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RESEARCH ARTICLE

Human Emotion Recognition with a Regression Classifier Based on a New Feature Definition for Multi-channel EEG Waveforms

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Abstract

A new feature definition for multi-channel EEG waveforms, which involves estimated second-order statistics, e.g. autocorrelation, of individual channel waveforms, is presented. Based on new features, a vector description with randomly chosen length and time lags as a multivariate process is employed to model human emotions. A regression classifier is designed and simulated to estimate a set of human emotion states based on the derived feature vector. Experiments with a real-world publicly available dataset indicate that the new feature and associated vector descriptions with chosen classifier lead to successful recognition of human emotion states. The simplicity and straightforward modeling of human emotions with use of new approach is expected to lead improved-performance human-computer interface systems in real-time in predictive manner.

Introduction

A human-computer interaction (HCI) system is expected to be able to analyze, interpret and model human sensory signals and then associate them to motor behavior patterns as response, e.g. emotional states, successfully. Besides assessing mental and physical status of a (human) subject, building similar activity patterns given a set of emotional states has been an important functionality sought from an HCI system for suggesting well-posed behavior and action. It is therefore significant to realize a feasibly versatile interface and processing scheme with improved brain signal acquisition and mapping capability for recognition of emotions, [1]-[2]. Electroencephalogram (EEG) is possibly the simplest yet the most widely used technique to observe and collect electrical potential signals induced by cortical neurons under the skull for this purpose. It has been widely used for recognition/classification of human emotions, [3]. Due to excessively large number of cortical neurons involved in generating electrical signals against relatively small number of electrodes to collect and record in short duration, temporal samplings of EEG usually are of limited capability in recognition of involved event sources and relevant processes, [4]. Moreover, sources of most cortical activities in EEG signals are to a great extent obscured due to relatively high-amplitude artifacts. Hence, success in identifying emotional states based on EEG waveform components is, to a great extent, subject to method or algorithm used for extracting features to represent spatio-temporal characteristics, [5]. Feature extraction for EEG signals has drawn considerable attention and emphasis as a research topic in studies on brain-computer interface (BCI) or HCI systems in identifying sources of major neurophysiological events, [6].

Various feature definitions and extraction methods have been proposed to represent supposedly distinct components involved in EEG waveforms: Joint time-frequency techniques and wavelet transforms (WT) have been known in obtaining relevant statistical summaries for spectral contents in a number of representative frequency bands given EEG signal observation window for representing spatio-temporal characteristics in terms of WT coefficients, which then can be used for classification, [7]. Autoregressive (AR) linear predictive coefficients (LPC), and its variant cepstral coefficients for modeling non-stationary signals have also been widely adopted in EEG waveform classification, e.g. [8] and [9], respectively. Above parametric methods mostly suggest a time-varying linear relationship between electrophysiological excitatory cerebral current sources and the observed scalp potential with optimally suppressed artifact and noise components. They perform with relatively short-time window segments in which statistically invariant cues need to be extracted for temporally sparse, almost noise-like components. For example visually evoked-response potential (ERP) components, which are usually around 10μV low-frequency theta- and alpha-rhythmic beats, are generally observed within a time window of about 10s, [10]. In the case of intrusive phenomena, e.g. epileptic seizures, recurring alpha- and delta-rhythmic beats may transiently occur with interictal electrical discharge (IED), which makes it more involved to extract invariant features within observation time interval as such, [11]. In most cases, these phenomena become more complicated when other abnormalities or inferences are also recalled by varying brain regions, [12]. On the other hand, nonparametric methods, such as amplitude distribution, spike interval distribution, correlation analysis etc., offer versatility and flexibility for obtaining spatial representation of individual EEG waveforms, [13].

In this study, a new and simple, non-parametric feature extraction method for representing spatio-temporal behavior of EEG signals is presented and employed for evaluation human emotional states. New feature description is based on the intuition that a common predictive model can be attributed to by and be replaced with estimated ensemble of second-order statistics or autocorrelation terms. It suggests that it can be adapted straightforwardly to characterize multi-channel EEG waveforms. The resulting feature vectors are, then, used with a linear regression classifier to map multi-channel EEG waveforms to emotional states. The success of proposed scheme is tested and validated with a real dataset on the basis of the nearest-neighborhood between estimated and true emotional state vectors in statistical terms. The simulation results indicate that the new feature definition leads to recognition of subjects' self-assessed emotions with success score between ≈ 80% - 85% in average.

New Feature Description and Linear Regression Classifier

Given a discrete-time signal vector $\mathbf{x} = [x_1\ x_2\ \ldots\ x_N]$ within an N-sample time slot, the sample value x_n at time stamp n, can be predicted or modelled as output of an autoregressive filter driven by past samples as

$$\hat{x}_n = -\sum_{j=1}^{p} a_j x_{n-j} = x_n + \varepsilon_n \tag{1}$$

where p and ε_n are the prediction order and error, respectively. The prediction error ε_n is assumed to be a (normally distributed) white-noise random process. The model parameters in vector $\boldsymbol{a} = [a_1\ a_2\ \ldots\ a_p]$ are called linear predictive coefficients (LPCs). They can be estimated based on least-squares by minimizing the prediction error power $E_p = \sum_{i=1}^{N} |\varepsilon_i|^2$ subject to $\partial E_p / \partial a_j = 0,$ where $j = 1,\ \ldots,\ p$, which yields Yule-Walker equations, [14]. The solution to Yule-Walker equations is usually obtained with recursive methods, e.g. Levinson-Durbin algorithm, in terms of estimated autocorrelation vector $\hat{\boldsymbol{r}} = [\hat{r}(0)\ \hat{r}(1)\ \ldots\ \hat{r}(p)]$ where $\hat{r}(|m-s|) = \frac{1}{N}\sum_{i=1}^{N} x_{i-m}x_{i-s}$, $0 \leq m, s \leq p$. It is noticed that the vector $\hat{\boldsymbol{r}}$ is fully informative about $\boldsymbol{a}$, that is, it suffices to have $\hat{\boldsymbol{r}}$ to uniquely determine the modelling vector $\boldsymbol{a}$. Furthermore, from the solution of Yule-Walker equations, it is known that the farthest autocorrelation term $\hat{r}(p)$ is a random quantity expressible in terms of smaller-lag autocorrelation terms, i.e. $\hat{r}(0),\ \ldots, \hat{r}(p-1)$ once $\boldsymbol{a}$ has been known. Thereby, we can suggest a feature to represent an L-channel EEG waveform as

$$v(p) = \frac{1}{\sum_{l=1}^{L} \sigma_l^2} \sum_{l=1}^{L} \hat{r}_l(p) - \sigma_l^2 \tag{2}$$

where σ_l^2 and $\hat{r}_l(p)$ are the variance and the p-lag autocorrelation of the EEG waveform in time slot for the l-th channel. Equation (2) implies a norm of vector whose contributions/coordinates are due to merely p-lag correlation terms against the variance for the signal considered. Recently, in [15], it has been demonstrated that above feature definition can be successfully applied in classifying normal and epileptic seizure components in EEG waveforms with a simple multivariate Gaussian classifier.

In order to show the use of new feature definition in a recognition task of emotional states for a multi-channel EEG waveform, we consider a feature vector $\boldsymbol{v} = [v(p_{k,1}) \dots v(p_{k,k})]^T$ of $v(p_{k,l})$ with $l = 1, \dots, k$, defined in (2) and a nonempty, distinct sub-vector $\mathbf{p}^{(k)} = [p_{k,1} \dots p_{k,k}]$ of $\mathbf{p} = [p_1 \dots p_d]$ where $p_{k,i} \neq p_{k,j}$ for $i \neq j$. For a particular $\mathbf{p}^{(k)}$, a suitable approach to estimate emotional state vector $\boldsymbol{c}$ of length h given $\boldsymbol{v}$ is to use a linear regressivon estimator $\boldsymbol{c} = \mathbf{A}^{(\boldsymbol{k})}\boldsymbol{v} + \boldsymbol{b}^{(\boldsymbol{k})} + \boldsymbol{e}^{(\boldsymbol{k})}$ where $\mathbf{A}^{(\boldsymbol{k})}$ is an h-by-k model matrix while $\boldsymbol{b}^{(\boldsymbol{k})}$ and $\boldsymbol{e}^{(\boldsymbol{k})}$ are the intercept and estimation error (column) vectors of length h, respectively. With M_{tr} training EEG waveform and respective emotional state vectors, by using the least-squares error with $min\ (\sum_{i=1}^{M_{tr}} ||\underbrace{\boldsymbol{c} - (\mathbf{A}^{(\boldsymbol{k})}\boldsymbol{v} + \boldsymbol{b}^{(\boldsymbol{k})})}_{\boldsymbol{e}^{(k)}}||^2)$, $\mathbf{A}^{(\boldsymbol{k})}$ and $\boldsymbol{b}^{(\boldsymbol{k})}$can be estimated as

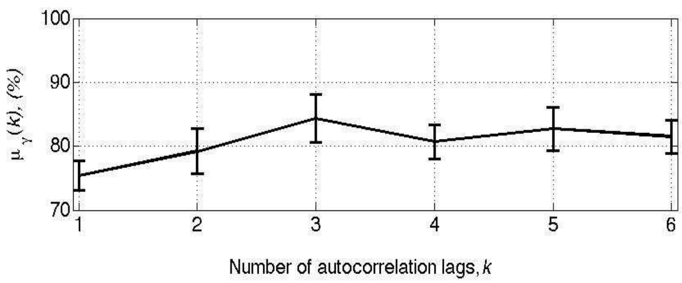
$$\widehat{\mathbf{A}}^{(k)} = \mathbf{C}\mathbf{V}^T(\mathbf{V}\mathbf{V}^T)^{-1}$$
$$\widehat{\boldsymbol{b}}^{(k)} = \widehat{\boldsymbol{\mu}}_c - \widehat{\mathbf{A}}^{(k)}\widehat{\boldsymbol{\mu}}_v \quad (3)$$

where $\mathbf{V}/\mathbf{C}$ is the matrix consisting of M_{tr} $\boldsymbol{v}/\boldsymbol{c}$ column vectors with estimated sample mean vector $\widehat{\boldsymbol{\mu}}_{v/c}$, [16].

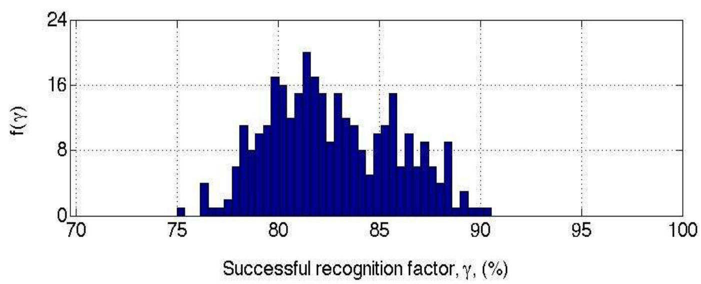
The proposed feature vector description was evaluated in recognition of human emotions with use of DEAP dataset, [17], available at http://www.eecs.qmul.ac.uk/mmv/datasets/deap. This dataset consists of recorded physiological modalities from 32 healthy participants of 16 males and 16 females with varying ages between 19 and 37. Recordings contain L = 32-channel EEG waveforms sampled at 512Hz and some other multi-peripheral physiological signals such as galvanic skin response, blood pressure, breathing and heart rate, skin temperature and facial electromyography signals. Each participant was recorded while watching 40 one-minute long high-light music videos. After watching each video, subjects were asked to assign numerical values to their emotional states corresponding to set **S** = {*arouse, valence, dominance, liking, familiarity*}, i.e. h = 5. The emotional assessment was made in a discrete scale 1 through 5 for familiarity and 1 to 9 for other emotions. It should be noted that each assessment vector is conditioned to mixture of emotion states considered above. Digitized EEG waveforms were down-sampled to 8 samples per second for reducing noisy artifacts and computation. Then, down-sampled waveform recordings were rearranged into split windows of N = 256 samples, i.e. each almost 32 seconds long. The vector p was set to be composed of lags from 0 to 7.5 seconds (60 samples) with increment of 1.5 seconds (12 samples), i.e. d=6 and k=1, ..., 6. For each $\mathbf{p}^{(k)}$, 10 distinct experiments were conducted. In each experiment, randomly chosen 40 EEG waveforms and corresponding self-assessment vectors were retained from the DEAP dataset. At the i-th experiment for each $\mathbf{p}^{(k)}$, $M_{tr} = 10$ of those 40 vectors were used to estimate model parameters $\widehat{\boldsymbol{A}}_i^{(k)}$and $\widehat{\boldsymbol{b}}_i^{(k)}$ in training while testing the trained model was performed with remaining M_{tst}=30 vectors. Prior to processing, the state assignments other than the familiarity were scaled down to 5 and rounded for compatibility and discretization. For example, state values 7.45 and 8.15 were assigned to 4 and 5, respectively. In testing, for a test vector $\boldsymbol{v}_j$, $j = 1, \dots, M_{tst}$, the nearest emotional state vector $\boldsymbol{c} = \boldsymbol{c}_{\boldsymbol{s}}$, which satisfies $s(||\boldsymbol{c} - (\widehat{\mathbf{A}}_{\boldsymbol{i}}^{(\boldsymbol{k})}\boldsymbol{v}_{\boldsymbol{j}} + \widehat{\boldsymbol{b}}_{\boldsymbol{i}}^{(\boldsymbol{k})})||^{\mathbf{2}})$ was found. This mapping was attributed to an indicator function $I(k, i, j)$ such that $I(k, i, j)$=1 if $s = j$, otherwise 0. Then, a recognition success score for the regressive model classifier with $\widehat{\mathbf{A}}_{\boldsymbol{i}}^{(\boldsymbol{k})}$ and $\widehat{\boldsymbol{b}}_{\boldsymbol{i}}^{(\boldsymbol{k})}$ was defined as

$$\gamma(p^{(k)}, i) = \frac{1}{M_{tst}} \sum_{j=1}^{M_{tst}} I(k, i, j) \quad (4)$$

In order to assess the estimation success of the regressive model with new feature vector definition for a given k, the average, $\mu_\gamma(k)$ of $\gamma(p^{(k)}, i)$ over i were evaluated and is depicted in Fig. 1(a) where the corresponding standard deviation, $\sigma_\gamma(k)$, is also included as error-bar. In forming these statistical quantities, since there are $d_k = \binom{d}{k}$ k-tuples, their averages were taken, i.e. $\mu_\gamma(k) = (1/d_k)\sum_{i=1}^{d_k}\mu_\gamma(k_i)$ and $\sigma_\gamma(k) = (1/d_k)\sum_{i=1}^{d_k}\sigma_\gamma(k_i)$. A histogram was also obtained to visualise the distribution properties of γ as a density profile $f(\gamma)$ over all $(\mathbf{p}^{(k)}, i)$ terms as shown in Fig. 1(b).



(a)



(b)

Fig. 1. Success in recognition of emotional states, γ for the linear regressive estimator with proposed feature vector definition: (a) variations of average, μ_γ, and standard deviation, σ_γ, with number of autocorrelation lags, k, (b) ensemble density histogram of γ.

From variation of statistical average, $\mu_\gamma(k)$, and standard deviation, $\sigma_\gamma(k)$, it is observed that the new feature vector definition with number of lags larger than 1 for a given multi-channel EEG waveform leads to estimation of the self-assessed emotions in success between almost 80% and 85% by using (linear) regression classifier. On the other hand, the histogram of overall experimental ensembles shows that classifier with regression estimator based on proposed feature vectors of randomly chosen length and autocorrelation lags for an EEG waveform yields estimation of the emotional states with success of average μ_γ = 81.89% and standard deviation σ_γ = 2.56%.

Conclusions

A new feature definition for multi-channel EEG waveforms, which involves estimated second-order statistics, e.g. autocorrelation, of individual channel waveforms as a random process, is presented. With use of new feature definition, a vector description with randomly chosen length and time lags is given for modeling human emotions. A regression classifier is constructed for simulating human emotion states based on the derived feature vector. Experiments with a real-world publicly available dataset reveal that the new feature and associated vector descriptions with chosen classifier allow successful recognition of human emotion states studied. The simplicity and straightforward modeling of human emotions with use of new approach is expected to lead improved-performance human-computer interface systems in real-time in predictive manner.

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