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Toolbox for Emotional feAture extraction from Physiological signals (TEAP)

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Physiological response is an important component of an emotional episode. In this paper, we introduce a Toolbox for Emotional feAture Extraction from Physiological signals (TEAP). This open source toolbox can preprocess and calculate emotionally relevant features from multiple physiological signals, namely, electroencephalogram (EEG), galvanic skin response (GSR), electromyogram (EMG), skin temperature, respiration pattern, and blood volume pulse. The features from this toolbox are tested on two publicly available databases, i.e., MAHNOB-HCI and DEAP. We demonstrate that we achieve similar performance to the original work with the features from this toolbox. The toolbox is implemented in MATLAB and is also compatible with Octave. We hope this toolbox to be further developed and accelerate research in affective physiological signal analysis.

Keywords: physiological signals, emotions, affective computing, electroencephalogram signals, physiological signal processing, code:MATLAB, code:Octave, toolbox

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1. INTRODUCTION

Affective computing thrives to teach machines to understand and express emotions (Picard, 1997). Emotions are multifaceted phenomena with physiological manifestations and bodily expressions (Scherer, 2005). Although the majority of existing methods for automatic emotion recognition are based on audiovisual analysis (D'Mello and Kory, 2015), there is a growing body of research on emotion recognition from peripheral and central nervous system physiological responses (Picard et al., 2001; Lisetti and Nasoz, 2004; Chanel et al., 2009, 2011; Kolodyazhniy et al., 2011; Koelstra et al., 2012; Soleymani et al., 2012b; Mühl et al., 2014). There are certain advantages for using physiological signals for emotion recognition compared to the audiovisual signals; for example, they cannot be easily faked, they do not require a front facing camera, and they can be used in any illumination and in noisy environments. Moreover, they can be combined with audiovisual modalities to construct a more robust and accurate multimodal emotion recognizer (D'Mello and Kory, 2015).

In order to train machines to automatically recognize emotions, we use machine learning techniques. Typically, the procedure includes translating raw signals to a lower dimensional representation space (features) that will be fed into a statistical model. Current physiological feature extraction methods involve calculating statistical moments and time-frequency analysis over

segments of physiological signals with the goal of generating emotionally discriminative features. For example, heart rate increase is associated with excitement and activation (arousal) and, as a result, we extract heart rate as a feature for detecting arousal or the level of activation.

To extract features from physiological signals, one can implement methods that translate raw signals into features. Emotional features extracted from physiological signals are often based on the previous work in psychophysiology (Kreibig, 2010). To facilitate research on physiological signal analysis, a number of tools have been developed to the benefit of the community, e.g., EEGLAB (Delorme and Makeig, 2004). To the best of our knowledge, the Augsburg Biosignal Toolobox (AuBT) (Wagner et al., 2005) is the only toolbox available with the goal of extracting emotionally significant physiological features. However, the number of features and the type of signals in AUBT are limited. In this paper, we introduce a Toolbox for Emotional feAture extraction using Physiological signals or TEAP. We aim to create an open source platform that can be further extended by the community with the goal of advancing the field of affective physiological signal analysis. We developed TEAP in MathWorks MATLAB but it also works with Octave, its free alternative. TEAP is able to preprocess and extract features from multiple central and peripheral physiological signals including electroencephalogram (EEG), galvanic skin response (GSR), electrocardiogram (ECG), blood volume pulse (BVP), skin temperature, respiration pattern, and electromyogram (EMG). New physiological channels can be easily added to this toolbox and the implemented statistical and time-frequency analysis functions can be applied on any signal.

TEAP is designed to be useful for both novice and advanced users. A user can simply choose the desired features, define the channels in the input files, and extract physiological features. More advanced users are able to add new functionalities and modules, including support for new signals.

2. TOOLBOXES FOR PHYSIOLOGICAL SIGNAL PROCESSING

In this section, we review the existing freely available and open source tools for physiological signal analysis. There are a number of toolboxes for processing physiological signals and most of them are tuned for only one type of signal. For instance, EEGLAB (Delorme and Makeig, 2004) and FieldTrip (Oostenveld et al., 2011) are dedicated to brain signal analysis, focusing on signals such as EEG and magnetoencephalogram (MEG). There are also tools for analyzing peripheral physiological signals such as Kubios,[1] which analyzes heart rate variability, Ledalab (Benedek and Kaernbach, 2010), and PsPM (Bach and Friston, 2013), which focus on the analysis of galvanic skin responses. There are also tools for analyzing a wide range of physiological signals including Biosig (Schlogl and Brunner, 2008) and the ANSLAB.[2] Tools dedicated to one specific physiological signal offer advanced functionalities (e.g., source reconstruction). More general purpose tools handle a diverse range of signals with a more limited set of choices for their analysis. The spirit of TEAP is to allow for the processing of several types of signals, e.g., BVP, ECG, EEG, while maintaining the possibility to extract specific features from each signal. In addition, its architecture and license permits further development in the future.

Most of existing toolboxes requires to have some knowledge about physiological signal processing. In contrast, TEAP can serve researchers who aim at developing data-driven techniques with limited knowledge on the nature of physiological signals. Taking advantage of the BioSig code in its data import interface (Schlogl and Brunner, 2008), TEAP accepts several data formats which are traditionally used to store physiological signals (e.g., the EDF—(European Data Format), while its output is a design matrix representing a set of features for several samples. The Augsburg Biosignal Toolobox (AuBT) (Wagner et al., 2005) has been designed with the same objective in mind. It can perform feature extraction, feature selection, and classification. However, the AuBT only offers the possibility to extract general features based on statistical moments of signal derivatives (e.g., mean of first derivative). In addition, the AuBT input data should be properly formatted and have limited filtering capabilities. This leads to the need to develop file parsers and to gain knowledge in the properties of physiological signals to build proper preprocessing filters. The reviewed characteristics of the existing and proposed toolboxes are summarized in **Table 1**.

3. TECHNICAL SPECIFICATIONS

3.1. Architecture

TEAP has been developed in MATLAB and is compatible with Octave. It is open source and is licensed under the GNU General Public License (GNU GPL). This makes TEAP a completely free and customizable solution. We avoided object oriented programming in MATLAB not to jeopardize Octave compatibility. Although TEAP is programmed without using MATLAB objects, two principal structures are used: *signals* and *bulksigs* (hereafter called bulks); bulks are structures containing *signals*. Functions were created as interfaces to the users to manipulate these two structures. Hence, a user does not need to know how the data are handled by the toolbox in order to use it. However it remains possible to access the content of the structures directly or using the available visualization functions (e.g., *Signal_plot()*).

TEAP can read many data formats including *EDF* and *EEGLAB*. TEAP accepts data recorded from any device as long as the format is supported by Biosig interface, e.g., Biosemi BDF format. Importing EEGLAB data allows performing some preprocessing, which is not available in TEAP. For instance, the raw signals can be segmented using EEGLAB (e.g., according to triggers) and the result can be imported in TEAP. TEAP relies on

[1] http://kubios.uef.fi/.

[2] http://www.anslab.net.

TABLE 1 | Relevant open source toolboxes for physiological signal analysis.

Toolbox	Signals	Language	Functionality
AuBT	GSR, ECG, EMG, and respiration	Matlab	Feature extraction and selection, classification
EEGLAB (Delorme and Makeig, 2004)	EEG, MEG	Matlab	Source modeling, time frequency analysis, forward and inverse source modeling
FieldTrip (Oostenveld et al., 2011)	EEG, MEG	Matlab	Time-frequency analysis, source reconstruction and modeling, non-parametric statistical testing
Ledalab (Benedek and Kaernbach, 2010)	GSR	Matlab	Continuous and discrete decomposition analysis, visualization
PsPM (Bach and Friston, 2013)	GSR	Matlab	Modeling
Biosig (Schlogl and Brunner, 2008)	EEG, electrocorticogram (ECoG), ECG, EMG, EOG, respiration	Matlab and Octave	Data acquisition, artifact processing, feature extraction, classification, modeling, visualization
ANSLAB	GSR, ECG, EMG, respiration, BVP, continuous arterial pressure, capnography, temperature, accelerometry	Matlab	Feature extraction and selection, classification
TEAP	EEG, GSR, ECG, BVP, EMG, temperature, respiration	Matlab and Octave	Feature extraction, visualization

MATLAB and only requires the signal processing and statistical toolboxes. TEAP can run on the equivalent settings in Octave with its freely available equivalent toolboxes.

The source code and user manuals are available on.[3]

3.2. Signals and Features

Each signal currently supported by TEAP is presented below. In addition to this list of signals, we added a template dummy signal (*DMY*), which will facilitate adding new signals and features. The set of features were chosen based on their proven performance in the literature (Kim and André, 2008; Chanel et al., 2009; Koelstra et al., 2012; Soleymani et al., 2012a). The list of existing features and their descriptions are given in **Table 2**.

3.2.1. Electrocardiogram—ECG

Due to the nature of heart muscles, cardiac activity generates an electrical potential difference, which can be measured by placing electrodes on one's chest. Electrocardiography (ECG or EKG) is a measurement of this electrical activity. ECG signals can be used to detect heart rate (HR) and heart rate variability (HRV). HR and HRV changes are associated with emotions. For example, pleasant emotions increase heart rate response (Lang et al., 1993), and HRV decreases with fear, sadness, and happiness (Rainville et al., 2006). In TEAP, we analyze ECG signals from one lead (a pair of electrodes) to detect inter-beat-interval (IBI) and HRV features. After calculating the IBI, we can construct a tachogram, which is a signal representing IBIs over time. Tachogram can be further used to extract additional HRV features.

3.2.2. Blood Volume Pulse—BVP

Blood volume pulse (BVP) is the measurement of blood volume in peripheral vessels generally obtained by photoplethysmography. A photoplethysmograph usually consists of a light emitter and detector. The measurement of the reflected light on skin (usually finger) is an indicator of the volume of blood in peripheral vessels. Since blood volume varies by pulse heart rate can be detected from BVP signals. Similar to ECG, TEAP can extract heart rate (HR) and heart rate variability (HRV) related features from BVP.

3.2.3. Galvanic Skin Response (GSR)

Galvanic skin response (GSR) is a measurement of electrical resistance (or conductance) on one's skin. Skin's electrical conductance varies with the activity of sweat glands which are controlled by the sympathetic nervous system. GSR responses consists of tonic (slow) and phasic (fast and associated with a stimuli) responses and are related to emotional arousal (Lang et al., 1993; Dawson et al., 2000). TEAP calculates features related to both tonic and phasic responses.

3.2.4. Human Skin Temperature—HST

Skin temperature is a reflection of blood flow and changes in different emotional states (McFarland, 1985). Although temperature changes are slower than other signals, they are associated with emotional responses (Kreibig, 2010). Skin temperature is measured by attaching a temperature sensor on one's skin. Statistical moments and low frequency power spectral features are extracted from HST by TEAP.

3.2.5. Electromyogram (EMG)

Activity of skeletal muscles generates electromyogenic electrical signals (EMG), which can be recorded by means of electrodes attached to the skin covering those muscles. Typically, a pair of electrodes is attached along the muscle of interest to record the electrical potential between two points. Facial and body expressions associated with emotions activate different muscles. One can record emotionally significant expressions using EMG. For example, smiling activates the zygomaticus major (Ekman, 2006). Spectral power density (in $f > 20$ *Hz*) and statistical moments are calculated by TEAP as features from EMG.

[3]https://github.com/Gijom/TEAP.

TABLE 2 | The signals supported by TEAP and features that can be extracted are listed.

Cha.	Feature	Description
GSR	Number of peaks	Number of peaks in resistance exceeding 100 Ω
	Amplitude of peaks	GSR peak amplitude from the saddle point preceding the peak
	Rise time	The time it takes GSR to reach its peak from the saddle point in seconds
	Statistical moments	Mean and SD
RES	Main frequency	Frequency at which the power spectrum reaches its maximum value ($f \in [0.16, 0.6]Hz$)
	PSD	$log(P_x(f))$, $f \in$ {[0, 0.1], [0.1, 0.2], [0.2, 0.3], [0.3, 0.4], [0.4, 0.7], [0.7, 1.0]}Hz (Wang and Gong, 2008)
	Statistical moments	Mean, SD, skewness, and Kurtosis
HST	PSD	$log(P_x(f))$, $f \in$ {[0, 0.1], [0.1, 0.2]}Hz (Wang and Gong, 2008)
	Statistical moments	Mean, SD, skewness, and Kurtosis
EMG	Power	$log(P_x(f))$, $f \in [20, f_s/2]$ Hz
	Statistical moments	Mean, SD, skewness, and Kurtosis
ECG	IBI	Mean IBI, HRV ($std(IBI)$)
	MSE	Multiscale entropy at 5 levels (Costa et al., 2005)
	Tachogram power	$log(P_x^{LF}(f))$, $log(P_x^{MF}(f))$, $log(P_x^{HF}(f))$, $log(P_x^{MF}(f)) / (log(P_x^{LF}(f)) + log(P_x^{HF}(f)))$ *where* $LF{:}f \in [0.01, 0.08]Hz$, $MF{:}]0.08, 0.15]Hz$, and $HF{:}]0.15, 0.4]Hz$
	PSD	$log(P_x(f))$, $f \in$ {[0, 0.1],[0.1, 0.2],[0.2, 0.3],[0.3, 0.4]}Hz $log(P_x^{LF}(f) / P_x^{HF}(f)$, *where* $LF{:}f \in [0.0, 0.08]Hz$ & $HF{:}\ f \in [0.15, 5.0]Hz$
BVP	IBI	Mean IBI, HRV ($std(IBI)$)
	MSE	Multiscale entropy at 5 levels (Costa et al., 2005)
	Tachogram power	$log(P_x^{LF}(f))$, $log(P_x^{MF}(f))$, $log(P_x^{HF}(f))$, $log(P_x^{MF}(f)) / (log(P_x^{LF}(f)) + log(P_x^{HF}(f)))$, *where* $LF{:}f \in [0.01, 0.08]Hz$, $MF{:}]0.08, 0.15]Hz$, and $HF{:}]0.15, 0.4]Hz$
	PSD	$log(P_x(f))$, $f \in$ {[0, 0.1],[0.1, 0.2],[0.2, 0.3],[0.3, 0.4]}Hz $log(P_x^{LF}(f) / P_x^{HF}(f))$, *where* $LF{:}f \in [0.0, 0.08]Hz$ and $HF{:}f \in [0.15, 5.0]Hz$
	Statistical moments	Mean
EEG	PSD	$log(P_x(f))$ in different bands: *delta*: $f \in]0, 4]Hz$, *theta*: $f \in]4, 8]Hz$, *slow alpha*: $f \in]8, 10]Hz$, *alpha*: $f \in]8, 12]Hz$, *beta*:$f \in]12, 30]Hz$, *and gamma*: $f \in]30, f_s/2]Hz$)

3.2.6. Respiration

Respiration pattern can be measured from the expansion of the chest or abdomen circumference. This can be done by a flexible belt with a piezoelectric crystal sensor, which measures the belt's expansion. Respiration pattern (RES) varies by emotional responses. Slow respiration is linked to relaxation and irregular rhythm, quick variations, and cessation of respiration correspond to high arousal, e.g., anger or fear (Rainville et al., 2006; Kim and André, 2008). Principal frequency, power spectral density, and statistical moments are the features that Teap extract from respiration pattern.

3.2.7. Electroencephalogram—EEG

There is a strong evidence demonstrating the neural activities and circuits engaged in different emotional states (Damasio et al., 2000; Adolphs et al., 2003). Electroencephalogram (EEG) signals are a measurement of electrical neural activity on scalp. EEG signals contain waves in different frequency bands that are associated with different cognitive states. Therefore, power spectral density (PSD) features from different frequency bands are calculated as features in TEAP.

3.3. Usage

The goal of this section is to give an example of TEAP's usage. Readers are redirected to the user manual (see text footnote 4) for a more detailed documentation.

Suppose a user has an ECG signal and that they want to extract some features. First, a user shall choose which feature to extract; users can use "include" or "exclude" arguments to add or remove features from the available set of features, or simply extract all available features. With TEAP, the process is as follows:

```
%import probe 1
probe1 = csvread ( ' ECG example_probe1 . csv ');
%import probe 2
probe2 = csvread ( ' ECG example_probe2 . csv ');
%create the signal from two electrodes and a given sampling
%frequency then display the resulting signal
ECG_sig = ECG_aqn_variable (probe1, probe2, 1,024);
Signal_plot (ECG_sig);

%compute some features (all available features)
[ECG_features, ECG_feats_names] = ECG_feat_extr (ECG_sig);
```

TABLE 3 | The recognition rate and F1 scores of emotion recognition compared to the original work.

	Peripheral signals				EEG signals			
(Soleymani et al., 2012a) (MAHNOB)—inter-participant, 3 classes								
	Classification rate↑		Average F1↑		Classification rate↑		Average F1↑	
Dimension	**Arousal (%)**	**Valence (%)**	**Arousal**	**Valence**	**Arousal (%)**	**Valence (%)**	**Arousal**	**Valence**
TEAP	49.3	46.0	0.347	0.346	56.1	57.7	0.489	0.557
Original	46.2	45.5	0.38	0.39	52.4	57.0	0.42	0.56
(Soleymani et al., 2012b)—inter-participant, 3 classes								
	Classification rate↑		Average F1↑		Classification rate↑		Average F1↑	
Dimension	**Arousal**	**Valence**	**Arousal**	**Valence**	**Arousal (%)**	**Valence (%)**	**Arousal**	**Valence**
TEAP	42.7%	41.3%	0.315	0.375	63.0	57.1	0.618	0.546
Original	–	–	–	–	62.1	50.5	0.60	0.50
(Koelstra et al., 2012) (DEAP)—intra-participant, 2 classes (mean)								
	Classification rate↑		Average F1↑		Classification rate↑		Average F1↑	
Dimension	**Arousal (%)**	**Valence (%)**	**Arousal**	**Valence**	**Arousal (%)**	**Valence (%)**	**Arousal**	**Valence**
TEAP	55.9	58.6	0.523	0.570	60.5	65.6	0.570	0.645[a]
Original	57.0	62.7	0.533	0.608	62.0	57.6	0.583	0.563
	Classification rate↑		Average F1↑		Classification rate↑		Average F1↑	
Dimension	**Liking (%)**	**Control**	**Liking**	**Control**	**Liking (%)**	**Control**	**Liking**	**Control**
TEAP	54.9	58.9%	0.494[a]	0.538	58.3	58.3%	0.534	0.533
Original	59.1	–	0.538	–	55.4	–	0.502	–
(Soleymani et al., 2011)—intra-participant, regression, mean absolute error (SD) ↓								
Dimension	**Arousal**	**Valence**	**Control**	**Liking**	**Arousal**	**Valence**	**Control**	**Liking**
TEAP	1.65 (0.46)	1.75 (0.38)	1.69 (0.58)	1.97 (0.57)	1.61 (0.46)	1.71 (0.37)	1.68 (0.58)	1.92 (0.49)
Original	1.70 (0.51)	1.81 (0.41)	1.64 (0.49)	1.96 (0.64)	1.53 (0.40)	1.59 (0.39)	1.53 (0.49)	1.78 (0.51)

[a]*Implies significant difference ($\alpha < 0.05$) in a two-tailed t-test on F1 scores. We were unable to perform the statistical test for Soleymani et al. (2011).*

%compute one feature (for example average inter_beat intervals)
[ECG_features, ECG_feats_names] = ECG_feat_extr (ECG_sig, ' include ' , ' meanIBI ');

%compute some features (all available features except HRV)
[ECG_features, ECG_feats_names] = ECG_feat_extr (ECG_sig , ' exclude ' , 'HRV ');

It should be noted that for some specific signals (e.g., *HST* or *GSR*), a preprocessing, e.g., filtering, will be automatically applied when the signal is loaded; thus, the user does not have to worry about all the necessary steps.

4. EXPERIMENTAL VALIDATION

In order to verify TEAP's performance in emotion recognition, we made use of two publicly available databases to serve as our benchmark, namely MAHNOB-HCI (Soleymani et al., 2012a) and DEAP (Koelstra et al., 2012). We tried to replicate the work presented in four original articles on these databases, i.e., Soleymani et al. (2011, 2012a,b) and Koelstra et al. (2012). In addition to TEAP, reproduction of these results required LIBSVM (Chang and Lin, 2001). We tried to re-implement the same procedure in terms of cross-validation strategy, feature selection, machine learning models, and evaluation metrics. For MAHNOB-HCI database, we only analyzed the emotion experiment whose original results are published in Soleymani et al. (2012a,b). The results of participant-independent cross validation on MAHNOB-HCI database are reported alongside the original results in **Table 3**. The regression and classification results on DEAP database are also given in **Table 3**. In most cases, TEAP features are performing similarly with small differences compared to the original work, the reasons behind this difference is twofold. First, we shortened and simplified the set of features in TEAP compared to the original work to make them more generally applicable. For example, EEG asymmetry features are not implemented in TEAP, since it depends on the electrode placement and do not make a large difference. Second, even though we tried to replicate the same machine learning models, our hyper-parameter optimization and feature

selection slightly differ from the original work. Nevertheless, the results from TEAP features are, in most cases, not significantly different from the original results and validates its effectiveness in capturing emotionally significant representation of physiological signals.

5. CONCLUSION

We propose a new open-source toolbox dedicated to extracting and calculating emotionally relevant representations from physiological signals. This toolbox will facilitate and accelerate research in emotional physiological signals analysis. This toolbox is able to import, preprocess, and visualize its signals. It can export features vectors that can be directly fed to the machine learning models. In this paper, we outlined its abilities and demonstrated its effectiveness according to the publicly available benchmarks. Ideal candidates for future feature implementation include synchronization, intermodality features such as pulse ejection time and event-related potentials (ERP). We hope this toolbox can serve the researchers interested in affective physiological signal analysis.

AUTHOR CONTRIBUTIONS

MS and GC developed and adopted the original features (Chanel et al., 2009, 2011; Soleymani et al., 2009, 2012b; Koelstra et al., 2012). MS performed the experiments and reported the results. FV-D designed the architecture and modules and created the toolbox. TP participated in drafting the article and the discussions.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at http://journal.frontiersin.org/article/10.3389/fict.2017.00001/full#supplementary-material.

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Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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