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Brute Force ECG Feature Extraction applied on Discomfort Detection

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Abstract. This paper presents the idea of brute force feature extraction for Electrocardiography (ECG) signals applied to discomfort detection. To build an ECG Discomfort Corpus an experimental discomfort induction was conducted. 50 subjects underwent a 2h (dis-)comfort condition in separate sessions in randomized order. ECG and subjective discomfort was recorded. 5min ECG segments were labeled with corresponding subjective discomfort ratings, and 6365 brute force features (65 low-level descriptors, first and second order derivatives, and 47 functionals) and 11 traditional heart rate variability (HRV) parameters were extracted. Random Forest machine learning algorithm outperformed SVM and kNN approaches and achieved the best subject-dependent, 10-fold cross-validation results ($r = .51$). With this experiment, we are able to show that (a) brute force ECG feature sets achieved better discomfort detection than traditional HRV based ECG feature set; (b) cepstral and spectral flux based features appear to be the most promising to capture HRV phenomena.

Keywords: Affective Computing, ECG, HRV, Brute Force Feature Extraction, Machine Learning, Low-Level Descriptors, Functionals

1 Introduction

Affective and behavioral computing is an emerging field of research that enables algorithms to detect and predict human emotions and actions. With this aim, an interdisciplinary research field spanning computer science and psychology is consolidating to foster multimodal signal analysis [21]. An increasing number of research groups is making use of biosignals - besides video imaging and individual speech patterns - to enhance performance and accuracy in emotion recognition.

While strong sentiments and emotions like joy and fear, sadness and disgust [10], fatigue [9] and depression [26] usually take center stage in affective computing research, others like discomfort have been mostly neglected. However, comfort is a very important component of daily life quality, and many interventions by health professionals are focused on avoiding and mitigating discomfort [19]. Discomfort is therefore an important aspect of patient care oriented affective computing for assisted living and computer assisted diagnosis.

Few reliable approaches to measure objective (dis-)comfort using Electromyography (EMG) and video- or pressure-sensor based body movement [18] fail to operationalize comfort by taking the impact of physical, emotional and environmental factors into account [19]. Electrocardiography (ECG) can describe autonomic nervous system (ANS) activity in ambulatory assessment and is not tied to postural expression of discomfort, as measured by body movement and posture changes with video data, EMG or pressure sensors. We hypothesize that the association between ECG and negative emotions [11] should be useful to capture discomfort from a psychophysiological perspective.

This paper aims to examine the feasibility of a multipurpose biosignal processing approach on an ECG data corpus to detect discomfort. In the following pages we propose a brute force feature extraction method to train machine learning classifiers on a discomfort target. Benefits of the proposed method over standard heart rate variability (HRV) based ECG analysis will be shown and brute force feature extraction techniques will be addressed. Section 2 will summarize discomfort induction, data collection, data processing and model training. Finally, performance results of both approaches will be compared in sections 3. Section 4 of this paper will show the main added value of the proposed approach through: (1) the introduction of brute force feature extraction schema using low-level descriptors (LLD), derivatives and functionals, (2) the analysis of several new or rarely used spectral and cepstral coefficients.

1.1 Standard Heart Rate Variability based ECG Analysis

ECG signals represent electric potential alterations on the skin caused by the depolarizing and re-polarizing pattern of the heartbeat. This data can be used to identify cardiac arrhythmia and atrial fibrillations in patients prior to onset of acute heart diseases [27], but can also be used to objectively measure pain [12], cognitive performance [22], and to analyze psychological states as fatigue [9] and thermal comfort [17].

Typical ECG analysis approaches use (1) morphological ECG features (characteristic voltage peaks and lows in the ECG waveform as displayed in Figure 2), (2) HRV features (time variations between heartbeats e.g. HR, pNN50%, RMSSD, Sd1, Sd2, SDNN), (3) frequency features (specific bands from the power density spectrum e.g. Hf, Lf) and (4) statistical features (e.g. linear predictive coefficients). Nevertheless only time and frequency domain HRV features are most widely applied [14].

Heart rate variability reflects the balance between sympathetic and parasympathetic activity in the autonomic nervous system. High energies in low frequency bands of the power spectral density (Lf) indicate increased sympathetic activity, an indicator of wakefulness, while high spectral energy in high frequency bands (Hf) indicate lower sympathetic and increased parasympathetic activity, an indicator of sleepiness [15].

Several scientific challenges like PhysioNet and Computing in Cardiology [16] have provided different approaches to overcome the ECG feature shortage with various analysis attempts. These ECG feature extraction approaches extending the traditional HRV measures have used cepstral and spectral features [2, 4], or dual tree complex wavelet transformation [25], to name a few. However, most do not aim to provide an extensive brute force solution. We present a brute force feature extraction approach including LLDs, ΔLLDs, $\Delta\Delta$LLDs and functionals applied on ECG data. Due to its high degree of abstraction, this approach can also be used to capture the concept of heart rate variability to a much finer-grained extend than traditional feature extraction methods.

1.2 Brute Force Feature Extraction

A promising approach used in e.g. computational paralinguistics is to outperform theoretically driven parameters with brute force feature extraction for machine learning applications [24]. Brute force feature extraction exploits the feature space by decomposing the raw signal in many descriptive coefficients with a high degree of abstraction [6]. This (over)generates a large, highly diversified feature set combining frame wise low-level descriptors (LLD) with temporal contour describing functionals to achieve an exhaustive description of the raw data.

The general procedure of brute force feature extraction runs as follows: Signals are framed to a usually sort frame length of about 500ms with overlapping windows (i.e. Hamming) to calculate about 10 to 60 low-level descriptors (e.g. spectral flux, spectral entropy, cepstral coefficients, zero crossing rates) per segment. LLDs are smoothed by simple moving average (sma) low-pass filtering with a window length of three frames. Next, their first and second order delta coefficients are computed for each LLD time series. Then, the time course describing 20-80 functionals (e.g. percentiles, inter quartile rates, bandwidth of peaks distance) are applied to all LLDs, ΔLLDs and the $\Delta\Delta$LLDs - resulting in typically several thousand features ([LLDs + ΔLLDs + $\Delta\Delta$LLDs] * number of functionals). The simplified workflow of brute force feature extraction is represented in Figure 1. Further feature description is provided in section 2.4, and an overview on LLDs and functionals is provided in Table 2.

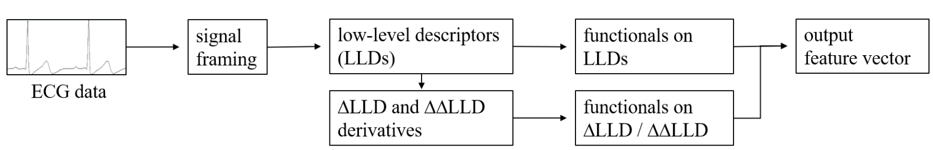


Fig. 1. Simplified brute force feature extraction in ECG signal processing.

2 Methods

2.1 Experimental Discomfort Corpus Engineering

To test the proposed approach on ECG data analysis for discomfort classification, a study was conducted to monitor ECG signals while inducing discomfort. A total of 50 subjects were tested in a within-subject design undergoing both experimental conditions (comfort and discomfort induction) in randomized order. (Dis-)comfort was induced, manipulating key seat qualities compared to the baseline seat. Living space, material and hardness was manipulated to up- or downgrade seat quality in respecting conditions.

Subjective discomfort was assessed during baseline, after 40 min, 80 min and 120 min of experimentally manipulated sitting. Different ergonomic seat quality factors were considered to generate an overall discomfort score ranging from 1 = very comfortable to 8 = very discomfortable. A mean difference of 15% in subjectively rated discomfort induction was reached between conditions through experimental manipulation ($p < .001$).

The resulting experimental discomfort corpus combines a total of 6376 features for 92 ECG intervals of 300sec length from 30 different subjects. All instances contain standard heart rate variability and brute force extracted features, labeled for subjectively rated discomfort on a 8-point Likert scale (ranging from 1 = lowest discomfort to 7 = highest discomfort). Corpus descriptives are summarized in Table 1.

Table 1. Descriptives of Experimental Discomfort Corpus

	Age	Height	Weight	BMI	Discomfort
M	25.90	170.62	66.21	22.66	2.92
SD	7.35	7.33	12.26	3.05	1.13
min	18	156	48	18	1.25
max	45	188	95	29	5.57

Note: Mean, standard deviation, minimum and maximum of age, height, weight, body mass index and discomfort.

2.2 Data Pre-Processing

Analysis intervals were extracted from ECG signal with a frame length of 300 seconds preceding subjective discomfort ratings. ECG recordings were digitally upsampled from 1024 Hz to 16 kHz as .wav file to meet processing criteria needed for brute force feature extraction. Exemplary sections of analysis intervals extracted from ECG signal can be seen in Figure 2.

ECG intervals were manually inspected and excluded if data quality criteria were not fulfilled. Corrupted signals showing no periodic QRS-complex pattern, see Figure 2(e) and 2(f), were excluded from further analysis. Analysis intervals with less than 20% corrupted QRS-complexes, see Figure 2(a) - 2(d), fell under a tolerable artifact range and were still considered for analysis.

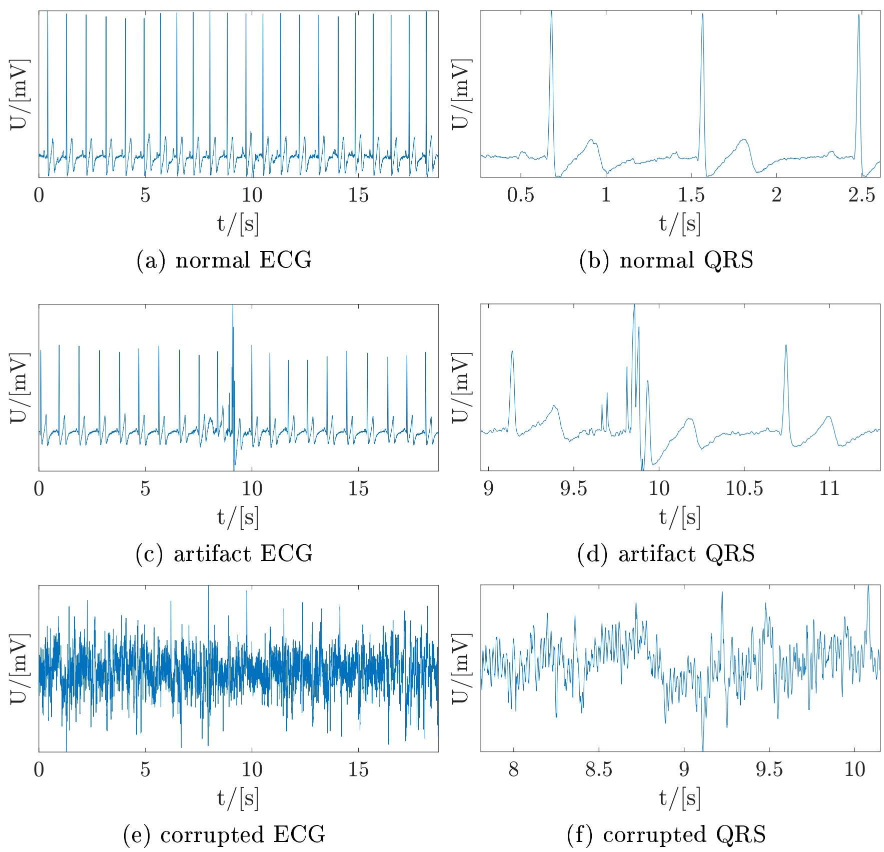


Fig. 2. Exemplary analysis intervals extracted from ECG signal for manual data quality inspection during pre-processing.

2.3 Standard ECG Feature Extraction

Raw ECG signals were firstly analyzed with DataAnalyzer (movisens GmbH). Heart rate variability parameters in time and frequency domain (i.e. RMSSD, pNN50%, SDNN, Sd1, Sd2, Sdsd, Sd2Sd1, Hf, Lf, LfHf and HR) were calculated for 10 sec analysis windows and averaged for the entire analysis interval [7]. The resulting output feature vectors were aggregated to a HRV_ECG feature set of 11 standard HRV parameter.

2.4 Brute Force ECG Feature Extraction

Raw ECG Signals are windowed at a 390ms frame length with 40% overlapping windows (i.e. Hamming) to calculate 65 low-level descriptors (e.g. spectral flux, spectral entropy, cepstral coefficients, zero crossing rates; see Talbe 2) per frame. The frame-wise computed series of LLDs is smoothed by simple moving average (sma) low-pass filtering with a window length of three frames. Next, the first and second order delta coefficients are computed for each series of LLD. Then, the 47 functionals (e.g. percentiles, inter quartile rates, bandwidth of peaks distance; see Table 2) are applied to all LLDs, Δ LLDs and the $\Delta\Delta$ LLDs - resulting in 6365 features for each 300 sec interval of ECG (brute force extracted feature set BF_ECG; for more details see [6] and [23]).

Table 2. Overview of low-level descriptors (LLDs) and functionals applied [5].

Energy related LLD	**Fuctionals**
Loudness spectrum	Quartiles 1-3, 3 inter-quartile ranges
Modulation loudness	1% and 99% percentile, range
RMS Energy	Position of min/max, range
Zero-Crossing Rate	Arithmetic mean, root quadratic mean
Fundamental frequency	Flatness, std.dev., skewness, kurtosis
Probability of fundamental frequency	Up-level time 25,50,75,90%
Logarithmic HNR	Mean, max, min, std. dev. of segment
Jitter (local, delta)	Rise time, left curvature time
Shimmer (local)	Linear Prediction gain
	Linear Prediction coefficients 0-4
Spectral LLD	Mean/std.dev. of peak distances
RASTA bands 0-25 (0-8kHz)	Mean/std.dev. of rising/falling slopes
MFCC 1-14	mean/std.dev. of inter max. distances
Spectral energy 250-650Hz, 1-4kHz	linear reg.: slope, offset, quad. error
Spectral Roll Off (.25, .50, .75, .90)	quadratic reg.: a, b, offset, quad. error
Spectral Flux, Entropy, Variance	mean and arithm. mean value of peaks
Spectral Skewness, Kurtosis, Slope	amplitude mean of maxima/minima
Psychoacoustic Sharpness	amplitude range of maxima
Spectral Harmonicity, Centroid	percentage of non-zero frames

Some of the most promising LLDs used were mel frequency cepstrum coefficient (mfcc), the root-mean-square of signal frame energy (RMSenergy), spectral flux, spectral entropy and spectral slope, the frequency bands reduction from the power spectrum to auditory frequency scale (audSpec) and the RASTA-style filtered spectrum (Rfilt) [6]. The central LLDs group of the proposed ECG brute force feature extraction are based on cepstral analysis.

The ECG signal has quasi-periodic characteristics as a result of the convolution between the excitation (heart beat rate) and the system response (ECG waveform shapes). Thus, in this work, we use cepstral features, that allow to separate such convolutive effects by simple linear filtering to model the frequency information of the native ECG. Standard formulas used to calculate several features are listed below:

The mfcc used, $C^{(mel)'}(k)$, is computed from a linear scale magnitude or power spectrum using triangular filters and 50% overlap. After logarithm is applied and a discrete cosine transformation type-II is performed, filtered coefficient is expressed as follows:

$$C^{(mel)'}(k) = C^{(mel)}(k)\left(1 + \frac{L}{2}\sin\frac{\pi k}{L}\right). \tag{1}$$

The Root Mean Square (RMS) energy for a normalized signal $x(n)$ is defined as:

$$E_{rms} = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} x^2(n)}. \tag{2}$$

The spectral flux S_{flux} represents a quadratic, normalized version of the simple spectral difference. With general normalization coefficient μ_k the definition of spectral flux is:

$$S_{flux}^{(k)} = \sum_{m=m_l}^{m_u}\left(\frac{X^{(k)}(m)}{\mu_k} - \frac{X^{(k-1)}(m)}{\mu_{k-1}}\right)^2. \tag{3}$$

The spectral entropy relates to the peakedness of the spectrum. $S_{entropy}$ is defined as:

$$S_{entropy} = -\sum_{m=m_l}^{m_u} px(m)\cdot\log_2 px(m). \tag{4}$$

The overall shape of a spectrum $X(m)$ expressed by its linear slope $\hat{y} = ax+b$ with $y = X$ and $x = m$ leads to:

$$a = \frac{N\sum_{i=0}^{N-1} x_i y_i - \sum_{i=0}^{N-1} x_i \sum_{i=0}^{N-1} y_i}{N\sum_{i=0}^{N} x_i^2 - \left(\sum_{i=0}^{N-1} x_i\right)^2}. \tag{5}$$

The predicted value in linear predictive coding can be calculated from:

$$\hat{x}(n) = -\sum_{i=1}^{p} a_i x(n-i). \tag{6}$$

Linear predictive coding has been used extensively in speech recognition because of its ability to detect poles. Even though the ECG signal is not speech, it shows similar quasi-periodic properties to a phonetic segment of speech. LPC is a technique of time series analysis used to predict future values of a signal as a linear function of previous samples.

2.5 Classifiers

For the sake of transparency and reproducibility, standard algorithms implemented in an open source data mining tool (WEKA 3; [8]) were used. Support Vector Machines (SVM), Random Forests and k-Nearest Neighbors (kNN) were used as machine learning paradigms to explore different classification performances. WEKA's SVM implementation with linear kernels was used with the sequential minimal optimization algorithm (SMO) for training [20], together with Random Forest [3] and kNN [1]. Predictive performance was assessed using a 10-fold stratified cross-validation procedure.

3 Results

3.1 Standard Heart Rate Variability based ECG Analysis

Spearman rank correlations show high intercorrelations between all heart rate variability parameters ($|r| = .40 - .99$) at a $p < .001$ significance level, but no significant correlation between discomfort, thus any HRV parameter was able to identify affective conditions. Frequency domain parameters Lf and Hf correlated with $r = .04$ and $r = .06$ with discomfort, while SDNN, RMSSD and Sd2Sd1 correlated with $r = .10$, $r = .11$ and $r = -.12$, respectively. Neither nonparametric Mann-Whitney U test accomplishes to differentiate discomfort states out of any standard HRV parameter.

3.2 Brute Force ECG Feature Performance

Over 100 different features of the highly diversified BF_ECG feature subset are correlated with discomfort $|r| = .29 - .45$, outperforming standard heart rate variability analysis (see Table 3).

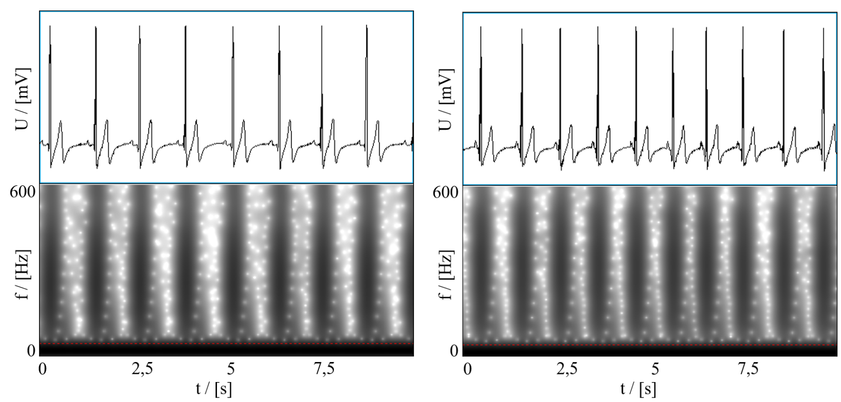
Table 3. Best Brute Force extracted Features correlated to discomfort.

Brute Force Features	r
mfcc_sma[9]_iqr2-3	.43
mfcc_sma[7]_lpc4	-.39
RMSenergy_sma_de_leftctime	.41
RMSenergy_sma_de_risetime	-.31
fftMag_spectralFlux_sma_risetime	.29
fftMag_spectralFlux_sma_leftctime	-.40
fftMag_spectralEntropy	.30
fftMag_spectralEntropy_sma_risetime	-.31
fftMag_spectralSlope_sma_de_leftctime	-.31
audSpec_Rfilt_sma_de[0]_lpc0	.30
audSpec_Rfilt_sma_de[3]_risetime	-.45

Note: The naming of all features is documented in [6].

The inter-quartile range of the smoothed time series of mfcc 9 correlates with $r = .43$ (mfcc_sma[9]_iqr2-3), and the linear predictive coding coefficient 4 of the smoothed time series of mfcc 7 correlates with $r = -.39$ (mfcc_sma[7]_lpc4) to discomfort. The time during which the first derivative of the smoothed root mean square energy has a left curvature (RMSenergy_sma_de_leftctime) is correlated to discomfort with $r = .41$, while the time during which the first derivative of the smoothed signal energy is rising (RMSenergy_sma_de_risetime) shows a correlation coefficient of $r = -.31$, to name a few.

Further frequency parameters describing spectral flux, entropy and slope reach a medium size correlation, higher than twice the correlation reached with the best performing standard HRV parameter. An exemplary spectral energy profile of two distinct analysis intervals is shown in Figure 3.



(a) low discomfort ECG (b) high discomfort ECG

Fig. 3. Exemplary spectral analysis on ECG intervals with low (< 2) and high (> 5) subjective discomfort.

3.3 Machine Learning Performance

Classification performance of all trained models is summarized in Table 4. Combination of different feature subsets trained with different classifiers resulted in nine different models tested in 10-fold cross validation. Random forest classification reached highest correlations and least mean absolute errors over all feature subsets, compared to k-nearest neighbors (kNN) and sequential minimal optimization (SMO).

Best discomfort prediction model based on standard HRV parameters outperformed simple statistical analysis, see Table 4, with a $r = .25$ correlation between prediction and target, and a mean absolute error of 0.89 (in a 8-point Likert scale). The brute force extracted feature subset reached the highest correlation ($r = .57$, MAE $= 0.80$), while predictions of the combined feature set of standard and brute force extracted features were correlated to discomfort targets with $r = .50$ and a mean absolute error of 0.81.

Table 4. Classifier Performance in different feature sets.

Feature sets	SMOreg		Random Forest		kNN	
	r	MAE	r	MAE	r	MAE
HRV_ECG	.18	0.91	.25	0.89	.20	1.11
BF_ECG	.50	0.80	.57	0.80	.47	0.91
Total_ECG	.30	0.91	.51	0.81	.43	0.89

Note: Predictive performance by correlation and mean absolute error.

4 Discussion

This paper shows that considerable results for the detection of discomfort from ECG Signals can be obtained with brute force feature extraction and machine learning classification, even when statistical analysis with heart rate variability data fails to show any notable effects. As seen in section 3.1, heart rate variability based ECG features fail to detect discomfort differences from the ECG signal. While best HRV based ECG features reached correlations of $r = |.12|$ with discomfort, over 100 brute force extracted features outperformed $r = |.29| - |.45|$ correlations, showing the added value of the proposed approach. Some of the most effective features for discomfort detection using ECG signal processing were based especially on cepstral coefficients, spectral entropy and spectral flux measures (see Table 3). Obviously, these LLDs capture the physiological concept of heart rate variability (HRV) to a more specified extend than the traditional HRV feature approaches.

After applying the extended concept of brute force feature extraction standard machine learning approached are trained. Random Forest outperformed SMO and kNN classifying discomfort in all feature subsets. A prediction performance of $r = .57$ was achieved with the brute force feature subset, slightly better than the combined feature set performance of $r = .51$. Model performance could be enhanced in future research by using more meticulous data pre-processing (e.g. blind source separation applying non-negative matrix factorization and independent component analysis) and identifying optimal frame length for the extraction of specific LLDs. Moreover non-linear dynamics feature extraction methods could be used, as reconstructed phase space features, fractal features (e.g. largest Lyapunov exponent, fractal dimension spectrum, minimum embedding dimension), and entropy features assessing regularity or randomness of ECG signal fluctuations [13]. Moreover, subsequent feature selection methods (e.g. sequential forward floating search) and ensemble meta classification methods (e.g. bagging, boosting) should be tested.

To overcome limitations in internal and external validity expanding the robustness of used data, a larger highly diversified discomfort corpus is needed: a higher number of instances and participants with a balanced variability in gender, age, and physical condition. Limitations of the collected corpus are restrictions in age (missing elderly subjects), health state (no subjects in need of care), discomfort range (no extreme (dis-)comfort values), and a disbalanced gender distribution (83% female).

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