. Varying recording conditions: The existence of external stimuli and complexity of brain activity result in nonstationary EEG recordings over different sessions.

The aforementioned difficulties have made EEG tumor diagnosis differ not only a among raters (inter-rater agreement) but also for the same rater under different experiments (intra-rater agreement). Thus, if we consider an automated system which mimics human rater practice and also improves on it by developing new ways of looking at the EEG, our problem can be described in two main steps.

1. Feature Extraction: The need for extracting the correct features, or clarifying what is "relevant information", in an EEG which closely relate to pathological cases with high rate of inter- as well as intra-rater agreement continues to be the major challenge.

2. Classification: The clustering of the features into different classes which lead to the final diagnosis of the EEG corresponds to a general scheme of pattern recognition. In general, the success of the classification procedure depends on how well the training data set represent different classes, and how separable various classes are, especially upon projection onto lower dimensional spaces [6].

## 3. Overview on generic EEG diagnosis

### 3.1. Feature Extraction

The problem of extracting generic features "embedded" in an EEG signal was tackled mainly with (1) **spectral analysis** methods which assumes short time stationarity and which typically study energy content of EEG channels in conventional frequency bands adopted by human raters physicians (Delta: below 3.5 Hz, Theta: $4 - 7.5$ Hz, Alpha: $8 - 13$ Hz, and Beta: usually $13 - 40$ Hz). Other techniques include (2) *time framework* (periodicity, auto and cross correlations), (3) *mimetic analysis*, which extracts template segments from baseline data records and hence mimics human raters by generating a statistical classification framework, possibly projected onto 2D brain schematics [1], and (4) *parametric modeling* with little physical insight (seizure detection in [12]).

Still, some researchers used methods ranging from modulation hypothesis (Barlow[4]) to nonlinear dynamical systems aimed at describing and analyzing EEG behavior [13].

### 3.2. Classification

With a set of features at hand, workers in the field have principally used *supervised learning* (conventional neural networks), mainly applied in epilepsy and seizure detection [3], *unsupervised learning* (such as self-organizing maps) with attempts at classifying various sleep patterns, seizure detection, and at separating alpha activity, theta of drowsiness, eye movement, and artifacts in EEG recordings of various subjects [9, 10]. Other techniques are *semi-automated*, that is, utilize the extracted features but require human evaluation of the extracted (mainly visual) information such as BEAM (Brain electrical activity mapping) which was developed mainly to detect epilepsy and glioma tumors, and Significance Probability Mapping which creates a dictionary of template segments according to which EEG is classified [2].

## 4. Conducted Experiments in EEG Tumor Diagnosis

Automatic classification of brain tumors from EEG has been nearly lacking in the literature surveyed, possibly due to the aforementioned difficulties, mainly variability of symptoms among different subjects and diversity of brain electric behavior under different lesions, the symptoms being most consistent under gliomas and less obvious under brain stem tumors [5]. With such problems, mimicking human raters with high experience continues to be a hard problem.

**Prevalent clinical practice**: Gliomas, Meningiomas, and Metastases commonly cause many EEG abnormalities, usually have been referred mostly to or thought of in terms of the conventional EEG spectral decomposition. General guidelines as to what physicians look for are [5]:

1. Polymorphic delta activity (PDA) or localized irregular delta activity (LDA): are very common in intra-cranial tumors and usually localize to the site of the tumor and does not block (or seize) due to external stimuli.

2. Intermittent rhythmic delta activity IRDA, occurring bilaterally and usually frontally and is remarkably reactive to external stimuli.

3. Localized loss of activity over the area of the tumor (a sure sign, but less common).

4. Disturbance, usually slowing, of alpha activity commonly seen in posteriorly placed tumors; localized theta, sharp waves, etc.

**Proposed approach:** A reflection on existing tools and clinical diagnostic measures calls upon the need of *a technique which learns both spatially and temporally various diagnosed patterns.* That is, a method which looks into all channels simultaneously and then learns from the changes occurring with time in various channels. With 20 or more EEG channels, this requires highly efficient feature vectors and a classification scheme which preserves topological information.

### 4.1. Wavelet expansions as time features

Wavelets have been used extensively in image coding where it provided a concise or compact representation with good accuracy and has been used in seizure detection applications ([7]). The ability to capture a global behavior of a signal on low resolution expansion and to move progressively into more details as needed provides a flexible tool for an efficient decomposition. This is especially useful in natural phenomena where slow changes are typically low frequency and transients occur on short intervals (details). Thus, we here aimed at exploiting this characteristic time-frequency decomposition of wavelets to capture main features of various tumors.

A main complication in using wavelets is that the decomposition is *not time invariant.* That is, a shift in the analysis window over which the decomposition is carried will result in different wavelet coefficients across resolutions. Although shift-invariant forms of wavelet-like decompositions (Best Basis in [8]) exist, these are computationally intensive and were avoided in the current experiment. Instead, we used the following:

1. Expand the EEG signal over several resolutions in time: coarse approximation $J_{max}$ up to a predetermined detail level $J_{min}$. Obtain an average coefficient over each of these expansion levels by finding the absolute mean of the expansion coefficients on a particular level. That is, for a signal $f(t)$ of length $N$ sample points

$$\begin{aligned} f(t) &\approx A_{J_{max}} f(t) + \sum_{j=J_{min}}^{J_{max}} D_j f(t) \\ &\approx \sum_{m=1}^{\frac{N}{2^{J_{max}}}} a_{J_{max},m}\phi_{J_{max},m}(t) + \sum_{j=J_{min}}^{J_{max}} \sum_{m=1}^{\frac{N}{2^j}} d_{j,m}\psi_{j,m}(t) \end{aligned} \quad (1)$$

where $A_{J_{max}}$ and $D_j$ are projection maps and their effect correspond to coarse approximation and added details respectively. $\phi_{J_{max},m}$ are bases functions for the coarse approximation (subspace is indexed by $J_{max}$) and $\psi_{j,m}(t)$ are wavelet functions or bases which constitute increasingly higher approximations over subspaces indexed by $j$. Next, obtain

$$\begin{aligned} \bar{a}_{J_{max}} &= mean\{|a_{J_{max},m}|\} & m = 1 \ldots \tfrac{N}{2^{J_{max}}} \\ \bar{d}_j &= mean\{|d_{j,m}|\} & m = 1 \ldots \tfrac{N}{2^j} \end{aligned} \quad (2)$$

2. Obtain the number of zero crossings (or sign changes) that the expansion coefficients undergo over individual scales

$$\begin{aligned} a_{zc_{J_{max}}} &= \text{Number of zero crossings in } a_{J_{max},m} \\ d_{zc_j} &= \text{Number of zero crossings in } d_{j,m} \end{aligned} \quad (3)$$

3. Use both $a_{zc_{J_{max}}}$ and $d_{zc_j}$ in the feature vector$x_f$ that describes the signal $f(t)$:

$$\begin{aligned} x_f = [ & \bar{a}_{J_{max}} & \bar{d}_{J_{max}} & \ldots & \bar{d}_{J_{min}}, \\ & a_{zc_{J_{max}}} & d_{zc_{J_{max}}} & \ldots & d_{zc_{J_{min}}} ] \end{aligned}$$

Hence with this average wavelet expansion, zero-crossing count feature vector we avoided the time shift problem of the original expansion. By obtaining these features over all the EEG channels, we have a set of descriptive impressions of the brain activity over an analysis window of length $N$, which is significantly lower in dimension than the original data set, and is expected to be efficient for classification purposes.

**frequency domain features:** The energy content in conventional frequency bands in the frequency spectrum was used for comparison purposes (windows similar to those used in [9]). The resultant is a 5 component feature vector for each channel, and a total of 110 features per time window over all the considered channels (22 of them).

### 4.2. Multi Self-Organizing Maps as classifiers

The Self Organizing Map (SOM) defines a mapping (or nonlinear projection) between the input data space $\mathcal{R}^n$ onto a two (or single) dimensional array of nodes. This clustering technique preserves the topographic information in input data sets where close nodes in the array are "closely" related or belong to a same cluster among a large data set [11]. Hence, being an unsupervised learning technique, SOM can represent structures in the input distribution with little intervention, especially that the wide variability of EEG tumor activity requires large input data sets that sufficiently sample the input space, thus making a supervised learning procedure quite cumbersome. SOMs have been utilized for EEG analysis in sleep patterns [10] or alpha attenuation [9].

**Multi-layer Maps:** As presented before, the EEG data was coded onto descriptive features using frequency or wavelet transform techniques. Even with such coding, however, multiple channels (22 up to 128) dictate a high dimensionality of the learning vector (For a 22 electrode scenario and if every channel has 5 features then the SOM should map a 110-dimensional input distribution onto a 2 dimensional topography). Although this has been dismissed as a problem in many applications, Ritter [14] has suggested combining several self-organizing maps to learn more complex tasks. That is, by employing several SOMS, each of which learns a subset of the input vector and whose outputs are adjusted so as to minimize the classification error, more precision in approximating the input function can be attained (as there will more discretization points over each coordinate axis)[1]. In another work, [15] used multi-layer SOMs to recognize 2D images in a distortion tolerant manner and shown its usefulness experimentally. Hence, we will adopt multi-layer SOMs to learn input features.

Subdivide the input feature vector $x$ so that different feature components of the recordings are learned separately. For the wavelet features, for example, expansions at each of $n$ scales (for all the channels) become teaching inputs $x_1, \ldots, x_n$ to different maps $SOM_1$, $\ldots$, $SOM_n$. After training these maps, the patterns formed on this layer of $n$ maps is learned as follows. For each input vector $x_i$ to map $i$, the 2 dimensional coordinates corresponding to the activated node in that map is taken as an "output" $y_i$ of the map. The outputs $y_1, \ldots, y_n$ of the $n$ maps are next used as a feature vector (of dimension $2n$) to be learned by a single SOM in the next layer $SOM_{out}$. Finally, labeled samples are presented to the multilayer maps and output clusters are correspondingly labeled and tested on new data.

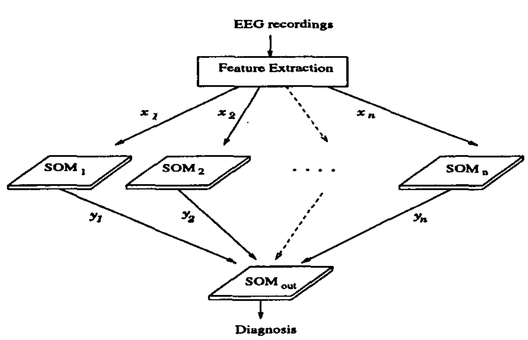


**Figure 1:** A schematic of using multi-layer SOMs in EEG classification

[1] In his work, [14] presents conditions on the outputs of each map (as they relate to the estimated function) where a global minimum of the classification error is attainable. It suffices for our current purposes, however to state that the classification error might be only local minimum.

## 5. Simulations and results

EEG data recordings of 9 subjects (3 Normal, 3 Glioma, and 3 Meningioma cases) were used (each recording is about 1 minute long and is sampled at 256Hz). The data of 22 channels is then windowed in 0.5 sec intervals, and overlapping windows at half width were used. Over each window the features were obtained and used as one learning vector for classification purposes. About 140 vectors from each recording were used to train the network and 25 used to test its performance. **Note** that the data was used in its original form (noisy segments included) and the obtained results reflect approximate diagnosis of the cases, mainly serving as *test-bed* of how the relative success of the different feature extraction /training techniques adopted.

**SOMS with wavelet features:** Following the formulation in section 4.1, and by setting $J_{max} = 7$, $J_{min} = 3$, we obtain for each channel a feature vector $x_f$ of dimension 10. For a 22 channel system, $x \in \mathcal{R}^{220}$ which could in principle be used to train a single SOM map (results not shown here). In the multilayer scenario, 5 maps are used where for each map the training vector is the averaged wavelet coefficients of all channels at a particular scale and the corresponding number of zero crossings (i.e., $x_i \in \mathcal{R}^{44}$, $i = 1 \ldots 5$). The training was performed using a software package SOM-PAK. A similar scenario of SOMS was constructed however with frequency features. It was tested with same data sets as before and results are summarized in table 1-(b).

Table 1-(a): Classification : Multi-layer Maps, WAVELET Features

| Case | | total | Correct Diagnosis(%) | Correct Diagnosis and subject (%) | false diag.(%) |
|---|---|---|---|---|---|
| Normal | N1 | 30 | 76.7 | 76.7 | 6.7 |
| | N2 | 30 | 63.3 | 60 | 26.7 |
| | N3 | 30 | 83.3 | 80 | 10 |
| Mening-ioma | M1 | 23 | 87.0 | 87.0 | 8.6 |
| | M2 | 30 | 63.3 | 56.7 | 30.0 |
| | M3 | 23 | 69.6 | 43.5 | 4.3 |
| Glioma | G1 | 30 | 87.0 | 87.0 | 0 |
| | G2 | 30 | 100 | 100 | 0 |
| | G3 | 13 | 94.4 | 94.4 | 0 |

Table 1-(b): Classification : Multi-layer Maps, FREQUENCY Features

| Case | | total | Correct Diagnosis(%) | Correct Diagnosis and subject (%) | false diag.(%) |
|---|---|---|---|---|---|
| Normal | N1 | 30 | 76.7 | 56.7 | 20 |
| | N2 | 30 | 46.7 | 36.7 | 40 |
| | N3 | 30 | 20 | 0 | 73.3 |
| Mening-ioma | M1 | 23 | 69.5 | 47.8 | 30.4 |
| | M2 | 30 | 36.7 | 23.3 | 53.3 |
| | M3 | 23 | 91.3 | 69.6 | 4.3 |
| Glioma | G1 | 30 | 76.7 | 60 | 23.3 |
| | G2 | 30 | 86.7 | 83.3 | 13.3 |
| | G3 | 18 | 94.4 | 94.4 | 5.6 |

It can be seen from Tables 1-(a) and 1-(b) that the wavelet based feature extraction approach is more successful in general than that based on conventional frequency features used in the EEG community. The wavelet-based features (averaged coefficients and zero crossings), although simplistic at this stage, appear to have captured the signals behavior at different scales in a time localized manner and hence provide a close description of the original signal features (compare, for example, the Normal, Glioma, and the (less successful) Meningioma series).

A multilayer SOM allows a visual representation of the weight assigned to each subspace decomposition level, and hence a mapping could be done between actual spatial topology of the scalp and various maps, giving a visual schematic similar to the BEAM model, however with more efficient codes (wavelet vs. frequency decomposition). Although original recordings were used in their initial state to label the subject and the related diagnosis, it is believed that with proper labeling of which channels possess the main features and at what instances of time (localization of the tumor spatially and temporally), a mapping of such EEG activity onto detectable clusters on each of the multiscale maps in the first layer and subsequently onto the output SOM is possible. For example, a slowing in some channel will appear at a certain scale map but not in others giving relevant clues as to how each channel is behaving.

## 6. Conclusions and future work

The simple exercise presented above demonstrated one of the many pathways that one can follow to improve on the understanding of observable EEG signals. With an incremental improvement in the features and classifying techniques, results continue to improve despite the vagueness and variability of tumor features. In this instant, we showed that a different decomposition of the time-frequency plane does provide a better opportunity to extract clues about aforementioned tumor classes than with conventional frequency bands. Also, with SOMs preserving topological information, new opportunities for visual human intervention in interpreting the results is possible. However, it is compelling at this stage, to mention that our belief was, and invariably continues to be after conducting the presented exercise, that a black box approach to observable signals is of limited scope in EEG analysis. Instead, the vast experimentation and knowledge building up in the last decade about the anatomical and functional structure in the brain carry the potential of linking this knowledge to a system theoretic approach, finding new ways of looking at EEG, and also utilizing these methods to support or refute current beliefs of activated structures responsible for EEG generation under prespecified states.

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