Gender-Specific Velocity Recognition of Caress-like stimuli through Nonlinear Analysis of Heart Rate Variability

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Abstract— **This study reports on the development of a gender-specific classification system able to discern between two levels of velocity of a caress-like stimulus, through information gathered from Autonomic Nervous System (ANS) linear and nonlinear dynamics. Specifically, caress-like stimuli were administered to 32 healthy volunteers (16 males) while monitoring electrocardiogram signal to extract Heart Rate Variability (HRV) series. Caressing stimuli were administered to the forearm at a fixed force level (6 N) and two levels of velocity, 9.4 mm/s and 37 mm/s. Standard HRV measures, defined in the time and frequency domain, as well as HRV nonlinear measures were extracted during the pre- and post-stimulus sessions, and given as an input to a Support Vector Machine (SVM) classifier implementing a leave-one-subject-out procedure. Results show an accuracy of velocity recognition of 70% for the men, and 84.38% for the women, when both standard and nonlinear HRV measures were taken into account. Conversely, non-significant results were achieved considering standard measures only, or a gender-aspecific classification. We can conclude that caress-like stimuli elicitation significantly affect HRV nonlinear dynamics with a highly specific gender dependency.**

I. Introduction

The human sensibility to slowly moving touch stimuli is mediated by low-threshold mechanoreceptors with unmyelinated afferents, called C tactile fibers [1], [2], producing affective sensations. The effect of velocity of the tactile stimulus was investigated in previous studies through single unit microneurography, recorded from single afferents belonging to the antebrachial cutaneous nerves during soft brushing stroking [3]. It has been found that the maximal unit response occurred during movement velocities in the range of 1-10 cm/s. Within this range, the tactile stimulation performed at a velocity close to 3 cm/s was considered as the most pleasant [3]. Accordingly, this velocity was demonstrated to be optimal for the activation of CT fibers [4].

Changes in ANS dynamics induced by passive touch stimuli were previously studied through the analysis of physiological signals such as Heart Rate Variability (HRV) [5]. Specifically, a study on facial massage highlighted how this stimulus significantly increases the LF/HF measure [6]. Moreover, caresses on hands and feet significantly reduced the parasympathetic nervous activity, as estimated through the HRV-HF component [5]. However, a comprehensive characterization of HRV nonlinear dynamics as a function of affective haptic stimuli, also investigating the gender effect, still need to be performed. To this extent, here we study such a nonlinear dynamics of cardiovascular variability during caress-like affective stimulation on the forearm. Indeed, the ANS signaling on cardiovascular control is characterized by multi-feedback neural interactions, leading to a nonlinear physiological control [7], [8], [9].

In order to quantify the role of HRV nonlinear features in recognizing the velocity of the stimuli, in this study, we constructed two different datasets: the first consisting of only standard features, defined in the time domain and in the frequency domains, and the second including also the nonlinear parameters. These datasets were considered as input to a support vector machine algorithm implementing a leave-one-subject-out procedure. The processing chain is suitable to be implemented in a wearable system [10], [11]. The same investigation was performed considering the group of men and women separately, in order to quantify the incidence of gender differences in the hedonic interpretation of touch.

Of note, gender differences in HRV parameters were studied in several works in the literature [12], [13], [14]. Significant differences were found in the parasympathetic regulation of healthy people during resting state (different values of HF power), probably connected to the different levels of estrogen, which improve cardiac vagal functions in women [12]. On the other hand, men have been associated to a higher sympathetic activity than women, as estimated by HRV frequency parameters LF/HF and LF% [12], [14]. In the current literature, few studies investigated the gender differences through HRV nonlinear parameters. The most relevant results report on the identification of higher HRV approximate entropy in female population than men, as estimated during long-monitoring (24-h) [13] and short-time (8-min and 15-min segments) resting state [15].

II. Materials and Methods

A. Experimental protocol

Thirty-two participants, aged 27 ± 2 (16 males), gave their informed consent to take part in the study. During the experimental protocol, participants were comfortably seated with the right forearm horizontally placed on the forearm support, hand palm down. For all trials, participants wore earplugs in order to prevent any auditory cues. We used a recently developed device able to administer caress-like stimuli using a layer of elastic fabric [16] (see Fig. 1). The extremities of the fabric were connected to two rolls, which were independently moved by one motor (HITEC digital DC

The research leading to these results has received partial funding from the European Union Seventh Framework Programme FP7/2007-2013 under grant agreement n 601165 of the project WEARHAP.

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servomotor HS-7954 H with an input voltage of 7.4 V). The velocity of the caress can be modulated by regulating the velocity of the motors.

Fig. 1. An overview of the haptic system worn by one of the participants during the experimental tests.

In this study, we considered 2 levels of velocity of the caresses, 9.4 mm/s and 37 mm/s, provided at a fixed force of 6 N. Stimuli were randomized among subjects, and administered with a pre-stimulus and a post-stimulus interval sessions of 35 seconds. During the elicitation, the ECG was continuously acquired, following the Einthoven triangle configuration, by means of a dedicate hardware module, i.e. the ECG100C Electrocardiogram Amplifier from BIOPAC inc. with a sampling rate of 500 Hz.

B. Methodology of Signal Processing

To obtain the HRV series from the ECG, an automatic QRS complex detection algorithm was used [17]. The methodology of HRV processing can be divided as follows:

- HRV feature extraction (standard and nonlinear)
- the LOSO procedure, which includes both the statistical analysis for feature selection, and the application of the SVM classifier.

1) Features extraction: Standard HRV analysis refers to the extraction of parameters defined in the time and frequency domain [18]. In particular, time domain features included statistical parameters and morphological indexes. Given a time window, several parameters were calculated, such as simple mean value and the standard deviation of the RR intervals. Moreover, we calculated the root mean square of successive differences of intervals (RMSSD) and the number of successive differences of intervals which differ by more than 50 ms (pNN50 % expressed as a percentage of the total number of heartbeats analyzed). Referring to morphological patterns of HRV, the triangular index was calculated. It was derived from the histogram of RR intervals into NN window (TINN) in which a triangular interpolation was performed. The time domain methods are simple and widely used, but are unable to discriminate between sympathetic and parasympathetic activity, while an appreciable contribution is given by the frequency domain parameters. All features extracted in the frequency domain were based on the Power Spectral Density (PSD) of the HRV. Three main spectral components were distinguished in a spectrum calculated from short-term recordings: Very Low Frequency (VLF, below 0.04Hz), Low Frequency (LF, from 0.04Hz to 0.15Hz), and High Frequency (HF, from 0.15Hz to 0.4Hz). In addition we calculated the LF/HF ratio which should give information about the sympatho-vagal balance.

From each HRV series, we calculated nonlinear indices based in particular on the following three methods: complexity measures calculation, Symbolic Analysis and the Lagged Poincaré Plot (LPP).

Complexity measures: we applied three different algorithms for the calculation of entropy of the HRV signals, namely Approximate Entropy (ApEn) [19], Sample Entropy(SampEn) [20] and the Coefficient of Sample Entropy (COSEn) [21].

Symbolic analysis: this is a powerful nonlinear method based on the conversion of the series into a sequence of symbols [22]. The full dynamics of the HRV series has been divided in six levels of amplitude and a symbol (from 0 to 5) was assigned to each data sample according to the level of belonging. After the data had been converted in symbolic series we analyzed patterns of 3 and 4 symbols. Patterns consisted of segments of n consecutive symbols, with $n-1$ of overlap from segment to segment. Then we investigated on the trend of the patterns, with $n = 3$ and $n = 4$. For the patterns of three symbols we identified four classes: 0V (number of patterns where all symbols were equal), 1Va (number of patterns with one variation between the second and the third symbols), 1Vb (number of patterns with one variation between the first and the second symbols), 2Va (number of pattern with a trend strictly increasing or strictly decreasing), 2Vb (all the others). For the patterns of four symbols we identified four classes: 0V, 1V, 2V, 3V, which were the numbers of patterns with zero, one, two, three variations respectively. Moreover the percentage values of the total of all these parameters were calculated and used as features.

Lagged Poincaré Plot: this method quantifies the fluctuations of the dynamics of the time series through a graphic (scatter plot of RR intervals) where each RR_n interval is mapped as a function of the successive RR_{n+M}, in this study we chose $1 \leq M \leq 10$[23]. The quantitative analysis from the graph can be made by calculating the dispersion of the points in the LPP:

- SD2 and SD1: the standard deviations related to the points along the identity line $RR_{n+M} = RR_n$ and along its perpendicular.
- SD12: the ratio between SD1 and SD2.
- S ($S = \pi SD1SD2$): the area of an imaginary ellipse with axes SD1 and SD2.
- SDRR ($SDRR = \frac{1}{\sqrt{2}}\sqrt{SD1^2 + SD2^2}$): an approximate relation indicating the variance of the whole HRV series.

From each of these parameters we calculated the area under the curve (AUC) of the plot of their values in function of the lag M, calculating two values of AUC, the first for lower values of M ($1 \leq M \leq 5$) and the second for upper values of M ($6 \leq M \leq 10$) . Moreover we calculated the ratio between these parameters and the total AUC for $1 \leq M \leq 10$.

2) Statistical Analysis and Pattern Recognition: All features were extracted from HRV series gathered from before and after the stimuli. For each parameter we calculated the difference between the post- and pre-stimuli sessions. Statistical analysis and pattern recognition followed a Leave-One-Subject-Out procedure (LOSO). Specifically, we applied features selection and SVM training on a set comprised of 1:N-1 subjects (where N is the total number of participants), and tested the prediction of the velocity level of data gathered from the Nth subject. This procedure was repeated N times. To select only the features which were more significantly different between the two velocities, we performed a nonparametric analysis through the Wilcoxon signed-rank test. Only the features which obtained a significant p-value were used to construct the dataset input of a Support Vector Machine (SVM) classifier, which used the radial basis function kernel ($e^{-\gamma|u-v|^2}$), where $\gamma =$(number of selected features)$^{-1}$.

III. Experimental Results

Classification results on the two datasets including i) linear and ii) linear and nonlinear features of HRV are shown in Tables I, II, and III in form of confusion matrix. The generic element r_{ij} of the confusion matrix indicates how many times in percentage a pattern belonging to the class i was classified as belonging to the class j. A more diagonal confusion matrix corresponds to a higher degree of classification. The matrix has to be read by columns.

Considering data from all of the subjects, i.e., men and women, standard HRV features were able to recognize the two velocities with an accuracy of 51.61%, whereas an accuracy of 58.07% was achieved considering also features coming from nonlinear methods.

TABLE I
Confusion Matrix of SVM Classifier for the two levels of velocities (All the subjects)

Standard features

	V1	V2
V1	45.1613	54.8387
V2	41.9355	58.0645

Standard and Nonlinear

	V1	V2
V1	61.2903	38,7096
V2	45.1613	54,8387

Given the poor classification performances, hypothesizing that gender significantly affected the system accuracy, we then split the dataset by gender. Considering data gathered from men exclusively, standard HRV features were able to recognize the two velocities with an accuracy of 68.50%, whereas an accuracy of 84.38% was achieved considering also features coming from nonlinear methods (see Table II).

TABLE II
Confusion Matrix of SVM Classifier for the two levels of velocities (Women)

Standard features

	V1	V2
V1	62.5000	37.5000
V2	25.0000	75.0000

Standard and Nonlinear

	V1	V2
V1	**81.2500**	18.7500
V2	12.5000	**87.5000**

Considering data gathered from men exclusively, standard HRV features were able to recognize the two velocities with an accuracy of 33.34%, whereas an accuracy of 70% was achieved considering also features coming from nonlinear methods (see Table III).

TABLE III
Confusion Matrix of SVM Classifier for the two levels of velocities (Men)

Standard features

	V1	V2
V1	40.0000	60.0000
V2	73.3333	26.6667

Standard and Nonlinear

	V1	V2
V1	**73.3333**	26.6667
V2	33.3333	**66.6667**

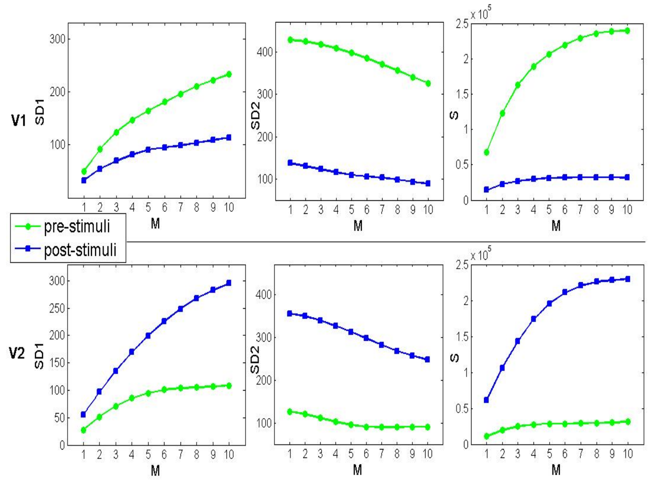

Fig. 2. Values of the features SD1, SD2 and S, as functions of the M lags in the pre-stimuli and in the post-stimuli sessions, for V1=9.4 mm/s and V2=37 mm/s. The values regards one female subject.

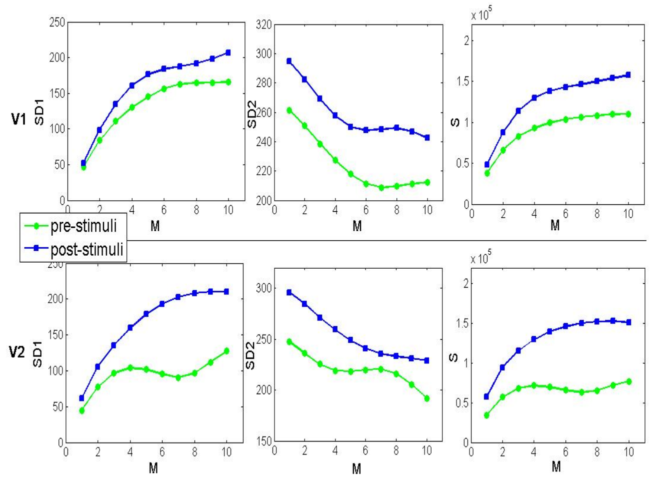

Fig. 3. Values of the features SD1, SD2 and S, as functions of the M lags in the pre-stimuli and in the post-stimuli sessions, for V1=9.4 mm/s and V2=37 mm/s. The values regards one male subject.

Furthermore, feature selection procedures highlighted the crucial role of Lagged Poincaré Plot (LPP) measures considering data coming from the women only, whereas symbolic analysis was identified as the most informative methods in classifying velocity levels in men. As an example, Fig. 2 shows how the LPP parameters changed from the pre-stimuli to the post-stimuli session for a women, considering two velocities of caressing. More specifically, it can be easily noticed that the parameters SD1, SD2 and S decrease with V1 (slower caress) and increase with V2 (faster caress) from pre-stimuli to post-stimuli. Conversely, the parameters increase during both V1 and V2 in men (see Fig. 3).

IV. Conclusion and Discussion

In conclusion, we presented a novel approach to automatically recognize two different levels of velocity of a caress-like stimulation, as elicited by a haptic device. To this aim, we used ANS features derived from standard and nonlinear analysis of HRV series. We tested the proposed approach on data gathered from 32 subjects (16 males), also grouping data by gender.

The average accuracy of the SVM classifier was of 70% for the group of men, only when nonlinear HRV features are also taken into account. Likewise, average accuracy 84.38% for the group of women.

The satisfactory classification accuracy obtained only when the men and the women were divided, suggests a significant gender effect on HRV nonlinear dynamics occurring during affective haptic elicitation. Accordingly, previous studies highlighted different effects of caress-like stimuli on gender, mainly related on perceived pleasantness associated to the stimulus. In particular, as velocity of the stimulus increased, at constant force level, males and females reported opposite valence perceptions: for the women, the more the velocity, the lower the pleasantness; for the men, the more the velocity, the higher the pleasantness. [24]. Of note, this opposite self-assessemnt of the stimulus valence recalls the changes in the trends shown in Fig. 2 and Fig. 3.

It is worthwhile noting that no significant classification accuracy was obtained when using standard HRV features. This results suggest that HRV nonlinear dynamics is strongly affected by affective tactile stimulation, according to different levels of velocity. Future work will focus on the study of HRV linear and nonlinear dynamics as a function of the force and velocity, as well as body site of an affective tactile stimulus. Moreover, other physiological dynamics related to, e.g., electrodermal responses, and EEG will be taken into account [25], [26], [27].

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