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Recognition of Emotional States using Nonlinear Range Compression of EEG Spectral Data

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Emotion recognition using ElectroEncephaloGraphic (EEG) recordings is a new area of research which focuses on recognition of emotional states of mind rather than impulsive responses. EEG recordings are found useful for the detection of emotions through monitoring the emotion characteristics of spatiotemporal variations of activations inside the brain. To distinguish between different emotions using EEG data, we must provide specific spectral descriptors as features to quantify these spatiotemporal variations. We propose several new features, Normalized Root Mean Square (NRMS), Absolute Logarithm Normalized Root Mean Square (ALRMS), Logarithmic Power (LP), Normalized Logarithmic Power (NLP) and Absolute Logarithm Normalized Logarithmic Power (ALNLP) for the classification of emotions. A protocol has been established to elicit five distinct emotions (joy, sadness, disgust, fear, surprise and neutral). EEG signals are collected using a 256-channel system, preprocessed using band-pass filters and Laplacian Montage and decomposed into five frequency bands using Discrete Wavelet Transform. The decomposed signals are transformed into different spectral descriptors and are classified using a two-layer Multilayer Perceptron Network (MLP). Logarithmic Power produced the highest recognition rates, 91.82% and 94.27% recognition for two different experiments, which is more than 2% higher than other features.

Keywords : Discrete Wavelet Transform, Emotion Recognition, Laplacian Montage, Logarithmic Power, Multi-Layer Perceptron.

1. Introduction

ElectroEncephaloGraphic (EEG) recordings have been used since 1924 to classify several types of psychological phenomena and diagnose different types of medical disorders. The P300 response, found by Chapman and Bragdon [1], was one of the most heavily researched areas that showed the relationship between the event-related potential inside the brain to a visual stimulus. This particular relationship sparked several other research topics, like Farwell [2] using the P300 response with the Guilt Knowledge Test for Interrogative Polygraphs, Wall and Ehlers [3] determining the effects of alcohol on the P300 response of Asians. Since EEG recordings are quantified in several voltages detected on the scalp of the brain, several efforts have been made to find suitable transformations for the analysis of the data. Frequency analysis, one of the more popular transformations of EEG data, specifically transforms the data into 5 specific frequency bands (Delta, Theta, Alpha, Beta and Gamma). Armitage et al., [4] and Feinberg et al.,[5] looked at the Delta frequencies (0 - 4Hz) in several sleep studies for depressed adolescent females and sleep-loss respectively. Schacter [6] analyzed the impact of the Theta frequency band (4 - 8Hz) for different psychological phenomena. The Alpha frequency band (8 - 13Hz) was found useful by Itil [7] for the EEG of adult schizophrenics and by Nowak and Marczynski [8] for trait anxiety from stress. Rangaswamy et al. [9] looked at the Beta frequencies (13 - 30Hz) to determine the magnitude at different spatial locations and its connection to an imbalance of the central nervous system in alcoholics. The correlation between Gamma frequency bands (30Hz - 100Hz) and visual stim-

pression technique compresses values that are high in magnitude while stretching values that are smaller. This type of technique is seen in image enhancement, where nonlinear gamma correction is used to bring out features in both underexposed and overexposed images.
To quantify the level of dispersion of a distribution, we can calculate the coefficient of variation of the distribution, as shown in Eq.(23).

$$c_v = \frac{\sigma}{|\mu|} \tag{23}$$

where, σ is the Standard Deviation, μ is the mean and c_v is the coefficient of variation of the distribution. Table 4 shows the coefficient of variation across all frequency bands for each feature type. The normalization and compression metrics provide coefficients of variation which are less than 1, which results in higher recognition rates. Note that having the lowest coefficient of variation does not give the highest recognition rate, but rather provides features along with the reasonable distribution of data.

3.3. Nonlinear Range Compression Effectiveness of the LP Algorithm

The logarithmic power algorithm is used for compressing the entire range of the signal for a given frequency band. High values within the range of the signal were compressed while low values were stretched to offer a Gaussian distribution of values. From Figure 7, we can see that the range compression of LP allows a more definitive distribution than the distribution shown from the RMS and ALRMS techniques. The logarithmic function offered the best nonlinear range compression for the data, as compared to the RMS function, which uses the square root of the value. Using range compression helps in preserving the relationship of values for all frequency bands while forming a normalized distribution suitable for classification. The normalization technique used by the REE algorithm normalizes across all of the frequency bands, which looses some information regarding the strength of the values with respect to the frequency band. Even though normalization offered better recognition than conventional techniques, range compression offered the best recognition because of the conservation of relationship of the values across different frequencies.

4. Conclusions

In this paper, we saw that using nonlinear range compression for conventional features metrics resulted in the highest recognition rates over all types of feature metrics (classical, normalized, and hybrid feature metrics). The Logarithmic Power (LP) algorithm gave 94.27% recognition across all emotions, which was due to the preservation of relationships in the values. Normalization offered high recognition rates, but due to the loss of some relationships between the different frequency bands, nonlinear range compression provide better results. We are currently implementing other nonlinear range compression techniques that may boost the recognition ability of the system.

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Table 4
The Coefficient of Variation for the Different Feature Metrics across Different Frequency Bands. The Normalized and Compression Methods (REE, NRMS, ALREE, ALRMS, and LP) gave the Lowest Coefficients of Variation, which Correlates to the Higher Recognition Rates found by using these Msethods.

Freq. Bands	Power	Energy	RMS	REE	NRMS	ALREE	ALRMS	LP
Gamma (D2)	7.84	7.30	1.17	1.43	0.59	0.29	0.16	0.21
Beta (D3)	13.50	7.59	1.01	1.12	0.49	0.34	0.18	0.21
Alpha (D4)	14.02	12.26	0.99	1.00	0.42	0.35	0.20	0.22
Theta (D5)	18.40	17.58	1.36	0.91	0.39	0.35	0.24	0.33
Delta (A5)	25.11	21.06	2.19	0.21	0.21	1.09	0.47	0.70

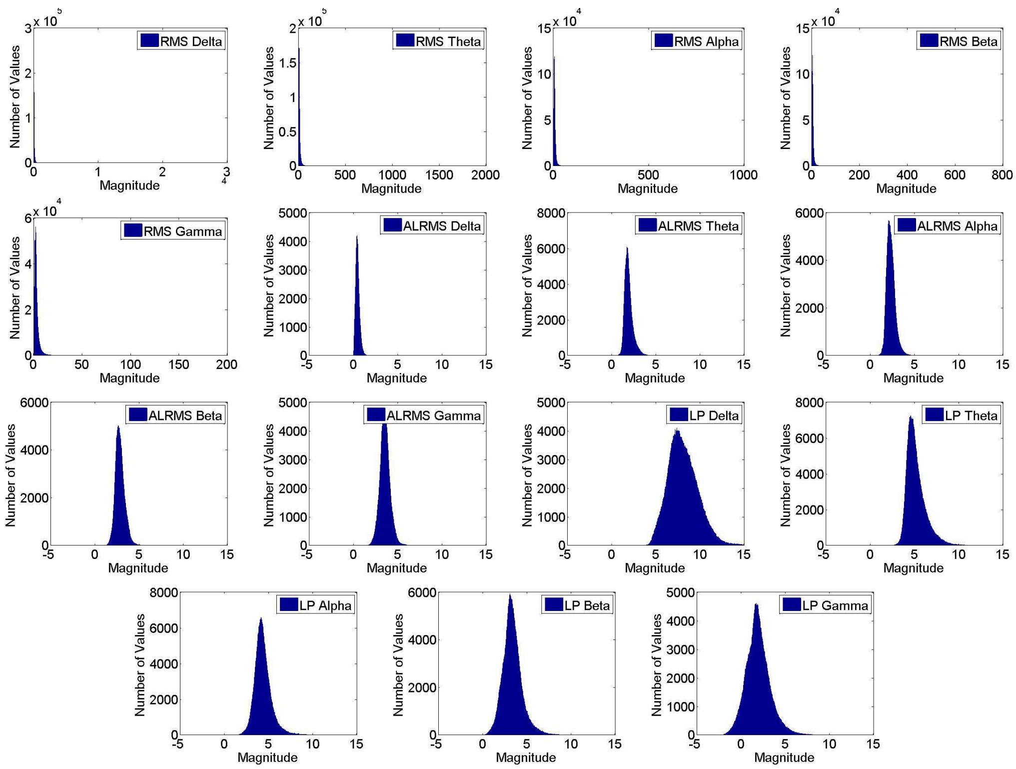

Figure 7. Histogram Distributions of RMS (top row), ALRMS (middle row), and LP (bottom row) for different Frequency Bands.

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