On the Impact of Lateralization in Physiological Signals from Wearable Sensors

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ABSTRACT

Wearable devices enable the continuous and unobtrusive monitoring of physiological data, e.g., electrodermal activity (EDA), and they allow to build machine learning models to recognize human emotions, stress, and more. However, the quality of the collected data can significantly impact the performance of such models. When wrist-worn sensors are used, this may happen due to differences in the signal collected on the left and right wrist. In this work, we quantify the impact of physiological signal lateralization in a laughter recognition task. Building upon an existing dataset from 34 users, we devise a laughter recognition classifier and compare the performance of models trained and tested with data from different wrists. Our results show that, when using EDA, classification performance might depend on the side used for training and testing. Our quantification of lateralization on model performance provides insights for the design of EDA-based models as well as of data collection studies.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**; • **Mathematics of computing →** *Exploratory data analysis*; • **Computing methodologies →** *Cross-validation.*

KEYWORDS

Lateralization Analysis, Correlation Analysis, Effect Size, Laughter Recognition

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1 INTRODUCTION

Recent advances in wearable technologies, in terms of data acquisition capabilities, number of sensors, long-lasting battery life, and comfort level, have allowed a continuous and unobtrusive monitoring of physiological parameters. Several researches have investigated the potential of such technology for the continuous assessment of emotions and activities in real-life settings [6, 10, 13, 28]. Wearable devices are capable of collecting different physiological signals – such as, e.g., Electrodermal activity (EDA), Electrocardiography (ECG), and Blood Volume Pulse (BVP) – that prove their feasibility in different self-monitoring systems. Such signals can be employed in emotion recognition and human activity recognition [2, 10, 27, 29].

However, low quality of physiological signals collected from wearable devices, especially wrist-worn, can hinder the performance of the previously mentioned applications [4]. One of the major issues is the way users tend to wear their wearables [4], and how this varies between people. Between 70 and 95% of the global population is right handed, leading to a dominance of left-hand positioning, i.e., non-dominant side, of wrist-worn devices [20]. Changes in this position can however occur, both in real-world scenarios and in controlled settings, and people may wear the device interchangeably on the left or the right [1, 31]. *Lateralization*, i.e., the phenomenon in which some function or activity has preference for one side of the body, of some physiological signals, could impact applications where the placement is not taken into account. Given these differences, placement of wearables has been explored: many researchers have compared the physiological signals collected from different body locations [10, 23, 29, 33]. Researchers have also investigated the impact of changing position of devices, e.g., from left to the right side, in relation to real world application and human activity recognition, but mostly through the use of accelerometer-based sensors [1, 7, 31]. However, there is a shortage in the number of studies that investigate the impact of wrist-worn positioning when dealing with physiological data, in human and emotion recognition tasks. Accordingly, in this paper we aim at comparing physiological signals collected from both body sides, during different experiments, and investigating their impact in a human behavior recognition task.

To address this, we performed statistical and classification analysis on the *USI_Laughs* dataset [6], which contains physiological data recorded from 34 participants during laughter moments. Specifically, we investigated the lateralization differences present in the data by exploring the correlation between raw physiological signals as well as effect size over hand crafted features. Then, we showcase a machine learning-based laughter recognition task, over which we carried out various experiments. In particular, we confronted models trained and tested on the same side with models trained and tested on different side; as well as using a set where data was chosen randomly between the left and the right, to simulate a "worst case scenario" application where users wear the devices interchangeably.

2 RELATED WORK

The comparison between physiological signals recorded from different body locations has been corroborated in many studies, such as [10, 23, 29, 33]. The key difference among these studies is the chosen physiological signal and the body location of recording devices. For instance, researchers in [23, 24] consider the Photoplethysmography (PPG) signal and other researchers rely on EDA signals in their comparisons, e.g., [10, 29].

Pilt et al. [23] analyzed the bilateral differences between second derivative of PPG signal (SDPPG) extracted from the left and right hand fingers of 34 participants. The paired t-test showed significant statistical differences between the two body locations. In [24], authors compared transmission and reflection PPG sensor modes, with sensors mounted on multiple body positions collected from 6 participants. They concluded that finger-worn sensors were more accurate than ear positioned ones, as well as that some relation to the finger size are present. Authors in [11] found high correlation between the HRV extracted from the PPG signal when comparing left and right hand.

Hossain et al. [10] analyzed EDA from different body locations, finding high correlation between finger and foot signals, while other positions did not. They also implemented a rest/stress classification procedure and showed that finger and foot achieved higher performance than other body locations. A similar comparison of different positions, for EDA responses, was performed by [29], who found high correlation among the left finger and the right foot.

Our review shows that several studies consider different body locations, but regardless of body side. There is a gap in the literature on investigating the impact of sensor placement with regard of the side of the body in human behavior recognition. Indeed, known lateralization in physiological signals, e.g., EDA, could have some effect in real-world applications: as such, analysis of lateral position of wearable devices could give insight, as well as suggestions, for future research. Accordingly, this gap is the main driving factor for our contribution.

3 DATA ANALYSIS

In this section we describe the dataset used and the procedure we followed to investigate the impact of lateralization. We made our code implementation available on GitHub: https://github.com/LeonardoAlchieri/LateralizationLaughter.

3.1 Dataset

We used the *USI_Laughs* dataset [6]. The aim of the work by Di Lascio et al. consisted in the recognition of laughter episodes using a combination of physiological and movement data. The dataset contains physiological recordings from 34 participants obtained during a controlled study in laboratory settings. Data was collected using two Empatica E4 wristband[1], placed for all participants on both the left and right wrists at the same time. The devices recorded Blood Volume Pulse (BVP), Electrodermal Activity (EDA), Accelerometer (ACC) and Skin Temperature (ST) data. We did not use ST for laughter recognition, since its changes are only noticeable over longer periods [26]. We also did not use ACC data, since it is not a physiological signal, and thus outside the scope of the current work. The experimental procedure consisted of a sequence of different events: relaxation (also called *baseline*), funny videos, acted laughter, clapping hands, cognitive load test (based on a Stroop test [32]). Manual annotations of people laughing, and their level of laughter, were recorded by Di Lascio et al.. During the recording procedure, throughout the whole experiment, the participants were asked to limit their movements.

3.2 Pre-Processing and Feature Extraction

To pre-process the data we follow the work by Di Lascio et al. [6]. In particular, we apply filtering, normalization for each user's data and segmentation. The procedure follows the description by Di Lascio et al. [6]. We applied a first order Butterworth low-pass filter (cutoff 0.4 Hz) on the the EDA signal (sampled at 4 Hz) and a FIR low-pass filter (cutoff at 5 Hz) on the BVP (rate 64 Hz). We decomposed the EDA signal into a phasic and tonic component with cvxEDA [9]. In this work we used only the phasic and the non-decomposed signal (referred to *mixed-EDA*), since the tonic component is not associated with short-term responses [3]. For the statistical analysis, we also divided the data into segments, each corresponding to an event in the experiment, e.g., relaxation period, cognitive load, etc. For the classification task, shorter fixed windows (2 seconds) were selected, as described in Section 3.4. The features we extracted are: for EDA, time-domain features; for BVP, time-domain and HR/HRV statistical. Table 1 presents a summary of the extracted features. The same procedure was performed for signals from both the left and right side device.

3.3 Quantification of Lateralization

To analyse lateralization effect in physiological data, a correlation analysis was performed over the pre-processed signals. We also devised a statistical analysis, based on effect size, over the features extracted, to investigate if differences would be propagated from the raw (filtered) signal. We implemented both only for the EDA (phasic) and BVP signals.

Correlation coefficients can be a good indicator if two time series, in our case the physiological signals from the left and right side of the body, represent the same phenomenon, even if with many limitations, e.g., the famous "correlation does not imply causation" dilemma [19]. To quantify lateralization, we considered three correlation coefficients: **Pearson's** ρ, **Spearmann's** ρ and **Kendall's** τ [17]. The first is a linear coefficient, while the other two

[1]https://www.empatica.com/en-gb/research/e4/

Table 1: Overview of hand crafted features evaluted for EDA and BVP filtered signals.

Sensor (# features)	**Features**
EDA mixed (11) & phasic (11)	minimum, maximum, mean, standard deviation, dynamic range, slope, absolute value of the slope, mean and standard deviation first derivative, number of peaks, peaks' amplitude
BVP (19)	minimum, maximum, mean, standard deviation, dynamic range, slope, area under the curve, number of peaks, ratio between # peaks and segment length, mean and standard deviation of the first two derivatives, differences between highest and smallest peak, Heart Rate, mean of the Heart Rate Variation (HRV) NN, standard deviation of the HRV NN (SDNN), standard deviation of HRV NN differences (SDSD), root mean squared sum of the HRV NN differences (RMSSD)

are so-called *rank* coefficients, which can account for non-linear dependencies. We calculated the coefficient per each event recorded in the dataset, e.g., cognitive load or laughter events, between the left and right side timeseries. These were considered after the preprocessing steps (subsection 3.2) and for each calculation, i.e., for each event, the timeseries of all users were concatenated together. Effect size analysis determines if two samples are related to each other, and to what degree [16]. To investigate effect size, we used **Cliff's** δ coefficient, which ranges from -1 (larger second factor) to 1 (larger first factor), with 0 identifying no differences [16]. Similarly to the correlation coefficients, Cliff's δ values were evaluated for each event between the left and right side. However, the confrontations were in this case performed over the features extracted. The idea is to show the impact of lateralization on features extracted as well, since its effect may differ from the correlation of raw (filtered) signals. Hand-crafted features are also mostly implemented in classical machine learning, when dealing with time series data [12], and as such differences in them could give insight for classification paradigms.

3.4 Laughter Recognition Task

To investigate the impact of wrist-worn sensor placement, we performed the task of recognizing laughter episodes, as proposed by [6] with machine learning methods. The classifiers implemented were trained for a binary prediction, to discriminate between a laughter episode (positive class) to a relaxation period (negative class).

Data Preparation. We selected the instances to include in the dataset with a segmentation similar to Di Lascio et al. [6]. However, instead of considering a whole event, i.e., laughter episode or relaxation period, a fixed window of 2 seconds was used. In order to have a balanced dataset, for each 2 second window from a laughter period, one over the relaxation period was selected. The choice of a fixed window, as opposed to [6], simulated a possible real-world application, when using time series data for classification [12]. The length of the window is selected as the shortest laughter episode in the *USI_Laughs* dataset. From this procedure, a total of **640 training points**, evenly distributed between laughter (positive) and baseline (negative) phases, were extracted.

ML Classifiers. Multiple machine learning classifiers were implemented for the laughter recognition task, from which the best classifier on average was selected. We chose the following models, since they are some of the most used in literature [14]: K-Nearest Neighbour Classifier (KNN), Support Vector Machine Classifier (SVC), Gaussian Process, Gaussian Naïve Bayes, Quadratic Discriminant Analysis (QDA), Decision Tree and some of its variations, i.e., AdaBoost [30], Random Forest and XGBoost [5]. All were implemented through the `Scikit-Learn` Python library [21].

Evaluation Metrics. As a measure of performance, we used **accuracy**: given the by-construction balanced dataset, it can be assumed not to have any negative drawbacks. Even when performing cross validation, we made sure to have always balance in the train-validation split. We run the classification task with the **Leave-One-Subject-Out** (LOSO) **cross validation** paradigm, similarly to [6]. This method allows to train a model with all users but one, and test with the one left out. It avoids overfitting due to not having the same participant in both train and test. We confronted only the best classifier per sensor of interest, i.e., EDA and BVP. The choice of "best" was taken by selecting the classifier with the highest average, for each sensor or combination of sensors, across all experiments.

Experiments. The ML models were trained with data from different body sides as well as different modalities. As far as sensor modalities, we tested models trained only on EDA and BVP features separately, to assess the impact of device position for the two physiological signals independently. In particular, we trained and tested ML classifier with data collected from the same hand-side or from different sides. This leads to four possible combinations: train and test data collected from the left hand ($\text{Train}_\text{L}, \text{Test}_\text{L}$); train and test from the right hand ($\text{Train}_\text{R}, \text{Test}_\text{R}$); train from the left and test from the right ($\text{Train}_\text{L}, \text{Test}_\text{R}$); or train from the right and test from the left ($\text{Train}_\text{R}, \text{Test}_\text{L}$). Since we chose to use a cross validation paradigm (LOSO), for each iteration the data from all users in the train is from the "train side" and that of the left-out user from the "test side". On the other hand, to account for cases in which the position of the device might not be constant, we created a "worst case scenario" dataset, in which data for each sample, i.e., laughter episode or relaxation period, was selected randomly between the left and right side. In this case, we compared model only trained and tested on this "random" side ($\text{Train}_\text{Rnd}, \text{Test}_\text{Rnd}$. This way, we checked for if using a random side, i.e., not having consistency in device position, could have some performance impact, be it positive or negative.

4 RESULTS

In this section we present and discuss the results obtained using the procedures introduced in Section 3.

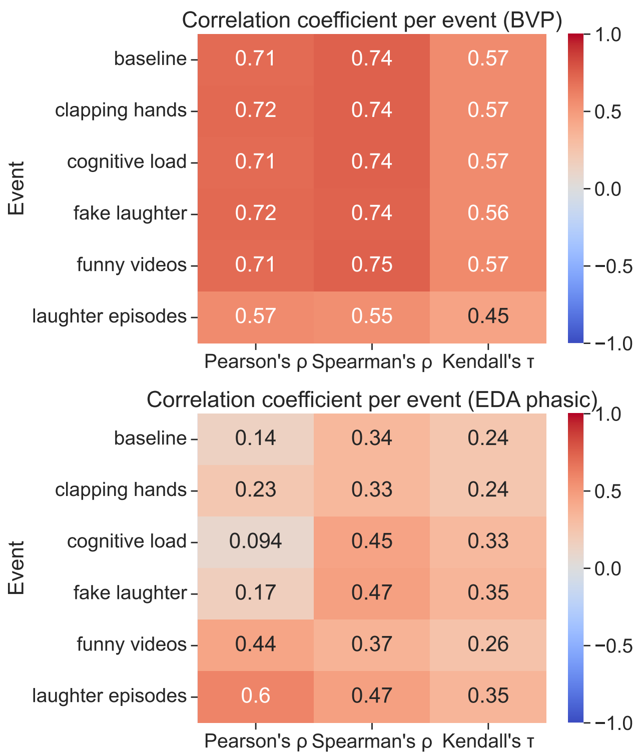

Figure 1: Correlation coefficients, per event, between left and right side, for EDA (phasic) and BVP signals. Statistical significance, with the null hypothesis of no correlation, is true for all values (Bonferroni corrected).

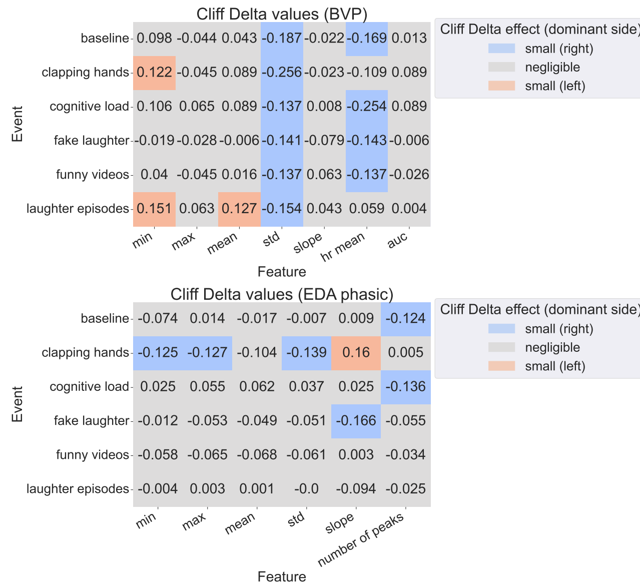

Figure 2: Cliff's δ values, per event, between left and right, for some EDA (phasic) and BVP features. The features shown here are those considered more easily interpretable. Size difference bins are evaluated according to the suggestions of [34].

4.1 Quantification of Lateralization

Raw (Pre-Processed) Signal Correlation. Figure 1 shows the results of the correlation analysis, per event, for the filtered and normalized BVP and EDA phasic signals. We observe that the BVP signal presents high values (> 0.5) for all correlation coefficients, consistently across different events. These results suggest that the BVP signal is mostly similar between the left and right side of the body and that it does not have a dependency upon event: this is expected and in line with existing literature [11, 24].

On the other hand, we notice that the phasic component of the EDA signal has a much lower overall correlation (< 0.5) and has a very stark dependency upon event, with especially low values of linear correlation in the *cognitive load* task. It also has variation across coefficients, suggesting the presence of non-linearity, e.g., the cognitive load task has a very low Pearson's ρ, but much higher Spearman's ρ and Kendall's τ. Overall the EDA signal shows that, for some events, opposite sides of the body may react in slightly different manners. Indeed, it has been known for years that stimulating different parts of the brain, through different activities, can lead to significant variations in the skin response on the two sides of the body [18, 25]. As such, our results can be considered in line with similar findings in literature [15, 22].

Extracted Features Effect Size. In Figure 2 we show the results for the effect size calculation, where we show the statistical differences between lateralization of extracted features. While the previous analysis aimed at identifying similar patterns between the raw (filtered) signals, here the interest is to see if differences can be seen when extracting hand-crafted features. For most events and features, the Cliff's δ value has a *negligible* effect, i.e., there is no difference between features calculated with left or the right hand signals. In the BVP signal, some features show higher values for the left side, e.g., *min* and *mean*, or the right side, e.g., *std* and *hr mean*. However, these differences have, for each feature, the same sign across event, e.g., all δ values for the *standard deviation* (std) are negative, indicating some consistency. For the EDA, where less significant differences are present, the *slope* feature presents a change in sign across two events. In general, however, the differences presented here are, at best, considered **small**. The impact of such changes can be analysed with a classification task (subsection 4.2).

4.2 Laughter Recognition Task

Table 2 shows the accuracies obtained from the "best classifiers", i.e., the classifier that on average obtained the highest accuracy for a specific combination, to recognize laughter. With respect to training and testing on different sides (Train_L, Test_R and Train_R, Test_L), the results suggest that, for both physiological signals, there could be a decrease in performance, when opposed to a fixed side. For the EDA, the highest accuracy when training and testing over the same side (59.0% left side) is higher, but not statistically significant, when compared to the highest model where the sides are swapped (59.7%, train on right and test on left). For the BVP, on the other hand,

Table 2: Accuracy (%), with standard errors, for the best models (on average) for each modality. Specifically Random Forest for both *EDA* and *BVP*.

Side / Sensor	EDA	BVP
Train_L, Test_L	59.0 ± 0.6	57.1 ± 0.6
Train_R, Test_R	54.4 ± 0.7	54.7 ± 0.7
Train_{Rnd}, Test_{Rnd}	49.2 ± 0.7	56.5 ± 0.6
Train_L, Test_R	54.8 ± 0.6	53.0 ± 0.5
Train_R, Test_L	58.7 ± 0.6	54.7 ± 0.5
Uniform Random Baseline: *50.9 ± 2.2*		

the results over the same confrontation are statistically significant, i.e., 54.7% for the model trained on the right and tested on the left compared to 57.1% for the model trained and tested only on the left side. However, for both signals, the models trained and tested on the right side present a much lower accuracy. This could be due to the prevalence of right-handed people, who have as non-dominant hand the left one, in the dataset: it could be due to a larger presence of artifacts in both signals in the dominant hand [8]. However, further investigation is needed to confirm these claims.

When analysing the "worst case scenario", i.e., simulating users wearing their device randomly between the left and right side, the results are different for the two signals. On the BVP, the best accuracy achieved for the "random" side is similar to other modalities (56.5%). As such, scenarios involving BVP data might not be impacted by randomly choosing a side. However, for the EDA we show that the best model trained in this scenario has an accuracy which is not above a random baseline (49.2), and much lower than all other models. This suggests that models trained on EDA could be impacted negatively by users wearing their devices on different sides of the body in different moments.

In conclusion, we can draw important insights on the behaviour of classification models Table 2. Both EDA and BVP-trained models show that training and testing on different sides of the body could have a negative impact on the performance and generalizability of classifiers. More work is though needed in this scenario. In a "worst case scenario", where users swap the wrist-worn device between different sides of the body randomly, models trained on EDA signal are negatively impacted and does not achieve a performance higher than a baseline.

5 LIMITATIONS & FUTURE WORKS

While the present work managed to showcase how lateralization of some physiological signals can impact a classification task, more work is however needed to further explore the results obtained. Indeed, while the USILaughs dataset contains physiological signals taken simultaneously from the left and right wrist, during the data collection procedure no control with regard of wrist position or wrist orientation was reported by Di Lascio et al. [6]. The use of other datasets could give a stronger validation to the results presented. Analysing other machine learning tasks, both with the same or new datasets, could give better insight into the impact of lateralization. Future work should also focus on classification tasks where EDA and BVP have a higher importance than the one presented, since in our multimodal settings the results were likely dominated by Accelerometer information. Also, exploring how different classifiers, and not only the "best" ones, are impacted could give a more general insight.

6 CONCLUSIONS

We investigated the impact of different body placements of wearable sensors on the performance of human behavior recognition tasks. We focused on BVP and EDA data collected using wrist-worn sensors and analyzed potential differences in the signals collected on the left or right wrist.

We first performed a correlation analysis between signals collected on the two body sides and, in line with other results in the literature, we found that BVP signals do not show lateralization effects, whereas EDA does. We further performed an effect size analysis that confirmed these results, but also highlighted that selected features of the BVP signal might differ, although only slightly, if measured concurrently on different body sides.

We further investigated the potential impact of lateralization on a specific machine learning task: laughter recognition. Our results show that training and testing a classifier with the physiological data collected on the same side of the body achieves higher accuracy than when training and testing use data from opposite sides. However, not all the observed differences are statistically significant, and thus further research is needed before we can make conclusive statements on this matter. We also analyzed the case in which it is picked at random, both during training and during testing, whether the classifier uses data from the left or right side of the body. In this scenario, EDA-trained models show a statistically-significant decrease in accuracy with respect to the case in which training and testing use data collected from the same side of the body or from opposite sides. BVP-trained models instead do not show significant differences in the three scenarios. These last results also hint at the need of further research to understand the impact of lateralization in real-world scenarios, in which users may wear their wrist-worn devices interchangeably on the left or right side of the body.

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