**AGE AND GENDER EFFECTS ON electroencephalograms**

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***Abstract*— EEG analysis is based on interpretation of changes in amplitude, frequency, and rhythmicity, among other variants, that define the morphology of the waveforms. Such quantifiable factors have shown to be influenced by demographic characteristics. Prior studies exploring aging effects on the EEG record demonstrated a marked decrease in frequency and reactivity of the posterior alpha rhythm, while a looser trend can also be seen in the coherences of children when separated by age and gender groups. The recent development of the TUH EEG Corpus, an ongoing project focusing on the collection of a demographically diverse database of EEG data, has allowed for a more detailed analysis of these observed trends. A subset of the TUH EEG Corpus, TUH EEG Abnormal, is used in this study to explore previous hypotheses by applying it to a larger, fine-tuned dataset focusing on more specific age ranges. Experimental analysis revealed an overall average [% and std dev] increase in energy and [% and std dev] decrease in frequency, with the greatest rate of change over [insert age range]. [Also mention statistically (in)significant change across gender groups regarding rate of changes]. These results allow for a closer look at the mechanisms of demographic trends on the EEG record and promote the use of the TUH EEG Corpus in global EEG application and research.**

# Introduction

The electroencephalogram (EEG) record is a useful tool in the study of brain activity and the mechanisms of neurological disorders. However, accurate identification and analysis of these abnormalities in the brain signal requires a thorough understanding of normal EEG features and the factors that influence waveforms. Normal variants include recognizable patterns of specific morphologies, frequency, or localization. Rhythmic mid-temporal theta of drowsiness [1] and positive occipital sharp transients of sleep [2] are both examples of patterns occurring in normal records, however they are distinct in the timing of their appearances relative to the state of the patient and in their focality to different regions of the brain.

Figure 1. Example of a standard alpha rhythm.

One of the most useful variants in the study of the EEG record is the posterior dominant, or alpha, rhythm, a pattern consisting of attenuated alpha waves situated in the posterior portion of the brain, particularly the occipital lobe [2]. As seen in Figure 1, the morphology of the alpha rhythm is typically sinusoidal, although in some cases sharply contoured, and symmetric across both hemispheres [2]. Deviations from the standard characteristics and reactivity of the alpha rhythm are notable in any EEG analysis, pointing to changes in patient status, drug use, or even cerebral dysfunction [2].

Despite its use in analyzing ongoing electrical impulses in the brain, the EEG record is sensitive to extracerebral qualities as well, often exhibiting artifact or other waveforms of physiologic or mechanical origins. The dipole nature present in the structure of the eye results in voltage differences as the eye rotates, translating to frontally predominant potentials in the EEG signal [2]. Equipment failures resulting in scalp-electrode interferences and high impedance can create the appearance of complex waveforms and noise in the signal [3]. The effects of these features may remain focal to specific regions, as in the case of eye movement, or may affect several areas of the brain. Although not considered cerebral activity, these factors, among others, must be taken into consideration as they play a significant role in shaping the morphology of the waveforms.

Along with the environmental and physical components that influence brain activity, the demographics of a patient is another extracerebral feature that has been shown to affect the EEG signal, namely age and gender. The brain signals of infants and young children vary greatly from those of older adults; normal EEGs for full-term newborns consist of high voltage, low frequency waveforms with a highly disorganized, asynchronous background [2]. The onset of the posterior dominant rhythm is established during this period, although not fully developed until later years [2]. Maturation brings about greater structure and organization of the electrical signals in the brain and in the EEG, correlating to decreases in energy and increases in frequency and symmetry across channels [?].

In the EEGs of adolescents and early teens distinctive features emerge, such as the posterior slow waves of youth: high voltage, transient theta or delta waves associated with the developing alpha rhythm [4]. The most visible changes in the EEG record occur over these formative years, however studies have shown that further developments in waveforms have occurred even among older patients. These changes are not as obvious as the ones seen in adolescent patients but instead involve subtle and gradual differences in the waveform morphology. Most commonly noted among all such studies is a general increase in slow waves seen in elderly patients, identifiable as a brief reduction in frequency and increase in amplitude. This stands in contrast to the wave behavior as the brain initially develops from its infantile state. Although the slow wave trend is generalized, there is a noticeable effect on the alpha rhythm in the very frontal and occipital regions, in terms of changes in frequency, energy, and alpha reactivity [6]. Due to the importance of the alpha rhythm on EEG analysis and pathology, this trend indicates the presence of a significant mechanism regarding the effect aging has on the EEG record.

Here we seek to confirm the previously described subtle evolutions in the frequency and energy of features like the alpha rhythm as it changes with age, as well as explore the possibility in trends across gender groups. Feature extraction on data collected from the TUH EEG Corpus is utilized in this study and, due to the vast array of data available in this corpus, allows for a more detailed analysis of these trends.

Figure 2. There are significant morphological differences in the EEG records of infants and adolescents as well as elderly patients. Examples of normal background in an infant (upper image), 14-year-old patient (middle image), and [70?]-year-old patient are shown above.

# Prior Research

Previous studies demonstrate that the age of a patient leads to specific changes in the frequencies of EEGs. Alpha wave is a frequency classification that lies in the range of 7-12 Hz and generally portrays symmetrical amplitude across both hemispheres [2]. Our research primarily focuses on posteriorly dominant alpha rhythm, a prominent waveform of normal background in adults, in the occipital region. An increase in age from adolescence to middle-age led to faster and broader alpha activities maximal in amplitude in the occipital region [6]. However, age groups past the category of middle-aged correlated to a general decrease in alpha rhythms also known as alpha slowing. Alpha responses in patients younger than adolescence were unable to be determined due to inadequate observation. Age does not only affect the frequency of alpha rhythm but also the strength of phase-locking of alpha responses. Phase-locking defines the synchronization of neural activity from EEGs. Middle-aged groups display higher magnitudes of phase-locking for faster alpha waves and lower magnitudes for slower alpha waves [6].

Some validation of a connection between gender and certain EEG features, more specifically coherence between two sites has been established as well. Coherence between two sites of EEG activity refers to the “correlation in the time domain between two signals in a given frequency band” [7]. Sexual differences in alpha coherence is observed starting from adolescence; males continuously increase in alpha coherence while females remain stagnant [7]. The effects of both demographic features outlined by previous studies are validated through our experiments while primarily focusing on the effects of age on the alpha rhythms found in occipital channels.

# Methods

Figure 3. Procedures for determining the normality of an EEG file, developed my neurologists.

The data used in this study was obtained from the Temple University Hospital EEG Corpus, a major resource in EEG research. The corpus consists of the largest publicly available database of clinical EEG data with records collected from a variety of patients at Temple University Hospital for over a decade [cite]. The files selected for evaluation in this study were taken from the TUH Abnormal subset. The TUH Abnormal subset is divided into records considered normal or abnormal based on the presence or absence of normal variants, namely the posterior dominant rhythm. Patient records were manually annotated by undergraduates at Temple University trained in accurate seizure identification and annotation and evaluated through inter-rater agreement tests. Criteria defining normal characteristics were developed, reflecting similar procedures to those followed by neurologists, as seen in Figure 3.

Over 1000 patient records were collected in the Normal set through manual classification, resulting in a diverse pool of patients able to be partitioned into multiple age subcategories. Data was selected and apportioned into eight groups based on age and gender; in order to maintain balanced subset, 200 male patients and 200 female patients were included in the study. Gender groups were each further divided into four age groups: 13-29 years, 30-45 years, 46-64 years, and 65+ years, with 50 records within each age subgroup. The groups were selected based on the data available in the TUH Abnormal-normal subset and research into prior studies that isolated morphological characteristics to certain age-groups. The age range of 0-12 is also studied as a separate group due to considerable differences and distinct features that appear only in infant and adolescent EEGs, however further study is required as there is still limited data currently available regarding this specific group.

The electrode channels P4-O2 and T5-O1, belonging to the differential TCP montage, were the focus of evaluation for this study, as the posterior regions have been shown to reveal greater variability correlating to age [5]. The alpha rhythm, a prominent feature under evaluation, is typically maximal in the occipital region as well [2].

Feature extraction was performed on the first 60 seconds of each file, with a focus on frequency and energy values in the relevant electrode channel. Trends were then analyzed across individual patients and between average feature values statistically determined for each subgroup. Separate analyses were drawn for age categories within each gender and between the two gender groups.

# Results

The experimental results yielded trends confirming significant changes in the features across each age and gender subgroup from data in the TUH EEG Abnormal set. Table 1 presents a summary of these results. Frequency was generally highest in the lowest age bracket and showed steady reduction corresponding to increasing age. Energy showed an opposing trend, positively correlating with increasing age. [Table 1 also demonstrates feature trends corresponding to gender as well \*\*need to elaborate]

\*\*Details about methods for feature extraction\*\*

Table 1: Shows average feature values for each of the eight groups. \*\*Possibly split genders into two tables?

Although preliminary experiments focused on the normal subset, these experiments can be expanded to include other subsets of the TUH EEG Corpus.

Figure 4. Relevant histograms or display of data/statistical analysis

# Summary

The experimental results of this study confirm the significance that age and gender play on EEG waveforms. From a subset of normal EEG data chosen from the TUH EEG Corpus, 200 patients were selected and divided accordingly, into two gender groups and four age brackets. Feature extraction was used to obtain the energy and frequency values of the first 60 seconds of each file with a focus on the P4-O2 and T5-O1 channels. Comparisons of the averages for each group confirmed [a decreasing trend in frequency and an increasing trend in energy as well as results about trends across genders].

A crucial shortcoming of this study is the lack of data in the 0-12 age range. This group is occupied by infants and adolescents who have unique morphological characteristics which further exemplifies the differences between age groups; however, relevant EEG’s are less abundant and consequently not a major part of this study. The TUH EEG Corpus is a continuously evolving database, and as time proceeds, more data within the age group 0-12 will be available for observation. Another noteworthy implementation is the study of demographic effects in frontal networks, as, due to the focus on changes in the posterior dominant rhythm, the results of these experiments represent discrepancies occurring primarily in the occipital region of the brain. Further investigation to see if these trends are upheld in other cortical areas is needed.

The TUH EEG Database provides us with an ever-growing EEG depository in which future testing will be conducted. More information about the free and publicly available database can be found on our website at *https://www.isip.piconepress.com/projects/tuh\_eeg.*

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