Transforming Physiological Data from a Generic Sensor to a Specialised One for Affect Detection

*Patrick Moratori, Christian Wagner, Robert Houghton,
Victoria Shipp, Jaspreet Johal, Peter Welch and Shakir Ali*

*Horizon Digital Economy Research
University of Nottingham
Nottingham, NG7 2TU, UK*

ABSTRACT

Continuous reduction on hardware costs has been bringing the opportunity to employ cheap sensors to measure physiological data. However, this comes at a price of capturing some noisy information, which most likely would compromise both analysis and interpretation of the raw results. This paper investigates the reliability of a generic and a specialised sensor on capturing heart rate data and the challenge of extracting meaningful information from it for affect detection. A controlled stimulus in a laboratory setting is performed, in which participants play different levels of the game Tetris while their signal variations are observed. Since only the generic sensor does not reproduce the expected behaviour, filtering techniques are proposed to approximate its signal to the specialised one. Experimental results confirm that this goal is achieved by applying either "Grubbs' test"' for outliers detection or "three-sigma rule". Such transformations highlight the need of filtering techniques for affective computing because they avoid misinterpretation of the results, as well as it represents a starting point towards finding a ground-truth to link possible user affect and physiological data.

Keywords: Affective Computing, Physiological Data, Sensor Comparisons, Emotions, Ground-truth Data Set

INTRODUCTION

Modelling user affect is a challenging and instigating task due to the complexity of understanding features from individuals. However, characteristics such as facial expressions and self-report statements could lead to misleading interpretations of current emotional states, i.e. a “fake”' smile representing happiness or a person completing a questionnaire when in a hurry. The use of physiological data represents an alternative to overcome this issue, since their signals are mostly involuntary. Their association with previously mentioned features would provide a more reliable interpretation of user affect.

Research efforts have been made to check possible links between emotional states and physiological data (Ben-Shakhar et al., 2007; Bailenson et al., 2008; Stemmler and Wacker, 2010; Park and Kim, 2011; Elices et al., 2012; Veld et al., 2012; Critchley et al., 2013). However, the reliable capture of information on users' affective state based solely on physiological data is still a remote goal. An important issue to highlight is the quality of captured signals by sensors, which might be producing noisy information due to their reduced hardware costs.

This paper focuses on the process of capturing heart rate signals (*HR*) as physiological data and the challenge of extracting meaningful information from it. The aim is to collect signals from different sensors, i.e. a generic and a specialised one, checking their reliability when users are exposed to controlled stimuli in a laboratory setting. Signals are compared and a filtering transformation from a generic to a specialised one is proposed. This study mainly emphasise the need of filtering techniques for affective computing, which represents an essential starting point to do further investigation on the identification of possible patterns on making links between physiological information and emotional states, since collected data should be accurate and purposeful. Upcoming studies have the ultimate goal of establishing a ground-truth dataset for subsequent learning and automatic recognition of user affect.

Background, Aims and Contribution

Affective Computing (AC) is “computing that relates to, arises from, or deliberately influences emotions” (Picard, 1995), as initially coined by Professor R. Picard (Media Lab, MIT). It has been gaining popularity rapidly in the last decade because of its significant potential in the next generation of human-computer interfaces. One goal of affective computing is to design computer systems that can recognize and respond in a rational and strategic fashion to real-time changes in user affect (e.g., happiness, sadness), cognition (e.g., frustration, boredom) and motivation, as represented by for example speech, facial expressions, physiological signals, and neurocognitive performance. Achieving the aspirations of the very young field of AC is a strongly multidisciplinary challenge with key contributions from Psychology, Human Factors, Computer Science and other disciplines. Recent years have seen a large expansion in the body of research in and around AC (Chanel et al., 2009; Al-Mulla et al., 2011), in particular from a Computer Science perspective (Calvo and DMello, 2010), highlighting the need for engagement across disciplines to align emotion theories proposed in the Psychology literature with current modelling techniques in Computer Science.

The study discussed in this paper has been launched as a multidisciplinary research project to establish foundations for the investigation of AC, in particular from a computational intelligence point of view. It is driven both by insights from Psychology as well as the potential of modern data aggregation and interpretation techniques from Computer Science. The key challenges across disciplines are:

- Psychology and Human Factors: What is emotion and how can we interpret physiological information in this context?
- Computer Science: How do we automatically recognize “emotions” from multiple uncertain information sources?

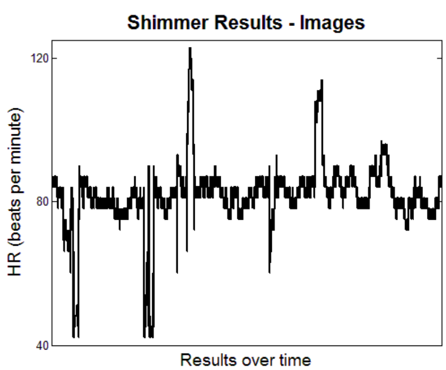
Creating a ground-truth dataset to link emotional states with physiological data is not a straight forward task, as previously discussed in (Moratori et al., 2013). Many issues could be related with experiment design (e.g., intensity of the applied stimuli, workload) and/or data capture (e.g., faulty or inaccurate sensors). This paper mainly focuses on checking the reliability of different sensors on capturing Heart Rate data to reflect possible user affects. These signals are collected, analysed and compared among them. The main contribution of this study is to discuss the process of collecting meaningful physiological data for AC and possible filtering strategies to acquire more reliable information.

The remainder of this paper is organised as follows. The next section introduces the investigated problem, followed by the experiment description which defines the experimental methodology and presents, analyses and discusses the obtained results. The last section concludes the paper and describes future work.

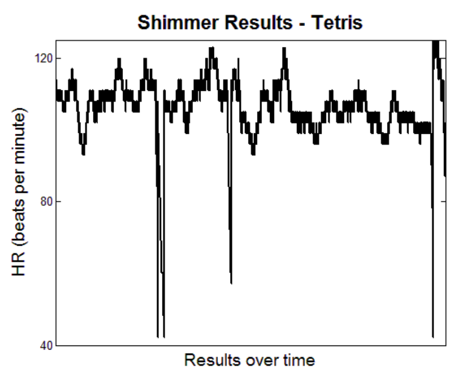
PROBLEM STATEMENT

A series of carefully crafted pre-experiments has been done to investigate physiological data for user affect. The following contexts have been analysed as stimuli: (*C1*) user behaviour when visualising a sequence of pre-rated images from the groups of emotions “happy”, “neutral” and “sad” and, (*C2*) levels of stress when playing a Tetris game with a continuous increasing workload.

ElectroCardioGram data *ECG* is captured by wireless Shimmer sensors (Burns et al., 2010) during the stimuli. Subsequently, heart beats per minute are extracted from this signal generating heart rate data (*HR*). Results from these initial experiments show that noisy signals are present for both contexts. Figure 1 (a)-(b), illustrates the presence of large peaks for *C1* and *C2*, respectively. Due to the nature of the stimuli, no drastic changes on *HR* are expected on a small period of time because no strong physical effort is required during the performance of task, i.e. in general, increasing levels of stress lead to a gradual increase of the *HR* over time. These results highlight a possible accuracy issue with the applied sensor.



(a)



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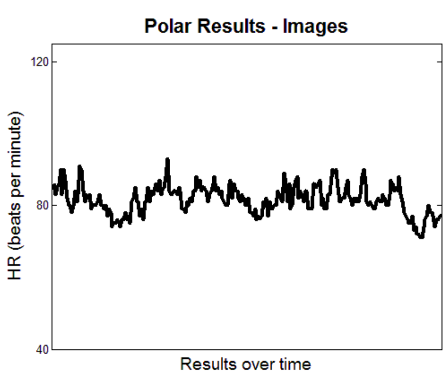
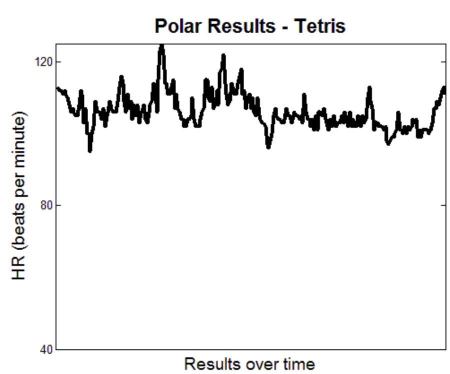


(c)



(d)

Figure 1. *HR* signals from Shimmer (a)-(b) and from Polar (c)-(d)

Polar sensor has been used by several researchers to monitor *HR* activity (Gamelin et al., 2006; Kent et al., 2009; Weippert et al., 2010; Quintana et al., 2012; Santos et al., 2013) and, consequently, this more specialised device has been employed to check the reliability of the acquired signals. Results from Polar resemble the expected behaviour, since no drastic changes on *HR* are observed overtime, as in Figure 1 (c)-(d) for both contexts. For instance, this smooth behaviour reflects slightly changes on *HR* when the user sees different groups of images on *C1*, or when moving between different levels of Tetris on *C2*.

Because of the practicability of conducting experiments and avoidance of repeating the same proceeded tasks, a step forward would be apply a filtering technique to transform the original signal into one that is similar to Polar, which would provide a reliable signal even from a generic wireless device as Shimmer.

EXPERIMENT DESCRIPTION

The investigated context relies on playing the game Tetris due to its interactive, engaging and continuous demanding nature, which facilitates the immersion of users while performing required task, i.e. progressing through different levels of the game. *ECG* and *HR* values are collected in parallel from both Shimmer and Polar, respectively. Note that Polar originally delivers *HR* data and Shimmer signals have to be post-processed to count heart beats, in which *ECG* data is transformed into *HR* values. More details about this post-processing procedure can be found in (Moratori et al., 2013). A time window of 20 minutes is predefined to observe 11 participants playing the game, with a recording sampling rate of 0.5Hz. Subsequently, comparisons overtime time are done among sensors, in which a deviation value *Dev* is calculated to represent the sum of the absolute differences between signals from Shimmer and Polar.

Two filtering techniques are then applied to reduce possible noisy data from Shimmer aiming to reduce deviating values. The first one (*F1*) is based on “Grubbs' test” (Grubbs, 1969) and the second (*F2*) on “three-sigma rule” (Upton and Cook, 2008). *F1* detects outliers based on the calculation of a “Z” value for each considered sample, which measures the distance to the mean divided by the standard deviation. Subsequently, each “Z” is compared with tabulated “Z critical” values defined by Grubbs, which checks if there is less than a 5\% chance to find an outlier so far from the others by chance alone. Conversely, *F2* has a more straight-forward approach in which deviations are detected when values are larger than three times the standard deviation. Note that both *F1* and *F2* are tested separately and the process of detecting outliers is repeated until no improvements are observed for *Dev*.

Analysis and Results

Overall results obtained by both filtering techniques *F1* and *F2* are shown in Table 1. In general, averages and standard deviations from transformed Shimmer and raw Polar are reasonably approximated. Decreasing *Dev* values reflect the outlier detection. Contrariwise, these values remain unchanged when deviations are not present or cannot be identified. The total average in Table 1 indicates that both transformations are able to deliver smaller deviations. A graphical representation with data from participant 1 is presented in Figure 2 (a)-(b), in which outliers are detected using *F1* and *F2*, respectively. Additionally, Figure 2 (c) illustrates an example when deviations are absent from the original signal captured for participant 9.

Exceptions were observed for participant 2, 4 and 8 with slightly increasing *Dev* because no prediction technique is applied on replacing outliers, which means that they are simply substituted by the average value of the curve. Figure 3 shows this behaviour when the outlier on the instant 77 is detected for participant 4. Note that replacing the outlier by the average leads to a transformed curve that is slightly more distant to Polar at this specific time. In such cases, a transformation of the *HR* signal is not required since no relevant changes are observed on the final results.

Table 1. Average, standard deviation and *Dev* values for Polar and Shimmer

	Raw values					*F1*			*F2*		
	Polar		Shimmer			Shimmer			Shimmer		
Participant	Average	Std	Average	Std	*Dev*	Average	Std	*Dev*	Average	Std	*Dev*
1	81.59	4.01	76.99	18.48	2332.00	81.95	3.15	713.00	81.63	3.83	813.87
2	60.31	5.19	61.41	5.41	524.00	61.27	5.15	551.00	61.26	5.15	552.18
3	76.50	5.32	77.08	4.85	1169.00	77.08	4.85	1169.00	77.08	4.85	1169.00
4	57.27	2.42	58.24	3.24	438.00	58.10	2.95	443.00	58.09	2.95	445.29
5	51.75	2.04	53.63	6.69	1030.00	52.32	2.79	691.00	52.33	2.79	696.20
6	~~77.53~~	~~4.93~~	~~72.98~~	~~45.63~~	~~9109.00~~	~~72.98~~	~~45.63~~	~~9109.00~~	~~72.98~~	~~45.63~~	~~9109.00~~
7	72.19	2.91	74.08	3.57	628.00	74.08	3.57	628.00	74.08	3.57	628.00
8	73.64	5.07	75.09	5.06	757.00	74.90	4.78	780.00	75.09	5.06	757.00
9	71.67	4.64	72.63	5.02	511.00	72.57	4.93	511.00	72.63	5.02	511.00
10	80.55	9.45	74.81	17.73	2711.00	80.58	3.48	1144.00	80.05	3.71	1245.81
11	106.18	4.96	100.34	22.39	2814.00	107.13	5.60	1259.00	106.52	5.88	1375.08
Total average	73.17	4.60	72.43	9.24	1291.40	74.00	4.12	788.90	73.87	4.28	819.34

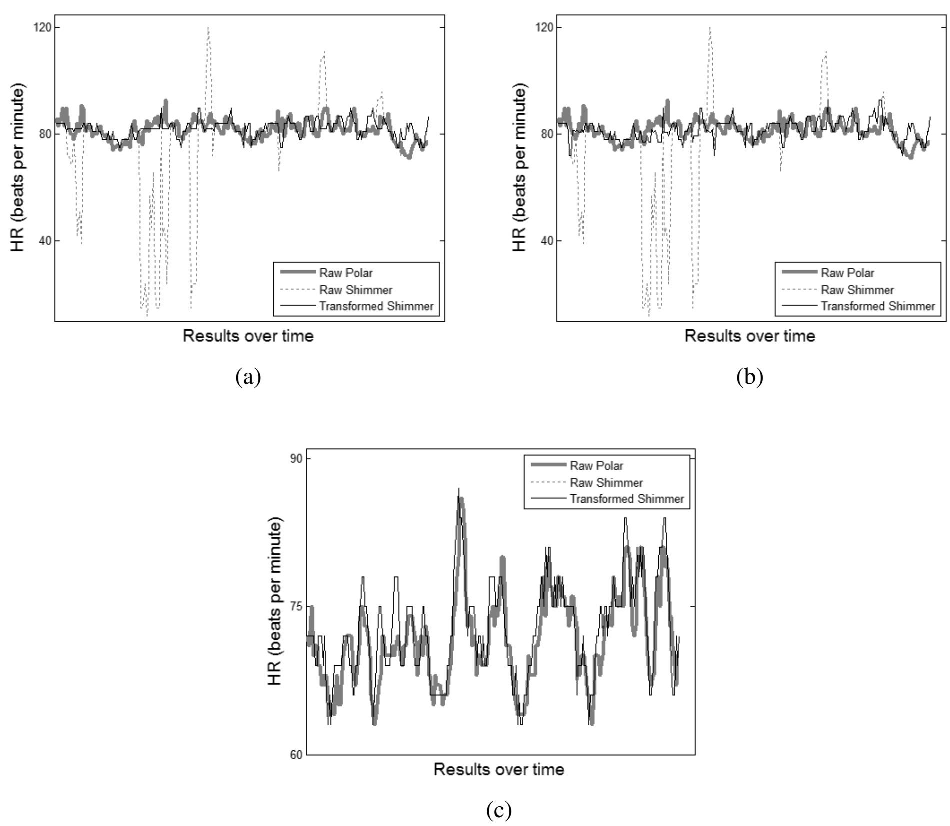


Figure 2. Outliers detection using *F1* and *F2* transformations (a)-(b), respectively; and no presence of deviating values (c)

In general, slightly better performance is observed for *F1* because “Grubbs' test” not only considers standard deviations and averages values, but also the t-distribution of the curve (Barnett and Lewis, 1994).

The presence of unchanged large standard deviation values after applying *F1* and *F2* indicates that the original signal is not a good representative of the observed feature. For instance, shimmer data from participant 6 reflects pure noise, even with an apparent similarity with Polar observing only its *HR* averages results, as in Figure 4. Such cases are detected and samples are automatically disregarded.

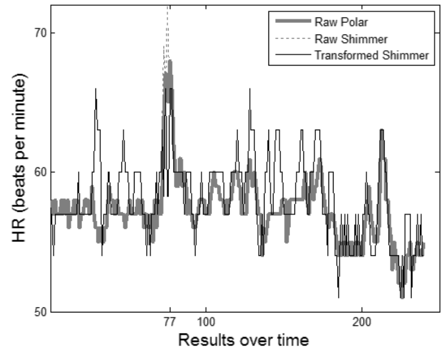


Figure 3. Slightly increasing *Dev* after removing outliers on the instant 77

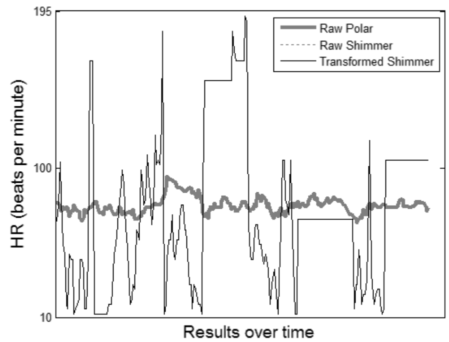


Figure 4. Example of data with pure noise captured by Shimmer

In order to check the relevance of the proposed transformations, an additional comparison with a straight average line from Shimmer is investigated. The goal is to confirm that smaller deviations can be found from both *F1* and *F2*, while relevant signal variations are kept. Figure 5 shows a graphical representation of this comparison, using 95% confidence interval plots. The dot indicates the average value on the whole set of samples obtained by the corresponding *Dev* value in the x-axis. The vertical lines denote the 95% confidence interval of the mean value. Statistical differences are immediately detected when there is no overlap between the confidence intervals of two or more instances.

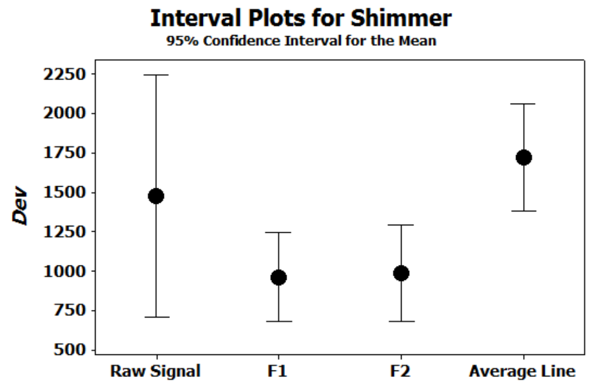


Figure 5. Comparisons between raw signal, *F1*, *F2* and average line from Shimmer; the x-axis shows each of these instances;
the y-axis shows the mean (dot) and 95% confidence interval (vertical bars) of *Dev*

According to the interval plots in Figure 5, *F1* and *F2* are the most competent with respect to *Dev*. As expected, both filtering methods are statistically superior to the average line. However, they not statistically distinct from raw Shimmer, even having the ability to deliver smaller *Dev* values, as previously stated using overall results from Table 1. Note that small *HR* variations are commonly observed for AC experiments due to nature of the required tasks, which are, in general, not physically demanding (Poli et al., 2007; Quintana et al., 2012).

Given the results in Table 1 and the additional comparison with average lines, it is confirmed that it is possible to transform a noisy signal from a generic *HR* sensor as Shimmer into a more specialised one as Polar, since they are reasonably approximated for the AC context.

CONCLUSIONS AND FUTURE WORK

This paper checks the reliability of different sensors, i.e. a generic and a specialised one, on capturing heart rate (*HR*) and the challenge of extracting meaningful information from it toward recognising possible user affects. Users are exposed to a controlled stimulus in a laboratory setting while their physiological data is recorded by both sensors. The task is to play different levels of the game Tetris, in which only small variations are expected on the captured signal due to the nature of this required task. Not surprisingly, the specialised sensor reproduces the expected behaviour while the generic one delivers outliers. Consequently, filtering techniques are proposed to approximate collected signals from both devices, i.e. data from the generic sensor is post-processed to generate signals that are similar to the specialised one. Both applied techniques, namely “Grubbs' test” for outliers detection and “three-sigma rule”, succeed on this approximation. Note that such transformations are highlighted as essential because they avoid misinterpretation of the results. This contribution represents an essential starting point to do further investigation on the identification of possible patterns on user affect, since observed data should be accurate and purposeful. Future work aims to test different prediction techniques to replace outlier values and the reliability investigation of different physiological data such as galvanic skin responses (*GSR*) and signals from electromyography (*EMG*)

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