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EEG Based Hearing Threshold Determination Using Artificial Neural Network

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Abstract:

A simple method has been proposed to distinguish the normal and abnormal hearing subjects (conductive or sensorineural hearing loss) using acoustically stimulated EEG signals. Auditory Evoked Potential (AEP) signals are unilaterally recorded with monaural acoustical stimulus from the normal and abnormal hearing subjects with conductive or sensorineural hearing loss. The extracted features are applied to machine-learning algorithms to categorize the AEP signal dynamics into their hearing threshold states of the subjects. To classify the normal hearing and abnormal hearing subjects with conductive or sensorineural hearing loss. To detect the hearing loss for all including neonates, infants and multiple handicaps which helps to improve their quality of life.

Keywords— **EGG signals, AEP signal ,Sensorineural hearing loss,Neonates.**

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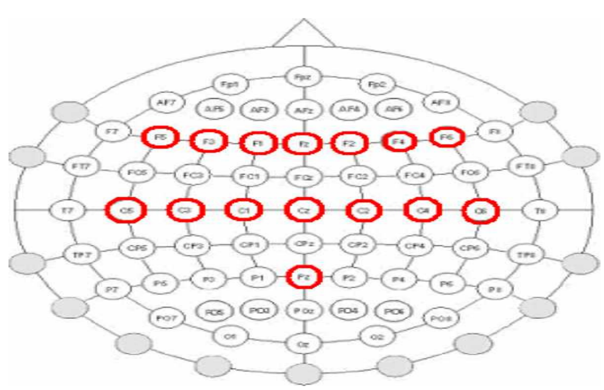
I. INTRODUCTION

EEG

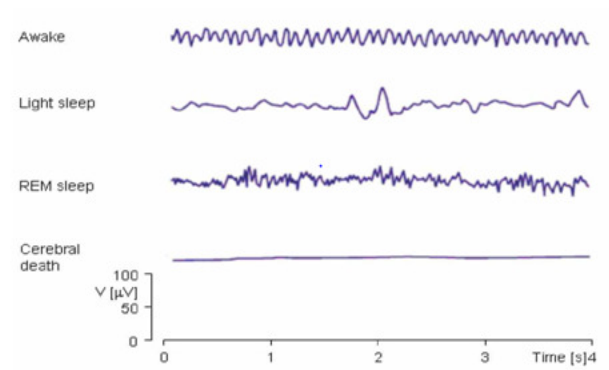
ElectroEncephaloGraphic (EEG) signals stem from measuring electric potentials (microvolts) using electrodes placed on the scalp according to the international 10-20 system (Jasper, 1958), as can be seen in figure 1.1. The electrode labels correspond to cortex areas, thus (F) denotes Frontal, (C) denotes Central, (T) denotes Temporal, (P) denotes Parietal and (O) denotes Occipital. Odd numbers correspond to the left side of the brain, smaller numbers being more medial locations than larger numbers, whileeven number correspond to the right side of the brain. The letter (z) denotes the central line, between the nose and the Putamen Magnum.



The International 10-20 EEG Electrode Placement Scheme. Electrodes Marked in Red are the Ones Used in this Study

EEG-based BCI

- Mental activities producing distinct EEG signals.
- EEG hardware for signal acquisition



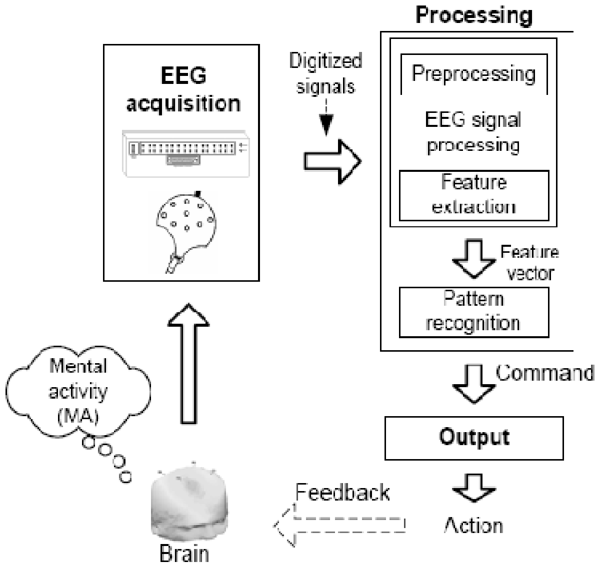
Examples of EEG signals in different levels of consciousness

Digital EEG signal processing (usually) consisting of:

(i) Preprocessing.
(ii) Feature selection.
(iii) Feature extraction.

A machine learning classifier for pattern recognition, translating EEG processed signals into computer commands.

- The output action, which also serves as feedback to the user.



EEG Processed Signals into Computer Commands

II. RELATED WORK

The ERP responses of twenty-nine 6-month-olds, nineteen 12-month-olds and ten adults to an auditory stimulus were derived from ElectroEncephaloGram (EEG) recordings. The most relevant wavelet coefficients corresponding to the first- and second-order moment sequences of the ERP signals were then identified using a feature selection scheme that made no a priori assumptions about the features of interest. These features are then fed into a classifier for determination of age group. To develop a high performance Machine Learning (ML) approach for predicting the age and consequently the state of brain development of infants, based on their Event Related Potentials (ERPs) in response to an auditory stimulus.

The Continuous Time Wavelet Entropy (CTWE) of Auditory Evoked Potentials (AEP) has been characterized by evaluating the Relative Wavelet Energies (RWE) in specified EEG frequency bands. Thus, the rapid variations ofCTWE due to the auditory stimulation could be detected in post-stimulus time interval. This approach removes the probability of missing the information hidden in short time intervals. Thediscrete time and continuous time wavelet based wavelet entropy variations werecompare donnon target and target AEP data. It was observed that CTWE can also be an alternative method to analyze entropy as a function of time.

Electro Encephalo Graphy (EEG) signals as the key indicator. Two timed of main features, spike rhythm city, autoregressive model using Levinson–Durbin algorithm and frequency domain features such as power spectral density estimation by Burg's and Yule–Walker methods are applied. Feed forward and feedback neural network models are used to distinguish the stimuli and non-stimuli EEGs. The neural network models are configured optimally by varying the hidden neurons and learning algorithms and their performance are evaluated in terms of specificity, sensitivity and classification accuracy. It can be concluded from the experimental study that the proposed methodology can be applied for neonatal healthcare applications.

The EEG data acquisition system was tested on 5 healthy young adults and the results were compared to those obtained using a commercial equipment (CADWELL 7200). The results show that the early brain stem evoked potential latencies, related to the hearing process can be detected, even when the system is operated in non-ideal locations for conducting hearing tests. Thus the results suggest that the equipment can be used in clinics without special facilities (i.e. sound proof rooms) as part of routine diagnostic activities.

III. PROPOSED ANALYSIS

Waveform Components

Wave I: The ABR wave I response is the far-field representation of the compound auditory nerve action potential in the distal portion of Cranial Nerve (CN). The response is believed to originate from afferent activity of the CN fibers (first-order neurons) as they leave the cochlea and enter the internal auditory canal.A study by Lin et al indicated that in the assessment of ABR in patients with Idiopathic Sudden Sensorineural Hearing Loss (ISSNHL), wave I latency is significantly associated with hearing outcomes, with a trend toward prolongation found between patients with complete hearing recovery and those experiencing only slight recovery.

Wave II: The ABR wave II is generated by the proximal EEG Signal nerve as it enters the brain stem.

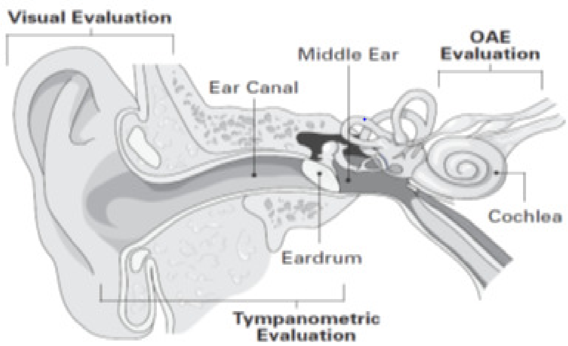
Wave III: The ABR wave III arises from second-order neuron activity (beyond CN) in or near the cochlear nucleus. Literature suggests wave III is generated in the caudal portion of the auditory pons. The cochlear nucleus contains approximately100,000 neurons, most of which are innervated by eighth nerve fibers.

Wave IV: The ABR wave IV, which often shares the same peak with wave V, is thought to arise from pontine third-order neurons mostly located in the superior olivary complex, but additional contributions may come from the cochlear nucleus and nucleus of lateral lemniscus.

Wave V: Generation of wave V likely reflects activity of multiple anatomic auditory structures. The ABR wave V is the component analyzed most often in clinical applications of the ABR. Although some debate exists regarding the precise generation of wave V, it is believed to originate from the vicinity of the inferior colliculus. The second-order neuron activity may additionally contribute in some way to wave V. The inferior colliculus is a complex structure, with more than 99% of the axons from lower auditory brainstem regions going through the lateral lemniscus to the inferior colliculus.

Auditory Brainstem Response Evaluation

In addition to retro cochlear pathologies, many factors may influence ABR results, including the degree of sensorineural hearing loss, asymmetry of hearing loss, test parameters and other patient factors. These influences must be factored in when performing and analyzing an ABR result.



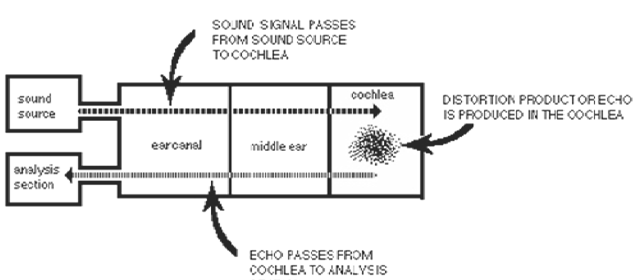
Visual Evaluation

Findings Suggestive of Retro Cochlear Pathology May Include Any 1 or More of the Following:

- Absolute latency interaural difference wave V (IT5) – Prolonged.
- I-V interpeak interval interaural difference – Prolonged.
- Absolute latency of wave V - Prolonged as compared with normative data.
- Absolute latencies and interpeak intervals latencies Wave I-III, I-V, III-V - Prolonged as compared with normative data.
- Absent auditory brainstem response in the involved ear.

In general, ABR exhibits a sensitivity of over 90% and a specificity of approximately 70-90%.

- OtoAcoustic Emissions (OAEs) are sounds measured in the external ear canal that reflect movement of the outer hair cells in the cochlea.
- Energy produced by outer hair cell motility serves as an amplifier within the cochlea, contributing to better hearing.
- Indeed, normal outer hair cells are essential for perfectly normal auditory function.



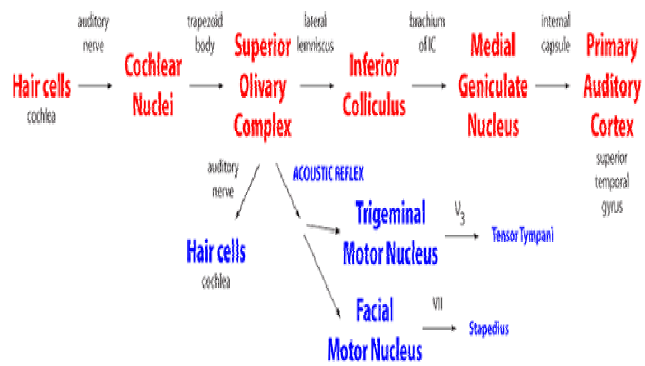
Echo Passes from Cochlea to Analysis Section

Auditory Brainstem Response in Surgery

- **Intraoperative Monitoring:** Auditory Brainstem Response (ABR), often used intra operatively with electroco chalcography, provides early identification of changes in the neurophysiologic status of the peripheral and central nervous systems. This information is useful in the prevention of neurotologic dysfunction and the preservation of postoperative hearing loss. For many patients with tumors of CN VIII or the cerebellopontine angle, hearing may be diminished or completely lost postoperatively, even when the auditory nerve has been preserved anatomically.
- **Auditory Brainstem Response Evaluation:** Wave I, which is generated by the cochlear end of CN, provides valuable real-time information regarding blood flow to the cochlea. Because ischemia is a primary cause of surgery-related hearing loss, wave I is monitored closely for any shift in latency or decrease of amplitude.

Wave I-II and I-III inter peak intervals can provide distal and proximal information during CN VIII surgeries.

Wave V and the I-V inter peak interval latencies are monitored for shifts or alterations in latency and amplitude. The I-V latency provides information regarding the integrity of CN to the auditory brain stem.



Auditory Pathway

- **Limitations:** Wave V alterations occurring intraoperatively do not necessarily reflect changes in hearing status. Changes in latency may instead be caused by resynchronization of neurons or other outside factors. Also, a potential time delay exists between the actual occurrence of insult and when the shift in wave V appears. Patients with preexisting sensorineural hearing loss may have poor waveform morphology and no wave I response.

The Levenberg-Marquardt Algorithm

In the following, vectors and arrays appear in boldface and is used to denote transposition. Also, ||.|| and ||.||oo denote the 2 and infinity norms respectively. Let / be an assumed functional relation which maps a *parameter vector* $p \in R^m$ to an estimated *measurement vector* $x = f(P), x \in R\, n$ An initial parameter e € $t=n^{x-2}$ intimate p_0 and a measured vector x are provided and it is desired to find the vector p^+ that best satisfies the functional relation /, i.e. minimizes the squared distance with. The basis of the LM algorithm is a linear approximation to in the neighborhood of . For a small, a Taylor series expansion leads to the approximation The Levenberg-Marquardt (LM) method consists on an iterative least-square minimization of a cost function based on a modification of the Gauss-Newton method. Let's state the problem formally before defining the algorithm. We will assume that derivatives of the cost functions are not available in closed form, so they will be approximated by finite-difference approximation

$$X^* -= Arg\ min_x (F(x))$$

The function $\mathbf{f}: \mathcal{R}^n \to \mathcal{R}^m$ may sometimes include a comparison to some reference, or observed, data. A very simple, linear example would be x* (f(x)). However in the following we assume can have any form:

$$F(x) = (f_1(x) \ldots.. f_m(x))$$

Step 1: The Hessian of the error function is the $ n \times n $ matrix of second order derivatives (n being the length of the parameter vector), and it's approximated by:

$$H(x) = J(x)_t\, J(x)$$

Step 2 : If we don't have closed form expressions for the derivatives needed for the Jacobian, we can estimate them from finite differences using some increments for each individual variable Δx_j:

$$\mathbf{J}_{ij}(\mathbf{x}) \simeq \frac{f_i(\mathbf{x}+\boldsymbol{\Delta}\mathbf{x})-f_i(\mathbf{x}-\boldsymbol{\Delta}\mathbf{x})}{2\Delta x_j}$$

Step 3: Then, the LM method minimizes the following linear approximation of the actual error function:

$$F(x+h) \cong L(h) = f(x) + h(g(x) + \tfrac{1}{2} h\, t\, (H(x)h$$

Step 4 : Now, denote as $\mathbf{x}_t^*$ for $t=0,1,2,…$ the sequence of iterative approximations to the optimal set of parameters $\mathbf{x}^*$. The first intial guess $\mathbf{x}_0^*$ must be provided by the user. Then, each iteration of the LM method performs:

$$\mathbf{x}_{t+1}^* = \mathbf{x}_t^* + \mathbf{h}_{lm}$$

Algorithm Implementation

$H = J^T(x)\, J(x)$

$g = J^T(x)\, f(x)$

found = || g || ∞ ≤ $\boldsymbol{\varepsilon 1}$

¥ = T max (diag (H))

While (Not Found) and ($k < k_{max}$)

$H_{tm} = -(H(x) + I)^{-1} g(x)$

If (|| h_{tm} || < e2 (||x|| + e2)

Found = true

Else

$X' = x + h_m$

$$L = \boldsymbol{x} = \frac{\mathbf{F(x)-F(x\ \ )'}}{\mathbf{L(0)-L\ (h(m))}} = \frac{\mathbf{F(x)-F(x'\ )}}{\mathbf{h(m)-L\ (h(m'))}}$$

If (l> 0)

X =X'

H= JT(x) J(x)

G= JT(x)f(x)

found = || g || ∞ ≤ $\boldsymbol{\varepsilon 1}$

$\infty = v(1/2, 1 - (2l - 1)^3$

V= 2

Else

V =2v

End

End

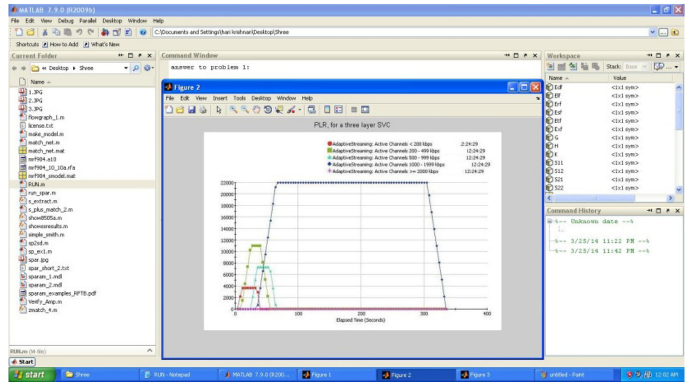
IV. EVALUATION RESULT

First, the effects of brain rhythm on perceiving auditory frequency of 1000 Hz and their auditory response for the PSGB19 and SEGB19 features have been investigated using feed forward neural network. Table 1 shows the classification performance of MLPN using PSGB19 and SEGB19 for left and right ears at hearing frequency of 1000

Hz. Form Table 1, PSGB19 has the maximum classification accuracy of 94.45% and 96.75% for the left and right ears in distinguishing the normal hearing, conductive hearing loss and sensorineural hearing loss subjects. Further, it was observed that SEGB19 features has the classification accuracy of 92.29% and 93.45%for the left and right ears in distinguishing the normal hearing, conductive hearing loss and sensorineural hearing loss subjects.

Feature	Ear	#	Value of	Sensitivity	Specificity	Classification
Technique	-	Epoch	MSE	(%)	(%)	Accuracy (%)
PSGB19	L	350	0.0585	273/305	278/305	94.45
SEGB19	L	420	0.0436	277/305	269/305	92.29
PSGB19	R	450	0.0287	284/305	291/305	96.75
SEGB19	R	520	0.0154	282/305	285/305	93.45

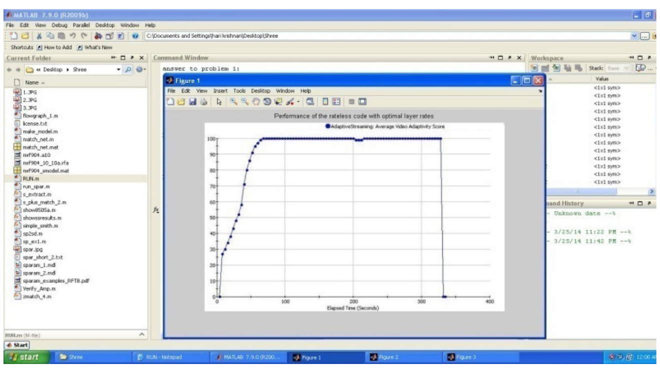
MLPN results using PSGB19 and SEGB19



ABR with Sensorial Layers with SVC

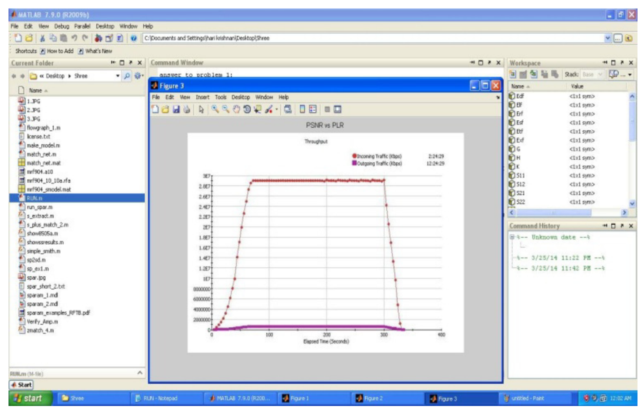
Feature	Ear	#	Value of	Sensitivity	Specificity	Classification
Technique	-	Epoch	MSE	(%)	(%)	Accuracy (%)
PSGB19	L	6500	0.0045	271/305	274/305	90.32
SEGB19	L	7250	0.0086	262/305	268/305	88.97
PSGB19	R	7405	0.0055	275/305	281/305	92.45
SEGB19	R	8000	0.0090	270/305	276/305	90.74

ELN Results using PSGB19 and SEGB19 Features



Performance of the Release Code with Optimal Layer Rates

Second, the effects of brain rhythm on perceiving auditory frequency of 1000 Hz and their auditory response for the PSGB19 and SEGB19 features have been investigated using feedback neural network. Table 2 shows the classification performance of ELN using PSGB19 and SEGB19 for left and right ears at hearing frequency of 1000 Hz. Form Table 2, PSGB19 has the maximum classification accuracy of 90.32% and 92.45% for the left and right ears in distinguishing the normal hearing, conductive hearing loss and sensorineural hearing loss subjects. Further, it was observed that SEGB19 features has the classification accuracy of 88.97% and 90.74% for the left and right ears in distinguishing the normal hearing, conductive hearing loss and sensorineural hearing loss subjects.



PSNR with PLR

Final when comparing the classification performance of the observed results of MLPN with ELN, applied to PSGB19 features, it was observed that MLPN outperformed ELN by 3% to 4% in classifying the normal hearing, conductive hearing loss and sensorineural hearing loss subjects. When comparing the classification performance of the observed results of MLPN with ELN, applied to SEGB19 features, it was observed that MLPN outperformed ELN by 2% to 3% in classifying the normal hearing, conductive hearing loss and sensorineural hearing loss subjects.

From the analysis, it can be observed that the PSGB features obtained from the nineteen channels can be used to distinguish the normal hearing, conductive hearing loss, sensorineural hearing loss subjects. From the results, it was evident that AEP signals elicited from the auditory stimuli determines the functional integrity of the auditory system. From the results, it indicates that asymmetric response in the classification performance for left and right ears was reported, which shows that the significant differences may be due to the inherent more active perception of the auditory stimuli made by the right ears while compared to the left ears.

Electrode Reduction

Feature selection method is used to choose a subset of input feature vectors which can reduce the size of redundant features and able to predict the output class with accuracy comparable with the complete input feature dataset. In this study, feature selection has been proposed based on the feature PSGB19 values because it has achieved the maximum classification accuracy when compared with SEGB19 features. This study proposes feature score index, where gamma power values estimated from the nineteen electrode channels have been used as a scoring function. High score of gamma power from the corresponding channel reflects the potential channels with more discriminative information than other channels. Further, sorting 19 gamma power values in the descending order provides with the information of discriminative electrode channels capacity.

Displays the gamma power score index from the nineteen electrode channels. The effects of hearing processing have been found statistically that gamma power derived from brain locations reflects hearing response to the stimuli. In this study, eight potentially significant channels were selected based on their gamma power score index, P4, C4, F8, T3, T5, T4, T6, O2. As can been seen, the features derived from the temporal lobes has more involved in processing the auditory sensory responses than other regions. The selected eight channels yield the classification accuracy of 86% in discriminating the normal hearing, conductive hearing loss and sensorineural hearing loss subjects.

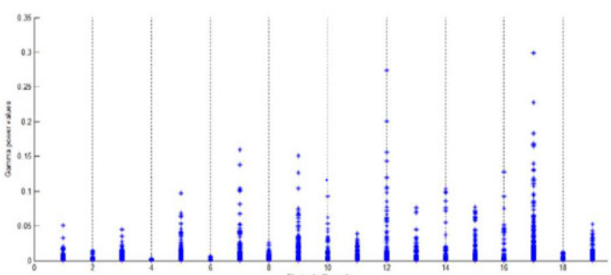


Figure 7.4: Gamma-Power Score Index From Nineteen

V.CONCLUSION

a BCI paradigm based on the modulation of exogenously evoked auditory ERP signals by a simultaneous endogenously executed motor imagery task. It have proved that the motor imagery task changes the auditory ERP signal enough to be classified for BCI use, and without the use of computational and time costly machine learning techniques usually incorporated in classic BCI paradigms. It also shown the potential for shortening the training period, so as to open the possibility of an individual per-subject and per-session calibration stage, in the order of minutes, and by that, addressing the current BCI challenges stemming from inter-subject and inter-session variability issues. Even though 70-80% of correct classification does not seem like a lot, surely not enough to connect any locked-in patient to control .Properly trained in producing highly synchronized and consistent mental activities. The 20% incorrectly classified samples might be attributed to this fact. Although producing robust, across subjects, classification results, a true per-subject calibration would necessitate finding the best latency and electrodes for each subject. Future studies of our BCI paradigm should involve an automated parameter optimization technique for improving classification accuracy.

FUTURE WORK

Further improvements to the neural-based vocoder implementation need to be made. For example, it would be very interesting to explore how more complex functionality (such as inhibition, synaptic learning, adaptation...etc) affects the output of the synthesizer, and whether the output from those models differs perceptually from the current one. Over and above, the spread or activity from one electrode to nearby neural populations should be explored as a function of the electrode location (basal vs. apical) as opposed to using the same current spread people for all electrodes. Moreover, the model parameters need tobe tested with CI subjects who have normal hearing in one ear. Additionally, psychophysical tests can be carried out using theaforementionedstimulation methods in order to assess how closethe vocoder simulations are in capturing the cues perceived via CI stimulation. This is a very crucial step to tune the model's output to more closely resemble the sounds perceived by CI subjects.

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