Classifying Haptic Caress-like Stimuli through Gender-specific Heart Rate Variability Nonlinear Analysis

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***Abstract*—This study reports on how velocity and force levels of haptic caress-like stimuli can be identified through the analysis of Autonomic Nervous System (ANS) dynamics. Affective touch stimuli were administered on the forearms of 32 healthy volunteers (16 women) through a haptic device with two levels of force, 2 N and 6 N, and two levels of velocity, 9.4 mm/s and 37 mm/s. ANS dynamics was estimated through Heart Rate Variability (HRV) linear and nonlinear analysis on recordings gathered before and after each stimulus. To this extent, we here propose and assess novel features from HRV symbolic analysis and the Lagged Poincaré Plot. Classification was performed following a leave-one-subject-out procedure on nonlinear support vector machines. Pattern classification was split according to gender, significantly improving accuracies of recognition with respect to a "all-subjects" classification. Caress velocities and forces were recognized with up to 80% accuracy for men, and up to 84.38% for women. Our results demonstrate that changes in ANS control on cardiovascular dynamics, induced by haptic caress-like stimuli, can be recognized by computational approaches, considering that they occur in a gender-specific and nonlinear manner.**

***Index Terms*—Sense of touch, caress, haptic, affective, Heart Rate Variability, Nonlinear Analysis, Lagged Poincaré Plot, Symbolic Analysis**

I. Introduction

Previous studies have demonstrated that the 'universal' emotions of anger, fear, disgust, love, gratitude, and sympathy can be communicated purely through touches to the forearm [1]–[5]. For example, sympathy was most likely to be communicated with patting or stroking, while anger was most likely communicated with pushing.

Wearable haptics refers to the development and use of lightweight, under-actuated devices able to convey haptic stimuli and to naturally fit human body, without constraining it. In this study, we exploit the use wearable haptic device to investigate cardiovascular linear and nonlinear dynamics as related to perceived pleasant/unpleasant haptic stimuli, which were delivered by properly modulating caressing force and velocity. Prior evidences, in fact, pointed out that the human tactile system is very sensitive to affective stimuli like caressing, stroking, or patting, being mediated by low-threshold mechanoreceptors with unmyelinated afferents, called C-fiber tactile (CT) afferents [2]–[5]. These fibers have been found to respond to soft and light touch and present limited somatotopic organization, suggesting that stimulation location is less important than for myelinated fibers. However, caress velocity plays a role in pleasantness of the stimulation and for low velocities, no difference between sites featuring both myelinated and unmyelinated fibers were found [6]. Slow and light touch is therefore recommended if pleasant stimulation of the hairy skin is the goal. Accordingly, we hypothesized that caressing administered at lower velocity would deliver a more pleasant perception than the ones administered at higher velocity, and vice-versa. We then validated such hypothesis through statistical analyses on subjects' SAM scores and, then, HRV series were processed to automatically discern the induced states/caressing setup. The maximal unit response of these receptors occurred during movements in the range 1-10 cm/s. Of note, the tactile stimulation performed at a velocity close to 3 cm/s was considered the most pleasant by the subjects and the optimal one for the activation of CT fibers [7]. These results were confirmed in a study where a pleasant tactile elicitation administered through a human hand was compared with robot performance [8]. An inversion of pleasantness rating trend was also observed as the velocity increased from the values of 3 cm/s. These findings are consistent with stimuli administered in different parts of the body (forehead, arm, palm, thigh) [6].

The relationship between the level of force and pleasantness of the haptic stimulus was also previously studied. It was demonstrated that subjects recognized the most pleasant stimuli associated to the lowest level of force [9]. As a matter of fact, the response of CT fibers is preferentially activated by low-force mechanical stimuli [10].

The modulation of Autonomic Nervous System (ANS) dynamics induced by passive touch has been observed through the analysis of several physiological signals, such as Heart Rate Variability (HRV), electrodermal activity, breathing signal [11]–[15]. Specifically, concerning previous studies using HRV series to objectively assess touch massage, inconsistent results were reported. For example, after the massage, an increased parasympathetic activity [16], and increased sympathetic activity [13] were observed. However, other studies suggested a decreased parasympathetic activity after a touch massage on hands and feet [11], [17].

Here, we study the effect of a tactile stimulation induced by a haptic device on the dominant forearm on ANS dynamics. Our objective was to provide a comprehensive assessment of HRV linear and nonlinear dynamics before and after caress-like stimuli. This information is used to perform an automatic recognition of the tactile affective perception relaying exclusively from the variations of the parameters after the tactile stimulation, and checking whether there is a detectable physiological difference at different levels of velocity and force of

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the caress. To this extent, caress-like stimuli were administered through an ad-hoc haptic device able to mimic caresses [18] (see details below). Physiological systems, especially the cardiovascular system, are intrinsically nonlinear systems, as they are characterized by multi-feedback neural interactions [19]. Previous works have demonstrated that, taking such a nonlinear dynamics into account, it was obtained a significant added value to the recognition of emotional reactions to stimuli of various kinds, from visual [20]–[22] to acoustic [23]–[25].

Considering the ANS response to affective touch stimuli, previous studies reported on gender differences, explaining also the associated neural correlates [26]–[28]. Gender-specific response of the anterior cingulate cortex, orbitofrontal cortex, insula, and amygdala was observed during emotional elicitation [29]–[31]. Importantly, all these regions are involved in the autonomic control [32]. Consistently, significant gender differences were found in ANS dynamics following emotional elicitation [26]. Heart rate variability in women was characterized by a relative dominance of vagal activity (i.e., greater high-frequency (HF) power) [33] with respect to men. On the other hand, men showed higher power in the low frequency (LF) band [26], [28], [34] than women. Note that the HRV LF power is modulated by both sympathetic and vagal activities, therefore limiting conclusions on the actual physiological correlates of [35], [36].

In summary, here we propose an algorithm which takes into account linear and nonlinear heartbeat dynamics estimated during the pre- and post-stimulus sessions, aiming at recognize the physical properties of affective haptic stimuli based on the user's physiological response. To this extent, we also propose novel nonlinear features from HRV symbolic analysis and lagged Poincaré plots. All features are taken as input to nonlinear Support Vector Machines (SVM), following a Leave-One-Subject-Out (LOSO) procedure (see section II). Results, expressed as confusion matrices and statistical analyses, from feature selection and gender-specific analysis are reported in section III. Discussion and conclusions follow section III.

II. Materials and Methods

A. *Subjects Recruitment, Experimental protocol and Acquisition set-up*

Thirty-two participants aged 27±2 years (16 women) gave their informed consent to take part in the study. No participants reported physical limitations and any experience of mental or personality disorder in their life that would affect the experimental outcomes. This study was approved by the Ethical Committee of the University of Pisa. During the experimental protocol the participants were comfortably seated, their eyes were closed and the right forearm was horizontal and placed on the forearm support, hand palm down. For all trials, participants wore earplugs in order to prevent any auditory cues.

The developed device uses a layer of elastic fabric to convey haptic like-caressing stimuli [18] (see Fig. 1). We selected the elastic Superbiflex by Mectex S.P.A for its high resistance to traction and the good elastic behavior exhibited in a large range of elasticity [37]. More specifically, the extremities of a rectangular-shaped fabric were connected by means of screws to two rolls, each of them was independently moved by one motor (HITEC digital DC servomotor HS-7954 H with an input voltage of 7.4 V). Motor positions and rotation velocity were controlled by means of a customized electronic board (PSoC-based electronic board with RS-485 communication protocol), which can read motor positions by using two absolute magnetic encoders (12 bit magnetic encoder by Austrian Microsystems AS5045 with a resolution of 0.0875°). We endowed the system with a load cell (Micro Load Cell [0-5 kg] with a resolution of 5g by Phidgets) placed at the basis of the forearm support, prior to the experiment, the load cell was auto calibrated with respect to the forearm weight. When the device was active, two different operating phases were distinguishable: a calibration phase and a movement phase. During the calibration phase, the forces of 2 N and 6 N exerted by the fabric on the user were calibrated, In the movement phase, the motors started to coherently rotate and the fabric moves forward and backward over the user forearm, simulating a caress. The velocity of the caress can be modulated by regulating the velocity of the motors (for further details see [18]).

In order to provide force stimulation, the fabric is wrapped around the forearm according to the desired level of static normal force, which is measured through a load cell placed

Figure 1: An overview of the haptic system worn by one of the participants during the experimental tests (from [18]).

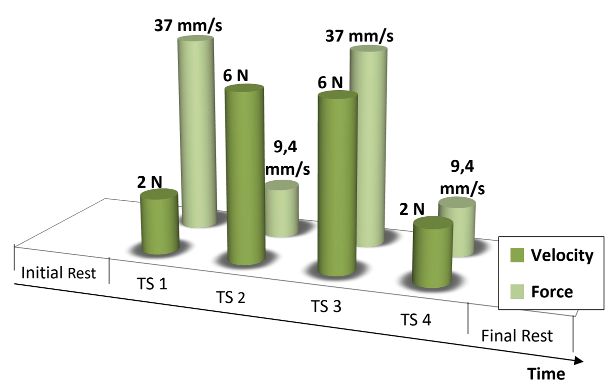

Figure 2: Example of experimental protocol scheme of one subject. Velocity and force combination is randomized. TS=touch stimulus.

at the base of the device. Then, once the target level of force is reached, the fabric is stretched transversely over the arm with different velocities. Figure 2 shows the timeline of the experimental protocol. In this study, we considered 4 different touch stimuli among 2 levels of force (2 N, 6 N) and 2 levels of velocity (9.4 mm/s, 37 mm/s). These stimuli have been elicited in a randomized order, different for each subject. Before and after each caress there were two resting state sessions of 35 seconds and after the post-stimulus rest, participants were asked to describe the caress in terms of arousal (how strong a stimulus is felt) and valence (how much pleasant/unpleasant a stimulus is felt), in agreement with the Circumplex Model of Affect (CMA) [38]. The rating was evaluated by administrating a graphic representation of arousal and valence levels, called the "Self-Assessment Manikin" (SAM) [39]. More specifically, participants were asked to assess the perception indicating a value of valence in the range from -2 to +2 (from very unpleasant to very pleasant), and a value of arousal in the range from 1 to 5 (from neutral to emotionally strong).
The two velocity levels were obtained by feeding the device motors with two different sinusoidal input trajectories, at the frequencies of 0.1 Hz and 0.4 Hz. The caress with the higher level of velocity lasted 4.31 seconds, whereas the other had a duration of 7.50 seconds. Each trial was constituted by four strokes. The values of velocity were chosen according to the following criteria:

- Previous studies investigating the hedonic aspects of caress-like elicitation on glabrous skin in a range between 0.1 and 30 cm/sec showed that highest pleasantness perception in the range of 1-3 cm/sec [7], [8], [40].
- Recently, we carried out a pilot study investigating affective perception of caress-like stimuli through 5 different force and 5 velocity levels [18]. Subjects' self-reports showed significant perceptual changes were found between 2 and 6 N.
- In a recent psychometric investigation [41] on the affective perception of caress-like stimuli, considering three levels of velocity (9.4 mm/s, 37 mm/s and 65 mm/s), subjects scored the most pleasant caressing velocity at 9.4 mm/s and 37 mm/s.

Therefore, we here considered these two velocity levels suitable for the study of hedonic touch and its physiological correlates.

Througout the experimental protocol, 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. To obtain the HRV series from the ECG, a QRS complex detection algorithm was used, i.e. the automatic algorithm developed by Pan-Tompkins [42]. Since caressing-like stimuli lasted few seconds, heartbeat linear and nonlinear dynamics were investigated by comparing estimates calculated within the post-stimulus session as normalized (i.e., subtracted) with respect to the reference value within the pre-stimulus session.

B. Methodology of Signal Processing

The methodology of signal processing used in this study can be divided in two basic parts:

- HRV feature extraction (standard and nonlinear parameters);
- Feature selection and pattern recognition, where the LOSO procedure is applied.

In Fig. 3 we report a block scheme including all processing steps. Remarkably, we here propose novel features derived

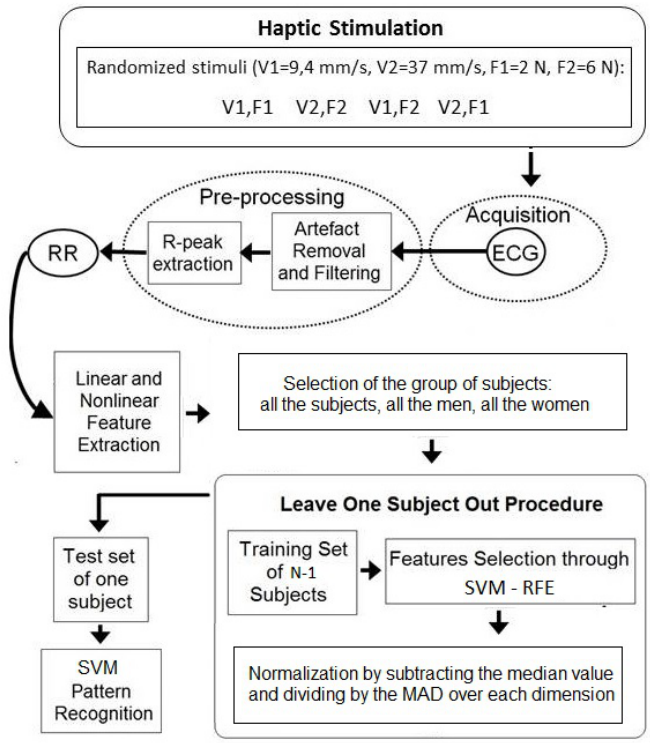

Figure 3: Block scheme of the data acquisition, biosignal processing, and machine learning procedure performed to automatically characterize the affective haptic stimuli using physiological signals such as ECG (to extract HRV series).

from HRV symbolic analysis and Lagged Poincaré plots [43]–[45]. These novel features, along with other standard and nonlinearly-derived HRV features, were taken as an input for pattern recognition in order to discern the velocity and the force of the haptic stimulation.

1) HRV feature extraction: All features were extracted from each HRV series in the pre-stimuli sessions of 35 seconds and in the post-stimuli sessions of 35 seconds. For each feature, we calculated the difference between the post- and the pre-stimulus sessions.
Standard HRV analysis refers to the extraction of parameters defined in the time and frequency domain [43]. Concerning the time domain analysis, we calculated the following features from the HRV series: RRmean, i.e. the mean of the duration of the intervals between a R peak and the successive (RR intervals); RR std, i.e.standard deviation of RR intervals; HRV triangular index; TIRR, triangular interpolation of RR interval histogram.

Concerning the frequency domain analysis, several features were calculated using the Smoothed Pseudo Wigner-Ville Distribution, SPWVD [46]. This method is an alternative to the Fast Fourier Transform (FFT), where a maximal time and frequency resolution is reached by using independent time and frequency smoothing, and it produces a spectral profile for approximately each beat. Three spectral bands of the power spectral density (PSD) were identified: VLF (very low frequency) with spectral components below 0.04 Hz; LF (low frequency), ranging between 0.04 and 0.15 Hz; HF (high frequency), comprising frequencies between 0.15 to 0.4 Hz. For each of the three frequency bands these features were computed as the values of the power, the respective percentage of the total and the normalized value, the frequency having maximum amplitude. Standard features described above, defined in the time and frequency domains, comprise 17 out of the 42 total number of features.

From each HRV series, we also calculated some nonlinear indices based, in particular, on two methods: Symbolic Analysis and the Lagged Poincaré Plot (LPP).

The symbolic analysis is a powerful nonlinear method based on the conversion of the series into a sequence of symbols [45], [47]. Amplitude of each HRV series was divided in six levels, and a numeric symbol (from 0 to 5) was assigned to each data sample. Then, trends of the patterns (i.e., sequences comprised of three consecutive symbols) can be investigated. The Lagged Poincaré Plot is a method which 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}, where M is the lag. In this study we chose $1 \leq M \leq 10$ [44], [48], [49]. The standard quantitative analysis from the graph can be made by calculating the dispersion of the points in the LPP, through these three features: the two standard deviation, SD1 and SD2, related to the points that are perpendicular to the line-of-identity $RR_{n+M} = RR_n$ and along the identity line respectively, and S ($S = \pi \cdot SD1 \cdot SD2$), the area of an imaginary ellipse with axes SD1 and SD2. We therefore obtained M realizations of each feature (SD1, SD2, and S). Of note, features derived from HRV symbolic analysis and LPP comprise the remaining 25 out of the total 42 features(10 calculated from the symbolic analysis, and 15 derived from LPP).

Extracting novel information from HRV Symbolic analysis and Lagged Poincaré Plots:

We here propose and assess novel features derived from HRV symbolic analysis and LPP. Concerning symbolic analysis, patterns, i.e., sequences comprised of three consecutive symbols of HRV series, were divided into five classes: *0V*, patterns with no variations (all symbols were equal); *1Va*, patterns with one variation (one variation between the second and the third symbol); *1Vb*, patterns with one variation (one variation between the first and second symbol); *2Va*, pattern with two variations, having a strictly increasing or strictly decreasing trend; *2Vb*, all others patterns with two variations. Of note, classical features were $1V$ (one generic symbol variation) and $2V$ (two generic symbols variation) extracted from symbolic analysis. The number of patterns in each class and their percentage values were calculated and used as features.

On LPPs, observing the trends of features SD1, SD2 and S in function of the lag M, we propose the calculation of the area under the curve (AUC) of the plot. Specifically:

- AUC value for lower values of M (AUC low, $1 \leq M \leq 5$) and upper values of M (AUC high, $5 \leq M \leq 10$);
- the ratio between the AUC low, and AUC high (AUC low/high);
- the ratio between AUC low and the total AUC, which is calculated for $1 \leq M \leq 10$ (AUC low/tot) and AUC high and the total AUC, which is calculated for $1 \leq M \leq 10$ (AUC high/tot);

Calculation of AUC values in these ranges, for lower lags M (from 1 to 5) and for higher lags (from 5 to 10), provides simple and effective indices of the short-term and long-term variability. The threshold of $M = 5$, allowing to take into account time windows of 6 seconds, was chosen to be consistent with the well-known HRV cut-off frequency of 0.15 Hz [43]. This value, in fact, separates between the high frequency band, which is associated with respiration, and the low frequency band, which is associated with sympathetic and parasympathetic activity [43]. Of note, this cut-off was applied in other existent nonlinear method in the literature, e.g. multiscale entropy, to calculate short term and long term complexity indices [50].

2) Feature selection and Pattern Recognition: This part of the study has been implemented following the LOSO procedure: we applied the features selection on a training set made by N-1 subjects (where N is the total number of participants), and repeated this procedure N times. Feature selection was performed by means of a Support Vector Machine-Recursive Feature Elimination (SVM-RFE) procedure in a wrapper approach (RFE was performed on the training set of each fold and we computed the median rank for each feature over all folds). We specifically chose a recently developed nonlinear SVM-RFE which employes a radial basis function kernel and includes a correlation bias reduction strategy into the feature elimination procedure [51]. All analyses were performed using Matlab v8.4 and an additional toolbox for pattern recognition (LIBSVM [52]). Only the selected features were used to define the feature dataset to be taken as input of Support Vector Machine (SVM) classifier. Specifically, we employed a nu-SVM (nu=0.5) with a radial basis kernel function with $\gamma = n^{-1}$, where $n = 42$ is equal to the number of features. Within the LOSO scheme, the training set was normalized by subtracting the median value and dividing by the MAD over each dimension. These values were then used to normalize the example belonging to the test set. During the LOSO procedure, this normalization step was performed on each fold. Classification results are summarized as recognition accuracy, calculated by averaging sensitivity and specificity.

III. Experimental Results

A. Statistical Results of SAM scores

Statistical analyses were performed on the SAM scores, along the arousal and valence dimensions. First, we evaluated the interaction effects between velocity and force on both arousal and valence dimensions, which resulted not statistically significant (p $>$ 0.05 according to a 2-way ANOVA). Then, we investigated differences in perceived arousal and valence scores between the two levels of force, and between the two levels of velocity, using the non-parametric Wilcoxon tests for paired samples. Such a non-parametric test was chosen because of the non-Gaussianity of data (as demonstrated by a $p < 0.05$ from Kolmogorov-Smirnov test with null hypothesis of having a Gaussian sample). Figure 4 shows the results of

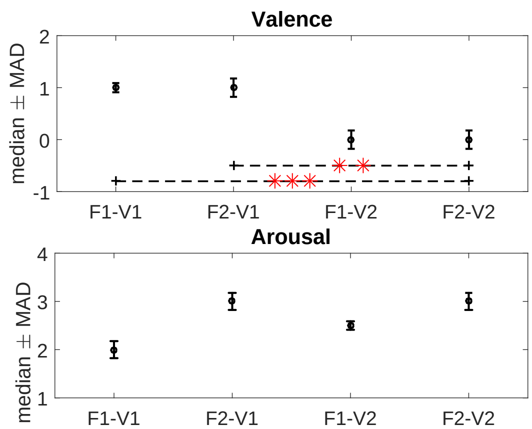

Figure 4: Results of Wilcoxon statistical test applied on SAM scores. *: 0.01≤p<0.05; **: 0.001≤p<0.01; ***: p<0.001.

statistical tests. Results from such statistical tests are shown in Figure 4.

Along the valence dimension, slower caresses resulted to be more pleasant and statistically different from the ones administered at higher velocity. No significant differences were found along the arousal dimension.

In Figure 5 the median values of SAM scores are represented in the bidimensional plan (CMA) of emotions. We can notice that the four stimuli can be divided into two classes according to valence dimension: stimuli with lower velocity can be considered pleasant (positive valence), instead stimuli with higher velocity can be represented as neutral (valence median score of 0). Moreover, looking at Figure 5, even if we did not get significant results, also concerning arousal dimension the median trend of arousal scores suggests a possible clustering into two groups. Indeed, caresses with higher force lie on the axis corresponding to a moderate level of arousal (arousal score=3), whereas caresses with lower force correspond to lower levels of arousal.

B. Classification and statistical results of HRV data

Confusion matrices of the highest accuracy obtained while recognizing the two levels of velocities are shown in Table III. Recognition accuracies of the two caressing velocity, shown as a function of the number of features taken into account (ordered by rank through the SVM-RFE algorithm), is reported in Figures 6 and 7. It can be observed in these Figures the loss of accuracy at higher feature counts, as an index of overfitting. Table I reports all the HRV features used as input of the SVM-RFE procedure, highlighting the features

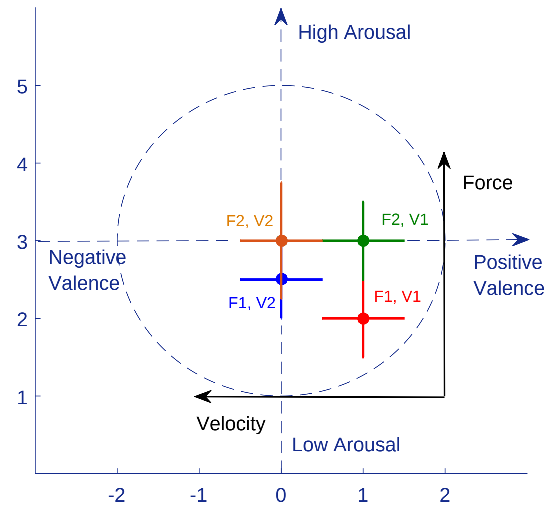

Figure 5: Scheme of SAM scores inside the CMA, considering the four touch stimuli, in relation to the levels of force and velocity. Values of arousal and valence are presented as median and interquartile range.

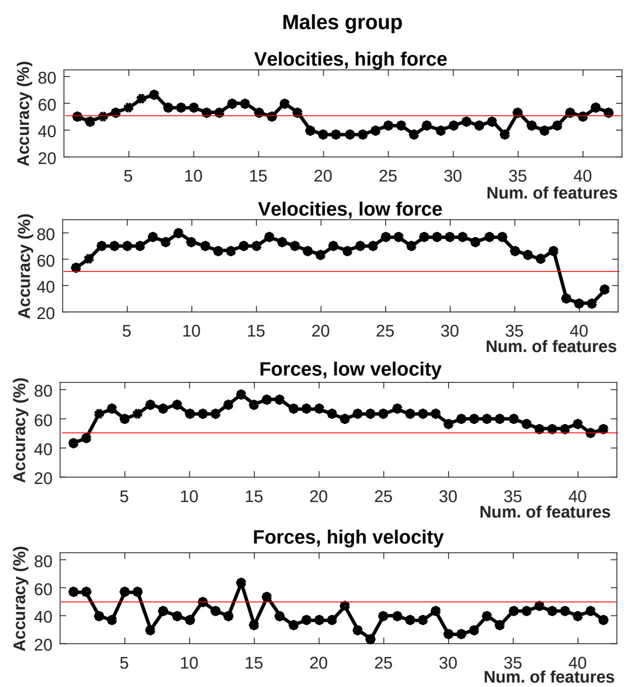

Figure 6: Accuracy of the recognition as a function of the number of features, ordered through SVM-RFE algorithm. These trends refer to the four classifications, for the dataset of men. The red horizontal line represents the accuracy level of 50%.

selected at least one time by RFE, in the eight iterations of the classification algorithm implemented for males and female groups. Moreover, in Table II, we reported in detail all selected features for each case study.

Considering cardiovascular data from all of the subjects, our classification system was able to recognize the two caressing

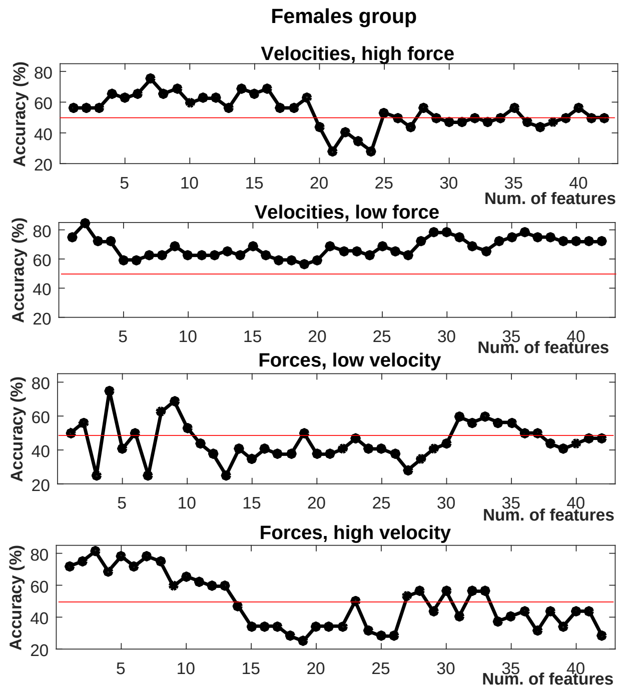

Figure 7: Accuracy of the recognition as a function of the number of features, ordered through SVM-RFE algorithm. These trends refer to the four classifications, for the dataset of women. The red horizontal line represents the accuracy level of 50%.

Table I: HRV features used as input of the SVM-RFE procedure. The symbol * highlights the features selected at least one time by RFE to find the maxim vale of accuracy, in the eight iterations of the classification algorithm implemented for males and female groups.

Time and Frequency	Symbolic Analysis	LPP
RR mean *	0V	AUC SD1 low
RR std	1Va *	AUC SD1 high
RMSSD *	1Vb *	AUC SD2 low
HRV tr. ind. *	2Va	AUC SD2 high
TINN *	2Vb *	AUC S low *
VLF peak *	0V%	AUC S high *
LF peak *	1Va% *	AUC SD1 low/tot *
HF peak	1Vb% *	AUC SD2 low/tot *
VLF power	2Va%	AUC S low/tot
VLF power % *	2Vb% *	AUC SD1 high/tot *
LF power *		AUC SD2 high/tot *
LF power % *		AUC S high/tot
LF power nu		AUC SD1 low/high *
HF power		AUC SD2 low/high *
HF power % *		AUC S low/high *
HF power nu *		
LF/HF *		

velocities with an accuracy of up to 64.52% when the force of the caress was low ($F_1 = 2N$), and with an accuracy up to 72.58%, when the force is higher ($F = 6N$) (see Table III). Considering cardiovascular data from men only, the accuracy of the SVM classifier increased up to 80% for caresses performed at low force and up to 66.67% for high levels of force.

Considering cardiovascular data from women only, the recognition accuracy of the two caressing velocity increased as well, achieving a recognition accuracy as high as 84.38% when referring to $F_1 = 2N$. Note that, for caresses at higher force level, accuracy decreased down to 75%.

Table III: Confusion Matrices from SVM Classifier for the caressing performed at two levels of velocity

All subjects

F1	V1	V2
V1	58.0645	41.9355
V2	29.0323	70.9677

Accuracy: 64.52%
N. features: 7

F2	V1	V2
V1	67.7419	32.2581
V2	22.5806	77.4194

Accuracy: 72.58%
N. features: 11

Men

F1	V1	V2
V1	80.0000	20.0000
V2	20.0000	80.0000

Accuracy: 80.00%
N. features: 9

F2	V1	V2
V1	73.3333	26.6667
V2	40.0000	60.0000

Accuracy: 66.67%
N. features: 7

Women

F1	V1	V2
V1	87.5000	12.5000
V2	18.7500	81.2500

Accuracy: 84.38%
N. features: 2

F2	V1	V2
V1	68.7500	31.2500
V2	18.7500	81.2500

Accuracy: 75.00%
N. features: 7

Table IV: Confusion Matrices from SVM Classifier for the caressing performed at two levels of force.

All subjects

V1	F1	F2
F1	67.7419	32.2581
F2	35.4839	64.5161

Accuracy: 67.74%
N. features: 3

V2	F1	F2
F1	64.5161	35.4839
F2	41,9355	58,0645

Accuracy:64.52%
N. features: 40

Men

V1	F1	F2
F1	80.0000	20.0000
F2	26.6667	73.3333

Accuracy: 76.67%
N. features: 14

V2	F1	F2
F1	66.6667	33.3333
F2	40.0000	60.0000

Accuracy: 63.33%
N. features: 14

Women

V1	F1	F2
F1	68.7500	31.2500
F2	18.7500	81.2500

Accuracy: 75.00%
N. features: 4

V2	F1	F2
F1	81.2500	18.7500
F2	18.7500	81.2500

Accuracy: 81.25%
N. features: 3

Figures 6 and 7 show the recognition accuracy of caresses performed at the two levels of force and at the two levels of velocity as a function of the feature number, for the men and the women, respectively.

When considering data gathered from all the subjects, our classification system was able to recognize the two caressing forces with an accuracy of up to 64.52% when the velocity of the caress was high, whereas at the lower velocity level, the accuracy slightly increased up to 67.74% (see Table IV).

Taking into account cardiovascular data from men only, the accuracy of the SVM classifier increased up to 76.67% for caressing forces performed at lower velocity, whereas caresses performed at higher velocity were recognized at 63.33%. Considering cardiovascular data from women only, the recognition accuracy of the two caressing forces was as high as 75% when referring to lower velocity, and up to 81.25% when referring to higher velocity.

Among all the obtained classification accuracies, the highest accuracy was achieved by women for caress velocities performed at lower force. In this case, the recognition accuracy was as high as 84.38%, with two features only (see Fig. 7).

Importantly, when we look at the most discriminant features chosen by the RFE model, for the classification of velocity at higher force, all of these are the novel parameters defined in this study, i.e., extracted by the calculation of the AUC in the LPP. Box-plots of these parameters are shown in Fig. 8. Consistently, Wilcoxon non-parametric tests showed significant differences between the two levels of caressing velocity ($p < 0.007$).

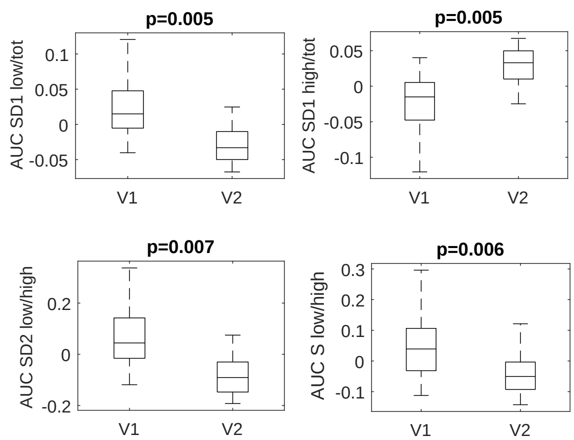

Figure 8: Box-plot statistics and results from the Wilcoxon tests on the four most informative features in recognizing caressing velocities performed at higher force in women.

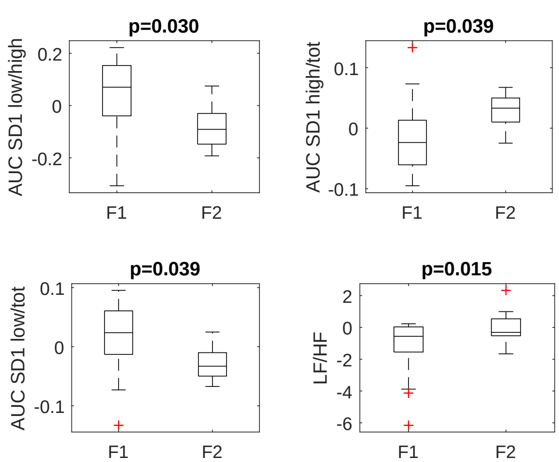

Figure 9: Box-plot statistics and results from the Wilcoxon tests on the four most informative features in recognizing caressing forces performed at higher velocity in women.

Of note, the same features were selected by the SVM-RFE algorithm while recognizing the two caressing levels of force (see accuracies in Fig. 7), performed in women at higher velocity of 37 mm/s (see Fig 9). As exemplary plots, Fig. 10 summarizes the four most discriminant features while recognizing caressing force levels at lower velocity, performed on men. In this case, our novel parameters 1Vb% and 2Vb% of HRV symbolic analysis were selected, along with a HRV time domain feature, HRV triangular index, and a frequency domain

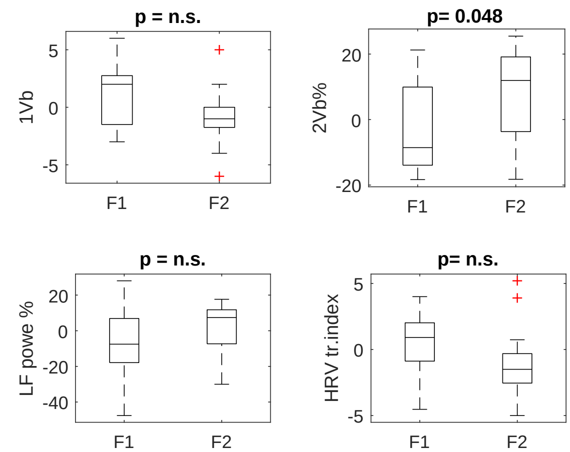

Figure 10: Box-plot statistics and results from the Wilcoxon tests on the four most informative features in recognizing caressing forces performed at lower velocity in men.

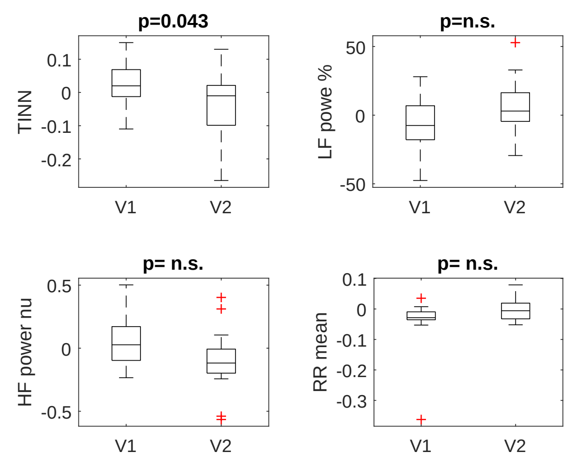

Figure 11: Box-plot statistics and results from the Wilcoxon tests on the four most informative features in recognizing caressing velocities performed at lower force in men (n.s.=not significant).

feature, LF power %. Fig. 11 summarizes the four most discriminant features while recognizing caressing velocity levels at lower force, performed on men. In this case, significant differences between the two velocities were found on TINN only ($p < 0.05$).

IV. Conclusion and Discussion

In conclusion, we presented a novel approach to automatically recognize two different levels of velocity and force of haptic caress-like stimuli by analyzing ANS dynamics. Specifically, we used features defined by standard (i.e., parameters defined in the time and frequency domain) and nonlinear signal processing techniques applied to HRV series. Data were gathered from 32 healthy subjects undergoing tactile elicitation, performed at different velocities and forces. In order to take gender into account, data were separately processed for women and men. Of note, HRV features were derived from

Table V: The most informative four features selected through SVM-RFE

	All subjects	Men	Women
Velocities low force	VLF power % LF power % HRV tr.index VLF peak	TINN LF power % HF power nu mean RR	VLF power % HF power % LF peak RMSSD
Velocities high force	1Vb 1Vb% 1Va 1Va%	1Vb% 1Va% 1Vb 1Va	AUC SD1 low/tot AUC SD1 high/tot AUC SD2 low/high AUC S low/high
Forces low velocity	LF power % 2Vb 1Va 2Vb%	1Vb % 2Vb% LF power% HRV tr.index	VLF peak VLF power % LF power% 2Vb
Forces high velocity	AUC SD1 low/high AUC SD1 low/tot AUC SD1 high/tot LF power	AUC SD2 low/tot AUC SD2 high/tot AUC S high AUC S low	AUC SD1 low/high AUC SD1 high/tot AUC SD1 low/tot LF/HF

the difference between a post- and pre-stimulus session. The choice of investigating gender differences and nonlinear HRV analysis was driven by previous art reported in the literature [19]–[22], [26]–[31], [34].

An ad-hoc haptic device [18] was designed to actively convey distributed normal force cues in order to replicate the strength and the velocity of a whole-hand caress performed by a human hand over the participant forearms. We are aware that we cannot exclude nonlinearities throughout the stimulus delivery, as well as differences in subjects' biomechanical arm properties, including the gender-related ones. Nevertheless, it is worthwhile mentioning that differences on skin elastic properties between sexes were proven to be not significantly different for most body regions [53]. Therefore, we are confident that observed gender-related differences are linked to a higher level of cognitive processing of the affective haptic stimulus, rather than different biomechanical arm properties between men and women. Moreover, other confounding factors such as subjects' mood/emotional state would surely increase the inter-subject variability of the physiological features we extracted. However, since we obtained very satisfactory inter-subject classification accuracies (using the leave one subject our procedure), we could speculate on the fact that our newly defined physiological features were somehow robust to other confounding factors. One of the possible limitation of the experimental design could be related to the duration of pre-, and post-stimuli sessions (i.e. 35 seconds), within which HRV parameters were computed. To mitigate this issue, we employed a SPWVD-based representation, which provides optimal spectral estimates at each heartbeat [54]

In this study, we also proposed novel features derived from HRV symbolic analysis and lagged Poincaré plots. All features were taken as input of nonlinear SVMs to separately classify velocities and forces. In order to investigate which features are the most informative for the gender-specific classification, we used a recently proposed SVM-based feature selection method employing a radial basis function kernel, and including a correlation bias reduction strategy into the feature elimination procedure [51]. Our results demonstrate that ANS control on cardiovascular dynamics changes significantly with the haptic caress-like stimuli. Such changes were recognized by HRV linear and nonlinear analysis, improving classification performance by considering gender-specific analyses. However, it is important to note that there are cases, such as men-F2 and men-V2, which showed no improvements in terms of classification accuracy. Women, on the other hand, show significant changes when referring to caresses performed at different forces and higher velocity. In support of our conclusions, in 6 cases out of 8 classification tasks, an improvement of the classification accuracy was achieved only when taking gender information into account. Besides improvement, the absolute value of such classification accuracies was very satisfactory, being between 75% and 84.38%. Moreover, the SVM-RFE algorithm confirmed the crucial role of HRV nonlinear dynamics, especially highlighting the informative role of the novel proposed features related to symbolic analysis and LPPs.

Although evidences in animal studies have suggested that α-adrenoceptors, the cholinergic (parasympathetic) system, as well as adenosine 3',5'-cyclic monophosphate are responsible for complex cardiovascular fluctuations [**?**], [**?**], [55], the actual correlates of autonomic activity on complex cardiac control are still unknown. This is also due to the simultaneous action of the sympathetic and vagal nerves in the LF band of HRV. At a speculation level, the AUC of LPP calculated at lags $1 \leq M \leq 5$ (*AUC low*) accounts for heartbeat short-term dynamics, which is likely to be related to the parasympathetic activity exclusively. AUC of LPP calculated at lags $5 \leq M \leq 10$ (*AUC high*), or $1 \leq M \leq 10$ (*AUC tot*) account for short and long-term heartbeat dynamics, therefore likely to be influenced by both sympathetic and vagal dynamics. Figure 9, shows that the median values of *AUC SD1 low/tot*, *AUC SD2 low/high*, and *AUC S low/high* increased when pleasant caressing-like stimuli were administered, whereas they decreased in case of unpleasant elicitation. Therese results, also in agreement with previous evidences [11], [17], suggest that a decreased parasympathetic activity is associated with pleasant touch, especially in women [56]–[58]. Table V shows that in all of the possible configurations of velocity, force and gender, except for classification of velocity at low force for all subjects, the novel proposed features resulted to belong to the most informative four selected features. This important outcome could significantly extend the set of non linear features to be used in pattern recognition. Of note, this study relied on preliminary results described in [59] in which we demonstrated that a satisfactory recognition accuracy to characterize the physical characteristics of affective haptic stimuli could only be achieved when both standard and nonlinear HRV measures were taken into account. Conversely, non-significant results (i.e., classification accuracy lower than 60%) were achieved considering standard measures only, or a gender-aspecific classification [59].

Finally, the new features here proposed could be successfully used in the field of affective computing. Moreover, these results confirm that the ANS activity is significantly modulated by affective haptic stimuli and it is gender-affected. Outcomes from this study can be profitably exploited in several scenarios. First, the proposed processing chain can be used to objectively assess the performance of a haptic device. In fact, we recently demonstrated that even haptic devices designed for discriminative purposes exclusively are able to convey affective cues, which can be effectively modulated by varying the device physical parameters (e.g., force, velocity, contact area, etc.) [60]. Also, the proposed system can be integrated into a, e.g., a virtual reality scenario, for the objective assessment of user experience during multimodal affective elicitations, including tactile ones. On the medium-long term, it is possible to investigate physiological responses during, e.g., pathological states including emotion dysregulation or, more in general, in case of mental disorders. Such responses can be compared to the healthy reference responses that have been characterized in this study. The achieved accuracy, which was as high as 84% (chance 50%), can be surely improved in future endeavours sufficient for some use case.

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Table II: Features selected for each classification problem.

Men				Women			
V1 vs V2		**F1 vs F2**		**V1 vs V2**		**F1 vs F2**	
F1	**F2**	**V1**	**V2**	**F1**	**F2**	**V1**	**V2**
TINN	1Vb%	1Vb%	AUC SD2 low/tot	VLFpower %	AUC SD1 low/tot	VLF peak	AUC SD1 low/high
LFpower %	1Va%	2Vb%	AUC SD2 high/tot	HFpower %	AUC SD1 high(tot	VLF power %	AUC SD1 high/tot
HFpower nu	1Vb	LFpower %	AUC S high		AUC SD1 low/high	LF power %	AUC SD1 low/tot
RR mean	1Va	HRV tri.ind .	AUC S low		AUC S low/high	2Vb	
AUC SD1 high	LF power	1Va	AUC SD2 low/high		AUC S high/tot		
LF power nu	LF power %	HF power	HF peak		AUC S low/tot		
HF power	VLF power	VLF power	LF power		0V		
RR std		HF power nu	AUC SD1 high				
HFpower %		LF power nu'	0V				
		2Vb	2Vb				
		TINN	AUC S high/tot				
		1Va%	LF power %				
		LF power	AUC SD2 low				