Data-mining Approaches for the Study of Emotional Responses in Healthy Controls and Traumatic Brain Injured Patients: Comparative Analysis and Validation

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Abstract. Relationship between Heart Rate Variability (HRV) and emotions subjectively reported by 26 healthy subjects during symphonic music listening have been investigated through Data Mining approaches. Most reliable decision models have been successively adopted to forecast an emotional assessment on a group of 16 Traumatic Brain Injured patients during the same type of stimulation, without algorithms retraining. The most performing decisional models have been a Rule Learner (ONE-R) and a Multi Layer Perceptron (MLP) but, comparing them, the first one was the best in terms of reliability both on validation and independent test phases. Furthermore, ONE-R provides a simple "human-understandable" rule useful to evaluate emotional status of a subjects depending only on one HRV parameter: the normalized unit of Low Frequancy BandPower (nu_LF). Specifically, the classification by HRV nu_LF matched that on reported emotions, with 76.0% of correct classification; tenfold cross-validation: 70.2%; leave-one-out validation: 71.1%. On the other hand, MLP approache has provided an accuracy of 82.69% on healthy controls, but it has decreased to 47.11% and 46.15% on 10folds-cross and leave-one-out validation respectively. Finally, the accuracy has resulted in 51.56% when the MLP model has been applied to the posttraumatic subjects, while the ONE-R accuracy has resulted in 70.31%. Data mining proved applicable in psychophysiological human research.

1 Introduction

Data-mining or hybrid techniques are used in medicine to sort significant information out of large databases in mutagenicity studies, predictive toxicology, disease classification, selective integration of multiple biological databases, etc. Applications in neurology have focused on prognostic studies [1-2] or in the classification of emotional responses [3] . The Heart Rate Variability (HRV) is an emerging objective measure of the continuous interplay between the sympathetic and parasympathetic autonomic nervous sub-systems. It is thought to provide information also on complex

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patterns of brain activation, including emotional responses [4-11]. For instance, HRV abnormalities are reportedly common in psychiatric or brain damaged patients [12-14]; HRV proved a useful predictor of outcome in brain injured patients [15-16]. HRV studies require quantitative approaches and large numbers of parameters are generated when the parametric and non-parameric HRV spectra are computed.

In our study we measured several HRV parameters from 26 healthy subjects during the listening of music samples, suitably selected to induce specific emotional status. At the end of each listening we asked to report felt emotions, without any reference to pre-selected categories and to the feelings that the subjects thought the music was intended to induce. On the basis of these interviews, we identified to macro-categories of emotions (positive and negative emotions) and defined a two-classes classification problem. The same procedure has been adopted for acquiring data from a group of 16 posttraumatic subjects. More details about the two datasets construction are reported in another our study [3]. Since the great amount of variables (35 HRV parameters) and the relatively weak consolidated knowledge about the problem, data mining techniques have represented an effective solution for identifying a relationship between HRV parameters and emotions, without any preliminary assumption about data distribution.

We compared different classification learning strategies through suitable validation techniques, such as 10folds-cross and leave-one-out validation and test on the independent test set.

2 Material and Methods

2.1 Patients and Controls

Two groups of subjects were studied:

1. twenty six healthy volunteers (14 women; mean age: 31.7±7.1 yrs., age range: 21-45 yrs.; high-school to university education);
2. sixteen patients without severe disabilities completing rehabilitation after severe traumatic brain injury (5 women; mean age: 21.6±3.0 yrs., age range: 17 to 33 yrs., grammar to high school education); and

Subjects were informed in full detail about the study purpose and experimental procedures and the ethical principles of the Declaration of Helsinki (1964) by the World Medical Association concerning human experimentation were followed. The procedures for data collection and the experimental setting caused no physical or emotional discomfort and were discontinued whenever the subject felt tired or tense or at the subject’s request. Controls and posttraumatic subjects had no musical training (see [3] for methodological detail).

2.2 Stimulus Conditions

Four music samples (Table 1) were selected following characterization by intrinsic structure and expected emotional response as indicated by the available formal complexity and dynamics descriptors. These descriptors reportedly relate music structure to self-assessed emotions and allow to characterize the emotional status along a continuum from euphoria and well-being to melancholy, severe anxiety and perceived aggressive tendencies [17-18].

Table 1. Selected music samples.

1) Luigi Boccherini: Quintet op. 11 n. 5, *Minuetto* (duration: 3' and 50");
2) Piotr Ilitch Tchaïkovski: sixth symphony, op. 74, *first movement* (duration: more than 10");
3) Modest Petrovich Mussorgsky: *St. John's Night on the Bald Mountain* (duration: more than 10");
4) Edvard Grieg: Peer Gynt, op 23, *The morning* (duration: 4' and 20")

Experiments on patients and control took place at the same time of the day in a familiar environment and did not interfere with the posttraumatic subjects' medical/rehabilitative schedules. Subjects were comfortably lying on an armchair, with constant 24º C ambient temperature and in absence of transient noises. They were exposed binaurally (earplugs) to the four selected music samples balanced for loudness and played in random sequence to minimize carry-on effects. There was a 20-min rest between consecutive samples to avoid overstimulation and excessive fatigue.

The heart beat was recorded from the beginning of the music sample and for a total of 300 beats (3',36"±24", with 83.7± 9.5 beats/min and a resulting total recording time between 3',12" and 3':55") by means of the *Virtual Energy Tester* (*Elamaya Instruments*, Milano, Italy). The photopletismographic sensors were positioned on the third phalange of the left hand middle finger in order to minimize the subjects' discomfort consistent with the guidelines of the Task Force of European Society of Cardiology and the North American Society of Pacing and Electrophysiology[19]. The photopletismographic signal was sampled at 100 samples/sec; the series of consecutive intervals between heart beats was analyzed in the time and frequency domains by the *HRV advanced analysis software* developed at the Department of Applied Physics, University of Kuopio, Finland [20]. The non-parametric (Fast Fourier Transform, Welch spectrum) and parametric (autoregressive) spectra were computed (Table 2). The power spectral density from 0.01 Hz to 0.5 Hz was computed with 0.001 Hz resolution and three frequency ranges (very low frequency [VLF]: 0.01-0.04 Hz; low frequency [LF]: 0.04-0.15 Hz; and high frequency [HF]: 0.15 Hz – 0.5 Hz) were considered (Table 2).

At the end of each music sample, controls and posttraumatic subjects were requested to classify their emotions, without reference to any pre-selected categories and irrespective of the emotional feeling they thought the music was intended to induce. The distribution of the emotions expressed for each music sample was determined [17-18].

Table 2. Spectral and Statistical Parameters.

Statistical Parameters	Spectral Parameters
Mean RR interval (Mean RR) and SD (STD RR); Mean Heart Rate (Mean HR) and SD (STD HR); Root mean square of SD (RMSSD); number (NN50) and percentage (pNN50) of NN intervals longer than 50 ms	Very Low Frequency (VLF), Low Frequency (LF), High Frequency (HF) and normalized unit (nu) in FFT and autoregressive spectra VLF Peak frequency in FFT and autoregressive spectra LF Peak frequency in FFT and autoregressive spectra HF Peak frequency in FFT and autoregressive spectra Power Spectrum of VLF, LF, HF and Total in FFT and autoregressive spectra % of VLF, LF, HF in FFT and autoregressive spectra Ratio LF/HF, nu LF, nu HF, nu LF/HF in FFT and autoregressive spectra

2.3 Data Mining Techniques

We adopted several classification approaches for identifying an association between HRV parameters and the self-assessed emotions. To this aim, two different classes or categories were defined for the reported emotional status: *positive* (happiness, joy, serenity, calm,…) and *negative* (fear, anxiety, tension, scare,…). The control group was selected as training set for several *data-mining* classification techniques, such as Decision Trees, Support Vector Machines, Artificial Neural Networks and Rules Learner, provided by the WEKA open source software (Waikato Environment for Knowledge Analisys) [21, 22].

Training set included 104 cases (26 healthy subjects x 4 music samples) and 35 variables (Table 2). In a first step, two internal validation techniques based on training data (namely the 10 folds-cross and leave-one-out validation) were used to evaluate how much extracted models would fit the new data.

Most reliable decision models have been selected and adopted to forecast an "*emotional status assessment*" on the independent test set (16 posttraumatic subjects). The models used to obtain this assessment on the test set has been not "re-learned" from it. The independent test set included 64 cases (16 posttraumatic subjects x 4 music samples) and the aforementioned 35 HRV parameters.

In this way, we have been able to estimate "real" reliabilities for the selected models. Figure 1 shows how we have designed our study.

Since every classification technique adopts a different structure for explaining the relationship between input variables and output (HRV parameters and subjectively reported emotions, respectively in our study) it may be really difficult to select *a priori* a strategy for learning the relationship from the available data. For such reason we decided to adopt several classification learning procedures applicable to our problem, such as Decision Trees, Support Vector Machines, Rule Learners and Artificial Neural Networks, all available in WEKA.

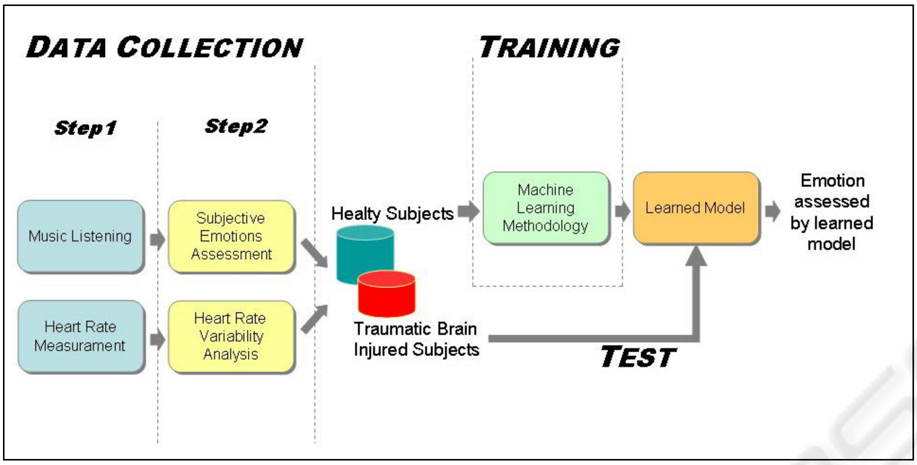

Fig. 1. Phases of the Study.

Respect to 10fold-cross and leave-one-out validation, we have obtained that the most reliable classification techniques were ONE-R [23] and Multi Layer Perceptron [24]. The first one is a Classification Rule Learner and works in a very easy way: it accepts a training set as input and searches for a “1-rule” classifying instances on the basis of a single variable (attribute). Initially, the algorithm ranks attributes according to error rate on the training set then, if the attribute is numerical, the algorithm divides the range of possible values into several disjoint intervals. In order to avoid overfitting (that is when each interval contains only a value belonging to one class) ONE-R permits to set a parameter named “bucket-size” that is the minimum number of instances in an interval. We obtained the best performing ONE-R configuration setting 7 as minimum number of instances in one interval. In figure 2 we report the extracted rule (note that *nu_LF* can belong to only one interval, so only one prediction is possible).

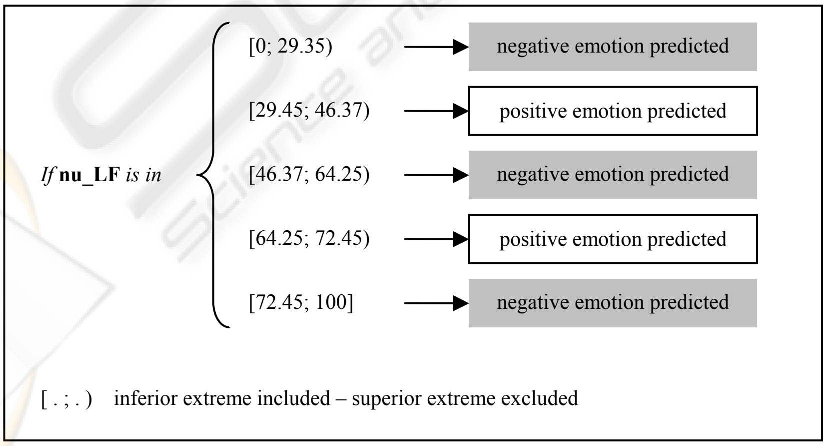

Fig. 2. Decision model for emotional status assessment learned through ONE-R algorithm on healthy controls.

Multi Layer Perceptron (MLP) is a particular Artificial Neural Network (ANN) architecture also known as "feed forward architecture", and it is composed by, at the least, three different layers: input layer, hidden layer and output layer. Generally, the hidden layer can be more then one and also the number of neurons into hidden layers can also vary, where a neuron is the "simple" processing unit of the net.

As each ANN, MLP is a mathematical/computational model based on biological neuronal networks and is commonly applied to model complex input/output relationships or to identify data patterns of distribution/correlation. Structurally, an ANN is composed by a set of neurons, linked each other by a large number of (usually nonlinear) weighted connections. Each neuron is able to calculate a specific function, given the inputs and the weights on the connections are adjusted in order to minimize some criteria as, usually, the errors number.

Using MLP we have obtained the best results setting up the following net parameters: only one the hidden layer with 5 neurons, Learning Rate=0.2, Momentum=0.1 and 1000 training epochs. Moreover we have previously ranked the variables by preprocessing the dataset by ONE-R WEKA Filter, which evaluates the worth of an attribute by using the ONE-R strategy. Finally, the best results for MLP were obtained selecting the first 8 ranked attributes (nu_LF, powerHF, STDRR, gender, powerVLF, peakVLF, peakLF and peakHF). The MLP architecture is showed in figure 2.

Fig. 3. Multi Layer Perceptron architecture.

3 Results

ONE-R procedure sorted out the nu_LF descriptor as the more significant spectral parameter in the selected experimental conditions and for the study purpose. The ONE-R allowed a good trade-off between the portion of correct sample/label association on the entire training set (recognition) and the portion of correct sample/label association on validation and independent test phases (generalization).

In table 3 we summarize our results both for ONE-R and MLP. For the first one, an overall correct classification on training set (healthy controls) has been obtained on about 76.0% of the instances, 81.0% and 69.0% of negative and positive emotions, respectively; (tenfold cross-validation: 70.2%; leave-one-out validation: 71.1%).

When applied to the independent test set (posttraumatic subjects), the classification accuracy performed by the ONE-R decision model was comparable: 70.3% of correct classification on the entire test set, 65% and 74% of positive and negative emotions, respectively.

Despite the greater accuracy of the MLP on the entire training set (82.7% vs. 76.0%, for MLP and ONE-R respectively), MLP accuracy decreased to 47.11% and 46.11% on 10folds-cross and leave-one-out validation phases respectively. Moreover, also the correct attribution for each class of emotion has decreased: 33.33% and 57.63% for positive and negative emotions, respectively, on 10folds-cross validation, and 26.67% and 61.02% for positive and negative emotions, respectively, on leave-one-out validation.

Furthermore, also on independent test phase MLP has provided lower reliability than ONE-R approaches: 70.31% of accuracy for ONE-R versus 51.56% for MLP (32% and 64.10% for positive and negative emotions respectively). All the results are summarized in Table 3.

Table 3. Results One-R vs MLP.

Analysis of data: ONE-R vs MLP				
	On training data	**10 Folds-cross**	**Leave-one-out**	**Independent Test Set**
OneR	75.96%	70.19%	71.15%	70.31%
MLP	82.69%	47.11%	46.15%	51.56%
Attribution of positive emotions				
	On training data	**10 Folds-cross**	**Leave-one-out**	**Independent Test Set**
OneR	68.89%	57.78%	64.44%	68.00%
MLP	68.89%	33.33%	26.67%	32.00%
Attribution of negative emotions				
	On training data	**10 Folds-cross**	**Leave-one-out**	**Independent Test Set**
OneR	81.36%	79.66%	76.27%	71.79%
MLP	93.22%	57.63%	61.02%	64.10%

4 Comment

Although the HRV is an emerging objective measure also in neurophysiology, there is still a lack of knowledge about a possible and tangible relationship between heart activity and the emotional status assessment. On the other hand, Data Mining techniques may offer practical advantages for analyzing data, also medical [25, 26], and they have proved useful analysis tools in our study, searching for the most reliable and frequent relationships between HRV parameters measured during symphonic music listening and emotions subjectively reported by a group of 26 healthy subjects at the end of each listening. Several data mining methods have been investigated and evaluated through the most suitable validation techniques. Reliability of resulting relationships has been then tested on an independent test group of 16 posttraumatic patients, without algorithm retraining.

ONE-R algorithm (a classification rule learner) has provided the best performances and reliability, identifying a single HRV parameter (notably the *nu_LF* measure) as the most relevant for assessing the emotional status, both for healthy controls and posttraumatic subjects.

In this study ONE-R proved more effective then the best MLP configuration and provided a simple *"if…then"* rule. Furthermore, this rule can be easily applied, in combination with the non-invasive technique for HRV data acquisition (by a photopletismographic sensor), to evaluate the emotional conditions of unconscious subjects (such as subjects in vegetative state) in order to establish, in a more objective way, when is better to continue or interrupt any contact or stimulation.

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