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A Nonlinear Heartbeat Dynamics Model Approach for Personalized Emotion Recognition

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***Abstract*— Emotion recognition based on autonomic nervous system signs is one of the ambitious goals of affective computing. It is well-accepted that standard signal processing techniques require relative long-time series of multivariate records to ensure reliability and robustness of recognition and classification algorithms. In this work, we present a novel methodology able to assess cardiovascular dynamics during short-time (i.e. $<$ 10 seconds) affective stimuli, thus overcoming some of the limitations of current emotion recognition approaches. We developed a personalized, fully parametric probabilistic framework based on point-process theory where heartbeat events are modelled using a 2^{nd}-order nonlinear autoregressive integrative structure in order to achieve effective performances in short-time affective assessment. Experimental results show a comprehensive emotional characterization of 4 subjects undergoing a passive affective elicitation using a sequence of standardized images gathered from the international affective picture system. Each picture was identified by the IAPS arousal and valence scores as well as by a self-reported emotional label associating a subjective positive or negative emotion. Results show a clear classification of two defined levels of arousal, valence and self-emotional state using features coming from the instantaneous spectrum and bispectrum of the considered RR intervals, reaching up to 90% recognition accuracy.**

I. INTRODUCTION

The study of human feelings represents an interesting on-going topic which involves multidisciplinary expertise including psychology, neurophysiology, and cognitive neuroscience. From a technical point-of-view, its outcome is constituted by the development of computational systems able to effectively map features extracted from human signs (e.g. physiological signals, behavioral correlates, facial expressions, movements, etc.) into a well-defined "emotional space", i.e., a multidimensional space in which each emotion occupies a distinguished region. This challenging task is one of the most ambitious objectives of the well-known technical field of affective computing [1]. A commonly used emotional space is defined by the Circumplex Model of Affects (CMA) [2] which takes into account two main dimensions: Valence, quantifying the degree of pleasantness, and Arousal, relating to the "impact" of the emotion. Focusing on physiological signals, several emotion recognition methods using the electrocardiogram (ECG), electrodermal response, respiration activity, electromyography, were proposed in current literature (see [3], [4] for reviews or details) as commonly associated with the Autonomic Nervous System (ANS). Current successful approaches require relative long-time series of multivariate recordings to accurately characterize the emotional state of a subject. These constraints dramatically reduce the impact on real applications of the affective computing systems. Nowadays, in fact, the widespread diffusion of digital media such as internet websites, television programs, smartphone applications, etc. surely presents us with short-time, even underlying, affective stimuli for which standard signal processing techniques would be unable to perform such a characterization because of low resolution or parameter estimation issues.

To overcome these limitations, in this paper we propose an effective, personalized, and fully parametric emotion recognition methodology able to perform an instantaneous cardiovascular assessment to recognize emotional swings (positive or negative), as well as two main levels of arousal and valence (low-medium and medium-high) using only heart rate variability (HRV) assessments [5]. We have perfected a novel stochastic model of heartbeat dynamics based on point-process theory such that an inverse gaussian inter-beat probability function is able to predict the waiting time of the next heartbeat given a linear and nonlinear combination of the previous events [6], [7]. The choice of including past nonlinear information is justified by both physiological reasons (the nonlinear neural signaling interactions and integrations occurring at the neuron and receptor levels) and experimental evidence [5], [8], [9]. In particular, concerning emotion recognition, we recently demonstrated the crucial role played by ANS nonlinear dynamics in arousal and valence recognition [4]. Accordingly, we based our methodology on a quadratic Nonlinear Autoregressive Integrative (NARI) model, which allows for n^{th}-order polyspectra of the considered signal [10] (see details in next section). The algorithm combines the usage of the derivative RR series in order to improve the achievement of stationarity [11] with the system identification method based on local log-likelihood [6]. Performances of the proposed point-process nonlinear model were evaluated in four RR interval series gathered from healthy volunteers undergoing a passive visual affective protocol using International Affective Picture System (IAPS) [12] images, which are scored as valence and arousal. Experimental results demonstrate that the proposed

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approach, novel in the field of affective computing, is able to instantaneously assess the subject's emotional state in short-time events (i.e., 10 seconds IAPS images) using spectral (linear) and bispectral (nonlinear) features.

II. Materials and Methods

The methodology here proposed for cardiovascular assessment of short-time affective stimuli can be seen as a further advance of our previously proposed point-process models of heartbeat dynamics (e.g. [6] [7]. The novel NARI model takes into account the series of the RR derivatives in order to improve the achievement of stationarity [11] along with a nonlinear expansion whose parametric structure is estimated by maximum log-likelihood optimization [6].

A. Point-Process Model of Heartbeat Nonlinear Dynamics

The point process framework primarily defines the probability of having a heartbeat event at each moment in time. Defining $t \in (0,T]$, the observation interval, and $0 \leq u_1 < \cdots < u_k < u_{k+1} < \cdots < u_K \leq T$ the times of the events, we can define $N(t) = \max\{k : u_k \leq t\}$ as the sample path of the associated counting process. The left continuous sample path is defined as $\widetilde{N}(t) = \lim_{\tau \to t^-} N(\tau) = \max\{k : u_k < t\}$. Given the R-wave events $\{u_j\}_{j=1}^{J}$ detected from the ECG, $\mathrm{RR}_{\widetilde{N}(t)} = u_j - u_{j-1} > 0$ denotes the j^{th} RR interval, i.e., the previous R-wave event before time t. Assuming history dependence such that $\mathcal{H}_t = (u_j, \mathrm{RR}_j, \mathrm{RR}_{j-1}, ..., \mathrm{RR}_{j-M+1})$, the probability distribution of the waiting time $t - u_j$ until the next R-wave event follows an inverse Gaussian (IG) model (see [6] for related physiological and goodness-of-fit motivations). For such an inter-beat probability function, we here propose to model its first-moment statistic (mean) $\mu_{\mathrm{RR}}(t, \mathcal{H}_t, \xi(t))$ as a NARI formulation:

$$\mu_{\mathrm{RR}}(t, \mathcal{H}_t, \xi(t)) = \mathrm{RR}_{\widetilde{N}(t)} + \gamma_0$$
$$\sum_{i=1}^{p} \gamma_1(i,t)\, \Delta\mathrm{RR}_{\widetilde{N}(t)}(i) + \sum_{i=1}^{q}\sum_{j=1}^{q} \gamma_2(i,j,t)\, \Delta\mathrm{RR}_{\widetilde{N}(t)}(j)$$

where $\Delta\mathrm{RR}_{\widetilde{N}(t)}(i) = (\mathrm{RR}_{\widetilde{N}(t)-i} - \mathrm{RR}_{\widetilde{N}(t)-i-1})$, $\xi(t)$ is the vector of the time-varing parameters which includes $\xi_0(t) > 0$ representing the shape parameter of the (IG) distribution. This choice of a second order NARI system retains an important part of the non-linearity of the system. Since $\mu_{\mathrm{RR}}(t, \mathcal{H}_t, \xi(t))$ is defined in continuous time, we can obtain an instantaneous RR mean estimate at a very fine timescale (with an arbitrarily small bin size Δ), which requires no interpolation between the arrival times of two beats. The unknown time-varying parameter vector $\boldsymbol{\xi}(t)$ is estimated by means of a local maximum likelihood method [6]. We use a Newton-Raphson procedure to maximize the local log-likelihood and compute the local maximum-likelihood estimate of $\boldsymbol{\xi}(t)$. The model goodness-of-fit is based on the Kolmogorov-Smirnov (KS) test and associated KS statistics (see details in [6]). Once the order $\{p, q\}$ is determined, the initial NARI coefficients are estimated by the method of least squares. In order to provide reliable results, we preprocessed all the heartbeat data with a detection and correction algorithm [13] to avoid errors in the dynamics estimation due to peak misdetection and ectopic beats.

B. Feature Estimation from the Input-Output Kernels

It is possible to map a quadratic NARI model to an n^{th} order input-output Wiener-Volterra model [10]. Therefore, the choice of a 2^{th}-order autoregressive model allows, after the input-output transformation of the kernels, the evaluation of all the high order statistics (HOS) of the system, such as the Dynamic Bispectrum and Trispectrum [14]. The quadratic NARI model can be linked to the traditional input-output Volterra models by using a specific relationships [10] involving the Fourier transforms of the kernels of the non-derivative model, $\Gamma'_1(f_1)$ and $\Gamma'_2(f_1, f_2)$. In this work, we chose to model the affective-related cardiovascular activity with a cubic input-output Volterra using the following recursive relationships:

$$H_1(f) = \frac{1}{\Gamma'_1(f)} \tag{1}$$

$$H_2(f_1, f_2) = -\frac{\Gamma'_2(f_1, f_2)}{\Gamma'_1(f_1)\Gamma'_1(f_2)}\, H_1(f_1 + f_2) \tag{2}$$

$$H_3(f_1, f_2, f_3) = -\frac{1}{6}\sum_{\sigma_3} \frac{\Gamma'_2\left(f_{\sigma_3(1)}, f_{\sigma_3(2)}\right)}{\Gamma'_1\left(f_{\sigma_3(1)}\right)\Gamma'_1\left(f_{\sigma_3(2)}\right)} \times H_2\left(f_{\sigma_3(1)} + f_{\sigma_3(2)}, f_{\sigma_3(3)}\right) \ . \tag{3}$$

1) Time and Frequency Domain Estimations: The time-domain characterization is based on the first and the second order moments of the underlying probability structure. Namely, given the time-varying parameter set $\boldsymbol{\xi}(t)$, the instantaneous estimates of mean RR, RR interval standard deviation, mean heart rate, and heart rate standard deviation can be extracted at each moment in time [6]. Moreover, given the input-output Volterra kernels of the NARI model for the instantaneous R-R interval mean $\mu_{\mathrm{RR}}(t, \mathcal{H}_t, \xi(t))$, we can compute the time-varying parametric (linear) autospectrum [11], [15] of the non-derivative series:

$$\mathcal{Q}(f,t) = 2(1 - cos(\omega))S_{xx}(f,t)H_1(f,t)H_1(-f,t) - \frac{3}{2\pi}\int H_3(f, f_2, -f_2, t)S_{xx}(f_2, t)df_2 \tag{4}$$

where $S_{xx}(f,t) = \sigma^2_{\mathrm{RR}}$. By integrating the eq. (4) in each frequency band, we can compute the indices within the very low frequency (VLF = 0.01-0.04 Hz), low frequency (LF = 0.04-0.15 Hz), and high frequency (HF = 0.15-0.4 Hz) ranges.

2) Higher Order Spectral Representation: In the proposed short-time affective assessment, we included instantaneous HOS representations in order to retain phase relations between frequencies and quantify deviations from linearity, stationarity or Gaussianity [14], [16], [17]. Particular cases of higher order spectra is the third-order spectrum (Bispectrum), i.e. the Fourier transform of the third-order cumulant sequence [14], [16], [17].The analytical solution for the bispectrum of a nonlinear system response subject to stationary, zero-mean Gaussian input can be found in

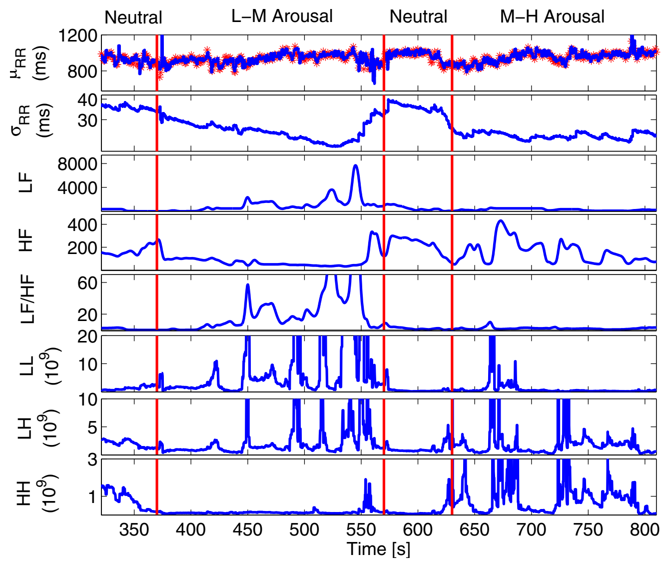

Fig. 1. Instantaneous heartbeat statistics computed from a representative subject (N. 1) using the proposed NARI model during the passive emotional elicitation (two neutral sessions alternated to a L-M and a M-H arousal sessions).The estimated $\mu_{\mathrm{RR}}(t, \mathcal{H}_t, \xi(t))$ is superimposed on the recorded R-R series. Below, the instantaneous heartbeat Power spectra evaluated in LF and HF bands, the sympatho-vagal balance (LF/HF) and several bispectral statistics are reported.

[17] which involves $H_1(f)$ and $H_2(f_1, f_2, t)$. Within the triangular region of non-symmetry, we estimated several features, such as mean and variance of bispectral invariants, mean magnitude of the bispectrum, phase entropy, normalized bispectral entropy and normalized bispectral squared entropy. For a detailed review of these features, please refer to [16]). Moreover, we further evaluated the nonlinerar sympatho-vagal interactions by integrating the bispectrum in the appropriate frequency bands related to the combinations of the LF and HF spectral limits [5].

C. Experimental Setup

The experimental protocol related to this work was extensively described in [4]. Briefly, an homogeneous population of 4 healthy subjects (age between 21 and 24, Patient Health Questionnaire^{TM} score less than 5 [4]) were included in the study. The affective elicitation was performed by 9 sessions of IAPS images projected to a PC monitor. The sessions alternated so-called *neutral* sessions and *arousal* sessions which were divided into Low-Medium (L-M) and Medium-High (M-H) classes, according to the IAPS arousal score associated. Such sessions included 20 images eliciting an increasing level of valence, which was also associated to L-M (unpleasant) and M-H levels (pleasant). The overall protocol utilized 110 images presented for 10 seconds each. During the visual elicitation, following Einthoven triangle configuration, the electrocardiogram (ECG) was acquired by using a dedicate hardware module, i.e., the ECG100C Electrocardiogram Amplifier from BIOPAC inc., with sampling rate of 250 Hz.

D. Classification

For each subject's RR interval series, the point-process NARI model was applied and all the mentioned linear and nonlinear derived features were extracted in order to define the personalized feature set whose 80% was used for training the pattern recognition algorithm, whereas the remaining 20% was associated to the test set. We performed 40-fold cross-validation steps in order to obtain unbiased classification results performed using the well-known Support Vector Machines.

III. Results

A tracking from a representative subject is shown in fig. 1, whereas overall results are summarized in Tab. I. The presence of nonlinear behaviors in the heartbeat series was investigated by using a well-established time-domain test [18] based on high-order statistics (number of laps: $M = 8$, bootstrap replications: 500). Such a nonlinearity test gave significative results ($p < 0.05$) on all of the subjects demonstrating that such series are, indeed, coming from a nonlinear system. Moreover, all the obtained KS distances are below 0.0397, ensuring that the NARI model well-performed a good prediction of the affective-related changes of heartbeat dynamics. Concerning the emotional pattern recognition, a two-classes problem was considered for the arousal and valence considering the L-M and M-H levels. The neutral sessions were associated to the L-M class for the arousal task and not considered on the valence task (neutrals could be equally associated to L-M or M-H levels). Regarding the self-reported emotions, we used the subjective labels (positive or negative) given by the self-assessment making report, which was filled out for each of the random seen image. For each cases, a comparative evaluation of the accuracy was performed in order to further validate the use of nonlinear features/model. First, in the SVM classifier we used five linear-derived features: the mean and standard deviation of the IG distribution (corresponding to the novel probabilistic definitions of mean and standard deviation of the RR intervals [6]), the LF and HF power, and the LF/HF ratio. Then, all the nonlinear features derived from the instantaneous bispectral analysis (see paragraph II-B.2) were added to the linear-derived feature set for further classification.

The recognition accuracy of the short-term positive-negative emotions is improved in two cases and, anyhow, is $> 58\%$ for all of the subjects, even exceeding 74% of successfully recognized samples. Concerning the arousal classification, the recognition accuracy of the short-term emotional data is improved in all cases and, anyhow, is $> 78\%$ for all of the subjects, even exceeding 92% of successfully recognized samples. Finally, for valence classification the recognition accuracy of the short-term emotional data is improved in two cases and, anyhow, is $> 68\%$ for all of the subjects even exceeding 85% of successfully recognized samples.

TABLE I

EXPERIMENTAL RESULTS FROM THE POINT-PROCESS NARI MODEL

Subjects	P-Value	KS Dist	Emotion Linear→Nonlinear		Arousal Linear→Nonlinear		Valence Linear→Nonlinear	
1	$< 10^{-6}$	0.0362	65.45→63.64		78.45→78.46	√	84.37→81.25	
2	$< 10^{-6}$	0.0397	73.13→74.63	√	83.61→85.25	√	79.03→85.48	√
3	$< 10^{-6}$	0.0321	66.15→58.46		87.69→92.31	√	75.00→73.44	
4	< 0.01	0.0372	47.83→60.87	√	80.00→90.77	√	54.69→68.75	√

P-values are obtained from the nonlinearity test.

IV. DISCUSSIONS AND CONCLUSION

We presented a novel methodology able to assess in an instantaneous, personalized, and automatic fashion whether the subject is experiencing a positive or a negative emotion (self-reported by the subject himself) along with two levels (L-M and M-H) of elicited arousal and valence. Such assessments are performed considering only the cardiovascular dynamics through the RR interval series on short-time emotional stimuli ($<$ 10 seconds). The methodology proposed here represents a pioneering approach in the current literature and can open new avenues in the field of affective computing. Standard signal processing methods, in fact, would be unable to give reliable and effective results because of resolution or estimation problems. We defined an ad-hoc affective computing framework based on the point-process theory and on NARI modeling of the IG mean using the derivative RR series [11] to improve the tracking of the affective-related non-stationary heartbeat dynamics.

The inherent nonlinearties of the cardiovascular systems [19] were confirmed by our experimental results. According to the nonlinearity test, in fact, all the RR series resulted to be the outputs of a nonlinear system. Moreover, the inclusion of the instantaneous nonlinear features in the system improved the accuracy in 8 out of the 12 considered cases (among all subjects for self-emotion, arousal, and valence recognition). Unlike other paradigms developed in the literature for estimating human emotional states [3], our novel approach is purely parametric, fully autoregressive and the analytically derived indices can be evaluated in a dynamic and instantaneous fashion allowing for an affective characterization using n^{th}-order input-output high order statistics such as the instantaneous bispectrum and trispectum. The framework proposed here is fully personalized, i.e. it does not require data from representative population of subjects. This is why the presented results, even if with only a very limited number of subjects, are very important and promising.

In conclusion, using only the heartbeat dynamics, we were able to effectively distinguish the two fundament levels of both arousal and valence, thus allowing for the assessment of four basic emotions [2] as well as the personal cognitive association related to a positive and negative emotion. Besides affective computing, these achievements could have an highly relevant impact also in the mood disorder psychopathology diagnosis and treatment (mood disorder produces an altered emotional response), and neuro-economics.

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