The Journal of International Advanced Otology

J Int Adv Otol 2019; 15(1): 87-93 • DOI: 10.5152/iao.2019.4553

Original Article

A Novel Approach for Classifying Native Chinese and Malay Speaking Persons According to Cortical Auditory Evoked Responses

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Cite this article as: Ibrahim AI, Ting HN, Moghavvemi M. A Novel Approach for Classifying Native Chinese and Malay Speaking Persons According to Cortical Auditory Evoked Responses. J Int Adv Otol 2019; 15(1): 87-93.

OBJECTIVES: This study uses a new approach for classifying the human ethnicity according to the auditory brain responses (electroencephalography [EEG] signals) with a high level of accuracy. Moreover, the study presents three different algorithms used to classify the human ethnicity using auditory brain responses. The algorithms were tested on Malays and Chinese as a case study.

MATERIALS AND METHODS: The EEG signal was used as a brain response signal, which was evoked by two auditory stimuli (Tones and Consonant Vowels stimulus). The study was carried out on Malaysians (Malay and Chinese) with normal hearing and with hearing loss. A ranking process for the subjects' EEG data and the nonlinear features was used to obtain the maximum classification accuracy.

RESULTS: The study formulated the classification of Normal Hearing Ethnicity Index and Sensorineural Hearing Loss Ethnicity Index. These indices classified the human ethnicity according to brain auditory responses by using numerical values of response signal features. Three classification algorithms were used to verify the human ethnicity. Support Vector Machine (SVM) classified the human ethnicity with an accuracy of 90% in the cases of normal hearing and sensorineural hearing loss (SNHL); the SVM classified with an accuracy of 84%.

CONCLUSION: The classification indices categorized or separated the human ethnicity in both hearing cases of normal hearing and SNHL with high accuracy. The SVM classifier provided a good accuracy in the classification of the auditory brain responses. The proposed indices might constitute valuable tools for the classification of the brain responses according to the human ethnicity.

KEYWORDS: Cortical Auditory Evoked Potentials (CAEPs), regression, support vector machine, sensorineural hearing loss, electroencephalography

INTRODUCTION

The classification of the cortical auditory-evoked potentials (CAEP) signal is difficult due to the small CAEP response amplitudes. However, research on the classification of brain electroencephalography (EEG) signals for different types of EEG signal cases has been reported in the past few years. The researches by Acharya U.R. or Guo L. or Kumar Y. or Siuly S [1-5] discussed various entropies used for an automated diagnosis of epilepsy using multiple classifiers of EEG signals. Other examples include the sleep EEG activity during hypopnoea episodes [6], the Early Detection and Classification of Dementia [7], and many other EEG signal applications [8-12]. Moreover, many systems used the auditory-evoked potentials (AEP) signal classifications process in their applications. The AEP signal classifications are used in brain–computer interface (BCI) applications [13], diagnosis of hearing loss [14], etc. [15].

Furthermore, the AEP signal classifications are regarded as a clear indicator in the BCI application. However, in BCI systems, the AEP signal classification serves as an alternative to visual-evoked potentials signal classification, where the extraction of suitable features from the AEP signals combined with a classification process leads to the stimulus and non-stimulus activities being identi-

This study was presented at the University of Malaya, 01.09.2017, Kuala Lumpur, Malaysia.

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Submitted: 12.09.2017 • **Revision Received:** 27.08.2018 • **Accepted:** 28.09.2018 • **Available Online Date:** 06.03.2019
Available online at www.advancedotology.org

fied alongside other hearing control activities [13, 16, 17]. Shangkai [13] reviewed the challenges in AEP signals processing of BCI systems. The classification of biomedical signals using an index is rarely reported in previous studies, particularly in cases using EEG signals. To date, some studies formulated biomedical indices in different biomedical issues that exclude the EEG signals. Dhanjoo in 2009 developed a new concept of a non-dimensional physiological index (NDPI) [18]. It is made up of several parameters characterizing organ function/dysfunction, a physiological system function and disorder, and an anatomical structure's property and pathology in the format of a medical assessment test; the NDPI combines these parameters into one non-dimensional number.

This study aimed to identify the human ethnicity based on the EEG (CAEP) signals that were recorded from Malay and Chinese subjects. For verification of this aim, we used two separated CAEP signals that were recorded from subjects with different hearing abilities. The affinity to one of two native language groups was investigated for normal hearing subjects and sensorineural hearing loss (SNHL) patients. This case study separated the EEG (CAEP) signals according to two human ethnicity groups, the Malay and Chinese. The study formulated classification indices (Normal Hearing Ethnicity Index [NHEI] and Sensorineural Hearing Loss Ethnicity Index [SNHLEI]) for separating the CAEP signals recorded from Malay and Chinese subjects with and without normal hearing abilities. These classification indices categorize affiliation to a native language group based on features derived from CAEP.

The CAEP classifications may be useful in hearing and language rehabilitation for patients on whom the normal hearing test pure tone audiometry (PTA) cannot be performed reliably (e.g., infants, children, and difficult-to-test patients). The lack of hearing screening tests at an early age will impede speech, language, and cognitive development [14]. Moreover, the existing ethnic disparities in auditory health care represent critical areas for research and intervention. Studies have indicated unique factors in hearing loss across ethnicities. Therefore, this type of ethnicity classification may help develop or design better hearing aids by detecting the original ethnicity of the patients [14, 19], similar to its use in BCI systems [13], and distinguish the age of infants [15]. The present article is organized in the following order. Section 1 introduces the subject. Section 2 will explain the methodology involved in this work. Section 3 will describe the EEG data analysis for the experiment, while Sections 4 and 5 will detail and discuss the results. Section 6 concludes the entire work.

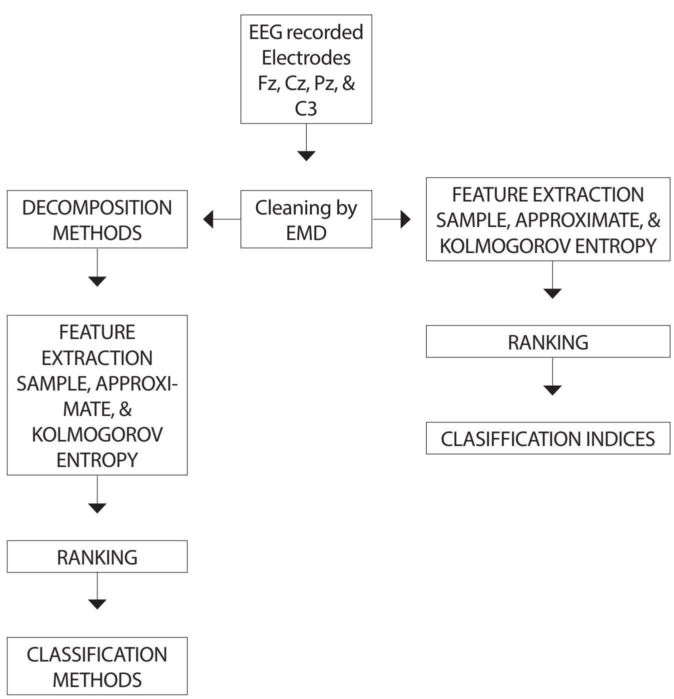

Figure 1. Proposed analysis.

MATERIALS AND METHODS

In this study, we collected, cleaned, decomposed, and extracted features and classified the EEG AEP signals. The proposed methodology is shown in Figure 1.

Participants/Subjects

The study was conducted on two ethnicity groups (Malays and Chinese). An ethnicity group is a category of people who identify with each other based on a certain common ancestral, language, society, culture, or nation. All participants involved in this study were tested by the Otorhinolaryngology (ENT) department using the routine PTA measurement. The groups are described as follows:

1- Ten adult right-handed Malay males (mean age=23.5 years, standard deviation [SD]=2.52) and 10 adult righthanded Chinese males (mean age=22.5 years, SD=1.55). The ENT department confirmed that all the subjects had a normal range of PTA response.

2- Seven adult right-handed Malay male patients suffering hearing loss (HL; fluent Malay speakers) who were 3550 years old and had bilateral SNHL for more than 6 months with no history of using hearing aids (mean age=41.7 years, SD=4.643) and seven adult right-handed Chinese male patients with HL (fluent Chinese speakers) aged 35-50 years and having bilateral SNHL for more than 6 months with no history of hearing aids usage (mean age=43.1 years, SD=2.63). The ENT department confirmed that all patients had SNHL in the moderate range according to their pure tone audiogram.

The experimental protocols were approved by the Medical Ethics Committee (IRB Reference Number: 1045.22). Each participant provided written consent prior to the experiments. The normal hearing and the SNHL patients were recruited from the local population. The subjects participating in this study were healthy normal hearing persons with no history of otological, psychological, or neurological complications (fluent Malay speakers) according to the ENT hospital department reports. All SNHL patients who participated in this work had no history of hearing aids usage. The study examined participant's EEG recordings. However, not all data could be used in the analysis because of several reasons. Certain subjects' recordings had artifacts, noise, recording calibration, and device setting problems. The study selected the recorded signals of the subjects that had clean recordings and free of artifacts. Table (1) shows the PTA results for all the subjects participating in this work. The values listed were the average reading for 1 kHz, 2 kHz, and 4 kHz presented in decibels. Most of the SNHL patients had HL for a long time, since their childhood. Moreover, most of them specified the reasons for their HL as illness.

Stimuli

The study consisted of two disparate types of auditory stimuli: pure tone frequency bursts (1 kHz versus 4 kHz) and speech consonant-vowel (CV) transitions (/ba/ versus /da/), presented at ~85-90 dB sound pressure level (SPL). The tone stimulus lasted for 200 ms and was generated by a software program in MATLAB R2013b (www.mathworks.com), with a fall time of 10 ms and a plateau time of 190 ms and represented at two different frequencies of 1000 Hz and 4000 Hz tone stimuli [20].

Table 1. PTA test results for the participants in this work

	Sample	Left Ear	Right Ear
Normal hearing	MALAY 1	12	11
	CHINESE 1	15	17
	MALAY 2	10	11
	CHINESE 2	13	11
	MALAY 3	12	11
	CHINESE 3	12	12
	MALAY 4	10	12
	CHINESE 4	15	17
	MALAY 5	11	10
	CHINESE 5	11	13
	MALAY 6	10	12
	CHINESE 6	11	13
	MALAY 7	12	11
	CHINESE 7	15	12
	MALAY 8	13	15
	CHINESE 8	17	15
	MALAY 9	15	11
	CHINESE 9	20	15
	MALAY 10	15	17
	CHINESE 10	11	10
SNHL	MALAY 1	53	55
	CHINESE 1	58	56
	MALAY 2	55	53
	CHINESE 2	57	55
	MALAY 3	58	57
	CHINESE 3	55	55
	MALAY 4	52	53
	CHINESE 4	58	55
	MALAY 5	55	55
	CHINESE 5	57	57
	MALAY 6	55	52
	CHINESE 6	58	55
	MALAY 7	56	55
	CHINESE 7	55	53

Results in dB

The /ba/ and /da/ tokens were characterized by their contrasting voiced/voiceless articulatory features of speech, where /ba/ has a lower second and third formant frequencies with lower onset frequencies of the formant transitions compared to /da/ [6, 21-23]. The stimuli with their spectrograms are shown in Figure 2.

The speech stimuli were recorded at a 44100 Hz sampling rate from the natural speech produced by a female Malay speaker. The CVs were edited to have a total duration of 200 ms by trimming the long voice onset time of the voiced plosives and the final part of the steady state vowel and by windowing of the offset (please note that /ba/ and /da are not contrasts in terms of the voicing feature; both /ba/ and /da/ are voiced plosives). The stimuli were presented with a pseudo-randomized oddball sequence of 80% standard and 20% deviant presentations, with an inter-stimulus interval of 800±500 ms, and delivered to both ears via a pair of Sennheiser HD 428 closed circumaural headphones. In this study, the Pure Tone stimulus had a standard stimulus of 1 kHz and a deviant stimulus of 4 kHz. Also, the CV stimulus had a standard stimulus of /da/ and a deviant stimulus of /ba/. The presented stimuli were calibrated at the ear level using a KEMAR ear-and-cheek simulator (G.R.A.S. Sound and Vibration, 43AG) and a type 1 integrating sound level meter (Norsonic, nor140) [24]. The tone and CV stimuli contrasts were delivered separately and tested in two trials. Each trial consisted of 350 stimuli, i.e., 70 deviant stimuli and 280 standard stimuli. Thus, there were 140 deviant stimuli and 560 standard stimuli presented over two trials. The order in which the stimuli were presented ensured that there were 3-5 standard stimuli between each deviant one. There was no counterbalance for this study, that is, the (1000 Hz/da) stimulus was always the standard, while the (4000 Hz/ba) stimulus was always deviant.

Eventrelated potential recording

The subjects were seated on a comfortable armchair inside a soundproof chamber. They were instructed to minimize, and if possible, eliminate any eye blinking or muscle movements. The recording was done in various sessions at ~35 minutes each. To ensure the continuation of passive listening conditions, written short stories were presented throughout the experiment. The recording was done at

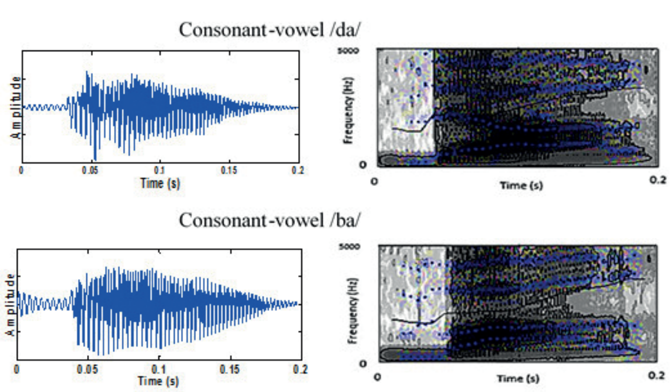

Figure 2. Consonant-vowel stimuli. Left: Time domain waveform of speech cues presented at 85 dB SPL (200 ms duration). Right: Spectrograms of speech stimuli. The bold solid and dotted line represents the sound's pitch and formant contour, respectively.

500 Hz sampling rate using the wireless Enobio EEG/eventrelated potential (ERP) acquisition system Enobio NE [25]. Data were recorded from four silver (Ag)/silver chloride (AgCl) electrodes mounted on a Neoprene EEG cap and located over the following scalp sites: three electrodes were located on the midline of the head: Fz, Cz, and Pz, and a fourth electrode was located on left-hand side of the scalp, C3 (according to the modified International 10-20 system). The recording device Enobio EEG/ERP provided an online filter, consisting of a band pass filter, with pass band (2 Hz-40 Hz) second order Butterworth Finite Impulse Response (FIR).

Component Analysis

After ERP data collection, the responses went through pre-processing to correlate the baseline drift and were filtered offline at 2-30 Hz using second order the Butterworth FIR band pass filter. The averaged trials were taken from successful runs that were free from artifacts, noises, and clearly evoked the auditory ERP signals. This averaging process was separately done for each used electrode. However, the standard average responses excluded responses to the stimulus occurring immediately after the deviant stimulus and vice versa for the deviant average response. The raw averaged EEG AEP signals were de-noised by the empirical mode decomposition (EMD) technique [26]. The EMD technique provided a simple, fast, and efficient artifact cleaning tool [27]. EMD de-noising could eliminate noises even if combined with the original data. The criteria used to determine ERP response presence or absence were (1) using visual inspection where the ERP is present if individual ERP peaks were larger than the level of the pre-stimulus baseline and (2) using ERP analysis included baseline-to-peak amplitude and latency comparison with a typical standard ERP waveform described elsewhere [28-30].

Segmentation of CAEP signals

The averaged CAEP signals were segmented individually into time segments per the CAEP latencies components, with P1 (latency window 20-100 ms), N1 (latency window 60-160 ms), P2 (latency window 140-240 ms), N2 (latency window 160-300 ms), and P3 (latency window 240-420 ms) [21]. The latencies were visually obtained using automated latency detection algorithms. This was done separately for each stimulus responses.

Feature extraction

To extract the features from the averaged CAEP data, non-linear feature extraction methods were used in this work, such as Kolmogorov–Sinai entropy (KolmogEnt.), Sample Entropy (SampleEnt.), and Approximate Entropy (ApproxEnt.). This was because brain neurons are controlled by nonlinear phenomena, such as the threshold and saturation processes.

Classification

The learning classifier is an algorithm that combines features and classes. The Support Vector Machine (SVM), Knearest neighbor (KNN), and Linear Discriminate Analysis (LDA) were the classifiers used in this work [31-33]. A feature extraction method, including Sample Entropy, Approximate Entropy, and Kolmogorov Entropy, was applied to the EEG signals in the time domain. These features were non-linear [1]. The classifier's performance was determined using the performance parameter (accuracy), defined as:

$$Accuracy = \frac{Number\ of\ correctly\ classified\ observation}{Number\ of\ total\ observation} \qquad (1)$$

Formulation of classification indices for classifying the human ethnicity

To accurately decide on a system that uses classification in its process, a very accurate classifier is needed. However, it is not as straightforward as it seems. It is more convenient for researchers to use a single integrated index that is significantly different in the two classes (accuracy 100%). This concept of the integrated index was conceived and advanced by Acharya [34].

Based on that fact, we formulated integrated indices, which could be defined as the NHEI and SNHL Ethnicity Index (SNHLEI). The NHEI was formulated using non-linear features constructed from the auditory brain responses evoked by the Pure Tone and CV stimulus. Similarly, the (SNHLEI) index was formulated using the non-linear features constructed from the auditory brain responses evoked by Pure Tone and CV stimulus. This consolidated index was formulated to produce values that are significantly different in different ethnicity SNHL patients.

RESULTS

In this study, the experiments were conducted and the results collected. Only the Cz electrode data were selected for further process and analysis, as it was most significant toward CAEP waveform in response to auditory stimuli. Furthermore, this electrode demonstrates the highest signal-to-noise ratio as opposed to other electrodes [35].

A cross validation method was used to determine the trained and tested sets. The cross-validation process could be done via multiple approaches (i.e. K-fold cross validation, Holdout validation, etc.). This study used K-fold cross validation, with k=4. This will use 75% of the data in the classification matrix to develop an automated system and obtain features used to train the classifier, while 25% were used to test the classifier performances. Training and testing were conducted four times, and the classification accuracy was averaged over 4 trials.

Cross-validation was used to define a dataset to "test" the model in the training phase (i.e., the validation dataset) for limiting problems of over fitting. The fitting process optimizes the model parameters to make the model fit the training data as well as possible [36].

Classification of the Human Ethnicity

Classification of normal hearing subjects ethnicity

The feature matrix formed and generated by the successful features extracted from the non-linear feature methods was (240 samples×5 intervals) elements. This matrix contains four types of stimuli (1 kHz, 4 kHz, da, and ba) and three features (KolmogEnt., SampleEnt., and ApproxEnt.) with the number of participated subjects (normal hearing subjects group contains 10 for Malay and 10 for Chinese subjects) multiplied by five-fold of CAEP responses intervals of the P1, N1, P2, N2, and P3. Therefore, the classification matrix consists of 240 samples×5 intervals elements using the four-fold cross validation. The training matrix was 180×5, while the test matrix was 60×5. This will be used to evaluate classification performance. The sets of segmented EEG CAEP signals with its features were classified using SVM with Radial Basis Function (RBF) kernel and LDA, KNN with k=1 classifiers for both cross-validation methods.

Thus, we used Eq. (1) to obtain the classification performance parameter (accuracy) for all used classifiers. Table 2 lists the performance parameters for classification of the (NH Malay and Chinese subjects) groups due to their auditory brain responses evoked by the auditory stimulus.

Classification of SNHL patients' ethnicity

As per the explanations in previous section, the feature matrix formed and generated by the successful features extracted from the non-linear feature methods was 168 samples×5 intervals elements. This matrix contains four types of stimuli (1 kHz, 4 kHz, da, and ba) and three features (KolmogEnt., SampleEnt., and ApproxEnt.), with the number of participating subjects (SNHL patients group contains 7 for Malay and 7 for Chinese patients) multiplied by five-fold of CAEP responses intervals. The classification matrix consists of 168 samples×5 intervals elements using the four-fold cross validation. The training matrix was 126×5, while the test matrix was 42×5. This was used to evaluate classification performance. Table 3 lists the performance parameters for classification of the (SNHL Malay and Chinese patients) groups due to their auditory brain responses evoked by the auditory stimulus.

Table 2. The performance parameter of classifiers for normal hearing subjects

Classifier	Performance Parameters	Sample	Classified as	
			Malay	Chinese
KNN		Malay	106	14
		Chinese	15	105
	Accuracy		211/240=0.8791	
SVM		Malay	109	11
		Chinese	13	107
	Accuracy		216/240=0.9000	
LDA		Malay	104	16
		Chinese	16	104
	Accuracy		208/240=0.8666	

KNN: K-Nearest Neighbor; SVM: Support Vector Machine; LDA: Linear Discriminate Analysis

Table 3. Performance parameter of classifiers for SNHL patients

Classifier	Performance Parameters	Sample	Classified as	
			Malay	Chinese
KNN		Malay	70	14
		Chinese	16	68
	Accuracy		138/168=0.8214	
SVM		Malay	72	12
		Chinese	14	70
	Accuracy		142/168=0.8452	
LDA		Malay	70	14
		Chinese	15	69
	Accuracy		139/168=0.82738	

KNN: K-Nearest Neighbor; SVM: Support Vector Machine; LDA: Linear Discriminate Analysis

Formulation of the human ethnicity classification indices

NHEI

The NHEI is developed by ranking the non-linear features extracted from the auditory brain responses evoked by the auditory stimulus. These features were then used to develop an optimally distinguishing index. Therefore, the mathematical formulation of this integrated NHEI is mentioned below:

$$NHEI=47.918-124.430\times SampleEnt.-327.347\times ApproxEnt.+264.306\times KolmogEnt. \quad (2)$$

Eq. (2) is derived using linear regression analysis through the "least squares" method to fit a linear equation to a set of classified data for maximizing the discrimination between the two classes, wherein the nonlinear features were first ranked from the least significant, which is the SampleEnt., as the first variable in the equation followed by ApproxEnt. And KolmogEnt as the second and highest significant variables, respectively. All feature values were sorted in a descending order (from largest to smallest) for each stimulus (1 kHz, 4 kHz, da, and ba) individually. The range of the NHEI is shown in Table 4. Figure 3 shows the plot of NHEI for the two classes of the human ethnicity.

SNHLEI

Like the approach reported in previous section, the SNHLEI is developed by ranking the non-linear features extracted from the auditory brain responses evoked by the auditory stimulus. These features were then used to develop an optimally distinguishing index. Therefore, the mathematical formulation of this integrated SNHLEI is:

$$SNHLEI=36.280-372.516\times SampleEnt.+197.703\times ApproxEnt.+22.648\times KolmogEnt. \quad (3)$$

Eq. (3) is derived using linear regression analysis through the same procedure as in previous section. The range of the NHEI is shown in Table 5. Figure 4 shows the plot of SNHLEI for the two classes of the human ethnicity.

Table 4. Range of NHEI for normal hearing subjects

Brain response to	Malay	Chinese
Average*	24.9386	58.0614
SD	11.1357	11.2408
Max.	38.85	75.52
Min.	9.15	42.46

SD: Standard Deviation
*Data set=10 subjects×4 stimulus for each ethnicity

Table 5. Range of SNHLEI for SNHL patients

Brain response to	Malay	Chinese
Average*	14.5177	35.5164
SD	4.8503	5.8415
Max.	21.13	46.75
Min.	11.82	27.68

SD: standard deviation
*Data set=7 subjects×4 stimulus for each ethnicity

DISCUSSION

The most important aspect of this study is the formulation of new classification indices using EEG CAEP signals. NHEI and SNHLEI classified the EEG CAEP signals recorded from two different human ethnicities with normal hearing and SNHL with an accuracy between 82% and 90%. Other experimental studies used classification algorithms to classify the human brain EEG signals for predicting the outcome of simple motor tasks recorded from different ethnic groups [37]. This study compared the classification of auditory brain responses evoked by an auditory stimulus. Tables 2 and 3 and the predicted new classification indices report a high classification performance in the time domain using the non-linear features. These indices and the classification approach described in this study could be used in BCI systems and other systems that use brain signal classification.

Moreover, the study compared the classification algorithms for the classification of the human ethnicity according to the auditory brain responses with new classification indices (NHEI and SNHLEI) classifying two types of human ethnicity (Malay and Chinese ethnicity) based on the auditory brain response (AEP EEG signal) evoked by auditory stimuli (Pure Tones stimulus and CV stimulus). The classification process using classification indices was conducted in the time domain at a very short processing time, suitable for real time implementation.

The indices (NHEI and SNHLEI) presented by equations 2 and 3 can separate the auditory brain response from two different human ethnicities with an accuracy of up to 100% based on the maximum and minimum values of these indices [1, 7]. Therefore, using these new classification indices, a high accuracy for classifying the human ethnicity was achieved. In this study, the algorithm proposed using SVM as classifiers resulted in a better accuracy than the system using KNN and LDA classifiers. This is because the features extracted with non-linear feature extraction methods are more accurate, and the fact that the structure of the classification algorithm depends on the RBF kernel threshold level design. The boundary conditions (or regions) resulting from the threshold level work in the same manner as the classification indices but with wide ranges (forbidden regions) of prediction areas [38].

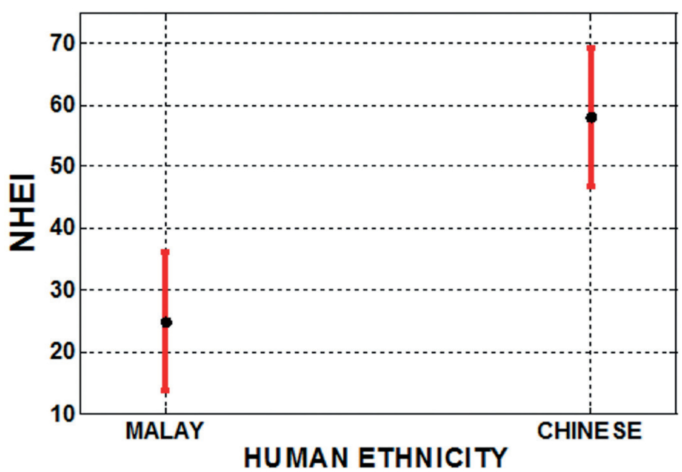

Figure 3. Variation of NHEI for normal hearing subjects.

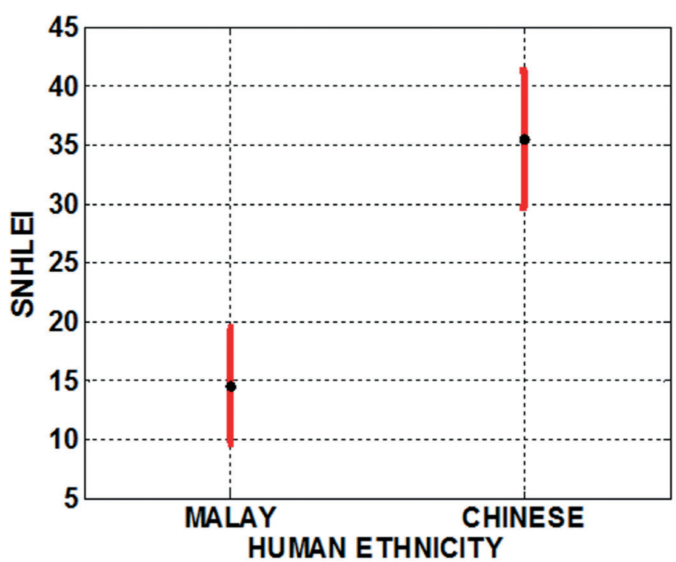

Figure 4. Variation of SNHL for SNHL patients.

CONCLUSION

Until recently, the separation of the human ethnicity according to brain signals (EEG) was rarely presented or reported. Based on this study, the auditory brain responses EEG (CAEP) according to the Malay and Chinese ethnicities can be classified efficiently based on the study's formulated classification indices. These indices used highly ranked nonlinear features to formulate simple linear binomial equations or formulas. These linear binomial equations enable the researchers and any applications that used classification of brain signals to easily and effectively estimate or predict the human ethnicity from the tested subjects. These classification indices can classify or separate the human ethnicity in both cases (normal hearing and SNHL). Furthermore, the study found that the SVM classification algorithm has the highest classification accuracy among other classification algorithms used in this study for classifying the human ethnicity based on the auditory brain responses (CAEP). This was concluded by establishing classification methods for brain response signals EEG (auditory-ERP) to classify two types of human ethnicity.

Ethics Committee Approval: The Ethics Committee approval was received for this study from the Medical Ethics Committee (IRB Reference Number: 1045.22).

Informed Consent: Written informed consent was obtained from patients who participated in this study.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – I.A.I., H.N.T., M.M.; Design – I.A.I., H.N.T.; Supervision – H.N.T., M.M.; Resource – I.A.I., H.N.T.; Materials – I.A.I., H.N.T.; Data Collection and/or Processing – I.A.I., H.N.T.; Analysis and/or Interpretation – I.A.I., H.N.T., M.M.; Writing – I.A.I., H.N.T., M.M.; Critical Reviews – I.A.I., H.N.T., M.M.

Acknowledgements: The authors express their gratitude to all volunteers participated and contributed in conducting the experiment. Furthermore, the authors have high appreciated the help from the staff of the ENT department (UMMC), Pusat Perubatan Universiti Malaya (PPUM). Especially, Dr. Rashidah Daud (Audiologist) and Mr. Marzuki Bin Che (Medical Technician).

Conflict of Interest: The authors have no conflicts of interest to declare.

Financial Disclosure: This research was funded by the University Malaya Research center with Grant No. UMRG RP016D-13AET.

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