IoT-Enabled Analysis of Subjective Sound Quality Perception Based on Out-of-Lab Physiological Measurements

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Abstract. Sound systems are usually evaluated by means of subjective listening tests that allow to analyze the sound perception from the listener's point of view. In several situations and domains, listening tests can be expensive and complex to arrange, and different variables may influence their reliability, such as ambiguous terminology or contextual biases. To help mitigate these aspects, an analysis of subjective sound quality perception enabled by an Internet of Things - based approach is presented in this paper, exploiting the out-of-lab measurement of physiological parameters by means of a wearable device. In particular, a possible correlation between the subjective assessment of perceived sound quality and the variations of the Inter Beat Interval (IBI) in the cardiac activity of the listeners is analyzed, reporting the measurements performed by a wrist-worn device.

Keywords: Wearable device · Sound stimuli · Physiological signals · Sound quality perception

1 Introduction

Sounds and sound perception play a key role in human life as they allow to communicate with others, by means of speech and music, and also enable self-alerting and orienting when new conditions or events take place [16,27]. The same happens also in the animal kingdom: as an example, sounds are among the most relevant communication strategies for insects and bees [26].

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In humans, sounds generate reactions, usually in the form of emotions, the classification of which is a powerful tool for a wide range of applications, spanning from industrial to medical ones [14]. In initial studies aimed at investigating the human reactions to acoustic stimuli, the perceived emotions were evaluated by means of self-reports, facial expression and speech analytic [23]. However, these tools were not completely reliable to detect and classify the emotional changes perceived by subjects, and new approaches and analyses were developed, exploiting physiological signals processing. In fact, compared with facial expression, physiological signals represent a more reliable approach to probe the internal cognitive and emotional changes of users, even the hidden ones [5]. For this reason, in the last decades, researchers have tried to develop methods for the automatic recognition of individuals' emotional arousal, starting from the physiological changes [25]. Indeed, since the Autonomic Nervous System (ANS) regulates the emotions producing variations in Heart Rate (HR), respiration rate and sweat secretion, the physiological changes are considered reliable to examine the psychological and emotional statuses of subjects [1].

The collection of physiological signals and the analysis of the variations induced by acoustic stimuli may be applied not only with the aim to recognize the corresponding evoked emotions, but also to develop automatic and quantitative approaches to classify the subjective sound quality perceived by the listeners [19]. Sound quality metrics can be classified into those that quantify some objective aspects of the sound (e.g., pressure level and frequency content) and those that try to quantify the sound effect at the listener's ear (e.g., impression of loudness, tone etc.). In general, subjective testing may involve a single person or many people; it includes the following steps: (i) presentation of sounds to listeners, (ii) judgment of those sounds from the listeners, based on the use of proper standardized scales, and finally (iii) appropriate statistical analysis on the obtained scores. Rigorous perceptual assessment has to be performed according to several standards, including ITU-R BS.1116-1 [9], ITU-R BS.1534-1 [10], and ITU-R BS.1284-2 [11], which define criteria for the selection of the listening panel, describe the test methodology and procedure, and also specify the statistical methods to elaborate the acquired data. Care has to be taken to prevent biased results, for example due to the context, which encompasses both the expectation and emotional state of the listener. In this sense, the acquisition of physiological signals from subjects, before starting the tests, creates the so-called baseline condition, hence the variations induced by the following sound quality perception may be quantified with respect to such a reference status, to limit the impact of bias as much as possible.

Subjective sound quality evaluation performed by means of efficient procedures could be very useful in several application fields, for example all those related to product sound design and quality evaluation (e.g., for appliances or electric vehicles): suitable and effective methods to quantify product sound quality could lead to great advances in the assessment process, and time-consuming studies involving test subjects could be replaced by objective models [4]. An additional advantage would be associated to the possibility of performing such type of tests by using wearable devices to collect physiological signals, instead of desk and laboratory equipment, that may be hard to move and adapt to different testing scenarios. Among the several applications and opportunities of the Internet of Things (IoT)-oriented technologies [13], the IoT devices, especially the wearable ones, support and enable the out-of-lab real-time collection of multimodal physiological data from subjects exposed to sounds and acoustic stimuli, in realistic and unconstrained conditions [24]. Based on the above considerations, this study focuses on the use of a wearable device, the IoT-enabled Empatica E4 multi-sensor wrist-worn one [6], to collect a number of physiological signals, aimed at the investigation of the variations associated to the perceived sound quality, tested from 15 subjects listening to six different types of audio tracks. In particular, the current work extends the preliminary findings presented in [19] and [18], which considered a few subjects, with the aim to explore possible correlations between the perceived sound quality and the variations of the Inter Beat Interval (IBI) in the cardiac activity of the listening subjects, measured by a wrist-worn device. Despite a not-so-huge test population, the outcomes confirm that listening to an audio track always triggers a reaction in the listener. Such response may be detected and recorded through a PPG sensor onboard an IoT-enabled wrist-worn device, allowing the analysis of the average IBI variation, and the corresponding quantitative evaluation of the perceived sound quality.

The paper is organized as follows: Sect. 2 presents the measuring device and the data collection protocol used in the study, while Sect. 3 gives details about the applied data processing procedure. Section 4 presents and discusses the experimental results obtained, and finally, Sect. 5 concludes the paper.

2 Materials and Methods

2.1 Measuring Device

As mentioned above, data collection was performed by using the Empatica E4 multi-sensor wearable device, the most relevant characteristics of which follow:

- Photoplethysmographic (PPG) sensor (sampling frequency: 64 Hz; resolution: 0.9 nW/Digit), measures the Blood Volume Pulse (BVP), from which heart-related parameters, namely the HR, Heart Rate Variability (HRV) and IBI, may be derived;
- 3-axis MEMS Accelerometer (sampling frequency: 32 Hz; resolution: 8 bit of the selected range), measures the continuous gravitational force (g) acting on each of the three spatial directions (X, Y and Z axes);
- Electrodermal Activity (EDA) sensor (sampling frequency: 4 Hz; resolution: 1 digit∼900 picoSiemens), measures the skin conductance changes related to Sympathetic Nervous System (SNS) arousal;
- Infrared (IR) Thermopile (sampling frequency: 4 Hz; resolution: 0.02 °C), measures the Skin Temperature (SKT) values.

In this study, data generated from all the available sensors were collected. However, only the HRV signals gathered by the PPG sensors were used for further investigation. The reason is that the HRV is considered the most meaningful indicator of the presence of an acoustic stimulus [3], and more in general, it is one of the most valid indicators of the autonomic regulation for the cardiac function, in response to any external stimuli [17].

2.2 Data Acquisition Protocol

The data collection process applied in each acquisition session is graphically shown in Fig. 1.

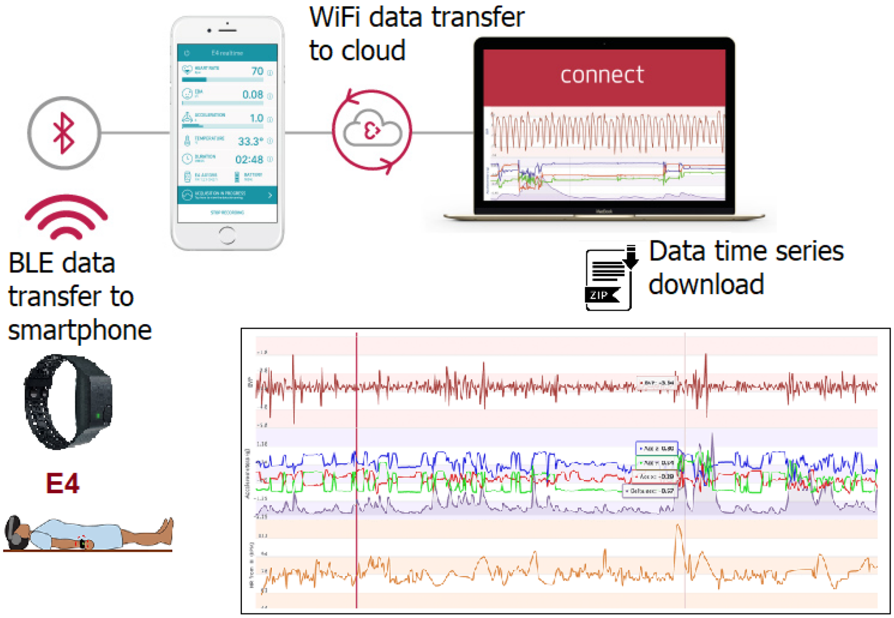

Fig. 1. The E4 IoT-enabled physiological data acquisition process: following the measuring session, data can be downloaded from the Empatica Connect cloud platform.

Experimental tests involved a listener panel of 15 participants (9 males and 6 females, aged between 18 and 60 years), referred to as S1 to S15 in this paper. Each of them performed six test sessions including the following steps:

– *Baseline acquisition* $[t_0; t_1]$: the subject stands in a quiet and relaxed condition for 10 min, during which the physiological parameters are collected. The corresponding signals provide the reference baseline condition;
– *Listening to audio clip* $[t_1; t_2]$: the subject listens to a 40 s-long audio clip, representing the acoustic stimulus in response to which a change in the physiological values is expected;

– *Paper-based evaluation* $[t_2; t_3]$: in the 3 min following the audio clip, the subject is requested to fill in two paper-based evaluation sheets. Firstly, the 100-point continuous quality linear scale (CQS) divided into five-grade sub-scales labelled (from the lowest to the highest) as: bad, poor, fair, good and excellent, as mentioned in the ITU-R norms; secondly, the 9-point Self-Assessment Manikin (SAM) [2] questionnaire to rate the valence and arousal evoked by the external stimulus, by a pictorial tool.

Based on the above description, it follows that each experiment includes a pre-stimulus phase (referred to as *baseline*) lasting 10 min, and a post-stimulus phase (referred to as *reaction to stimulus*), which includes 40 s of audio stimulation, and 3 min without stimulation. Six audio tracks, different in terms of valence (i.e., pleasant and unpleasant), were proposed to each subject: (a) buzzing bees (i.e., buzz of bee swarm), (b) music (i.e., electric guitar and piano cover), (c) distorted music (i.e., distorted electric guitar and piano cover), (d) white noise (i.e., random noise with equal amplitude at different frequencies), (e) rain (i.e., falling rain), and (f) snoring (i.e., human snoring). Each sound was played through headphones to reduce possible subject's distraction during the test.

The time sequence of steps described above is shown in Fig. 2: during all the experiment, the IBI values are measured from the subject, by the Empatica E4.

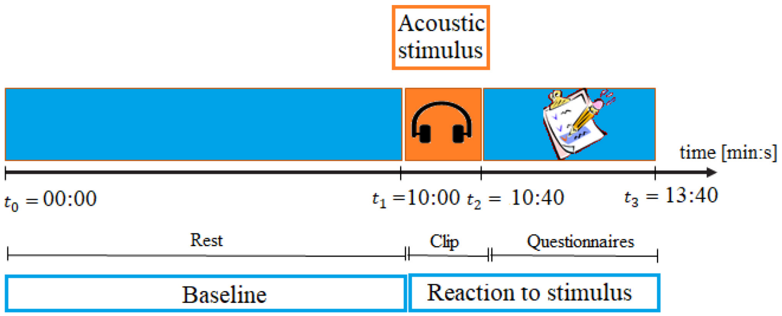

Fig. 2. Time sequence of the IBI measurement steps arranged in the data acquisition protocol.

3 Data Processing

Each element in the IBI parameter values series, for each subject, is obtained as the time distance (in seconds) between two consecutive peaks founded in the corresponding BVP signal, generated by the PPG sensor onboard the E4, which is measured on the wrist and reflects the peripheral blood circulation. Such a process is described in Fig. 3.

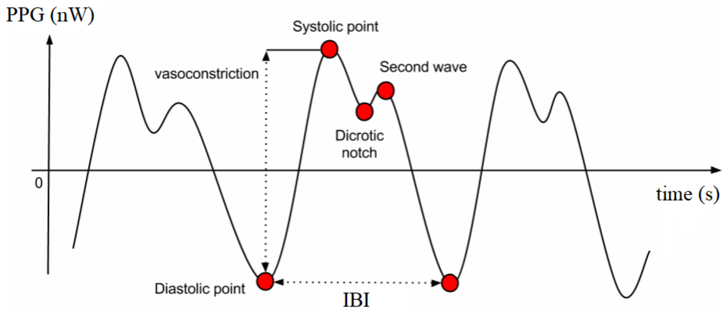

Fig. 3. Computation of IBI values from the signal generated by the PPG sensor (elaborated from https://support.empatica.com/).

For each recording, the average IBI measured during both the *reaction to stimulus* and the *baseline* acquisition (pre-stimulus condition) intervals were computed, and their difference (denoted by *Delta* and measured in seconds) considered to evaluate their corresponding physiological variation due to the specific audio track listening.

4 Results and Discussions

A first set of results obtained from experiments refers to the difference (*Delta*) between the average IBI values measured following the stimulus and those obtained before the stimulus, evaluated for each subject and for the six different audio tracks used. The whole set of results is given in the graphs of Fig. 4.

As a general remark, it is possible to notice how, for each audio clip, the majority of the subjects exhibits a positive *Delta*, meaning that following the acoustic stimulus, the average IBI increases and the average HR decreases. The highest increase of the average IBI (greater than 0.06 s, corresponding to a variation of the HR of approximately 3.6 bpm) is obtained from tests involving the (a) *bees*, (d) *white noise* and (e) *rain* audio tracks, for different subjects (S8, S15 and S14, respectively). Typically, the increase of IBI values, and consequently the decrease of HR ones, indicates effective relaxation state [22]. This trend is mostly evident for those cases in which the frequency of positive *Delta* values over the whole population is high, namely when the participants listen to the (a) *buzzing bees*, (b) *music* and (d) *white noise* tracks. This means that the listeners were in a relatively relaxed state. A preliminary insight shows that, contrarily to what often can be thought, the *buzzing bees* and the *white noise* sounds can have a relaxing effect on the listeners, probably because both the sounds have the same intensity, and constant variance during all the track duration. Being both these sounds evaluated as pleasing, they are often promoted for raising the serenity in the listener. In fact, many researchers recommend the ‘contact with

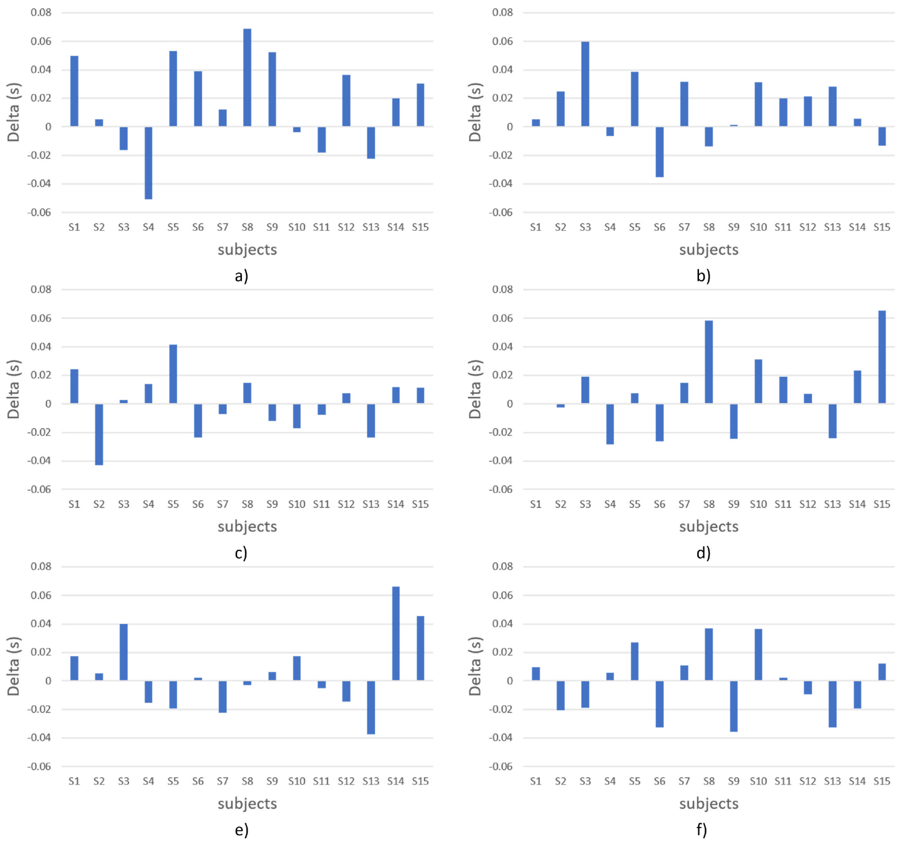

Fig. 4. Difference *Delta* (in seconds) between the average IBI measured after and before the stimulus, for each subject and for the six audio tracks used in experiments with listeners: (a) bees, (b) music, (c) distorted music, (d) white noise, (e) rain, and (f) snoring.

nature' in order to experience the sounds of birds or insects [15,21]; similarly in [8], the authors used the white noise for reducing anxiety in coronary care patients. Concerning the *music* clip, the reason can be referred to the fame of the pop song proposed during the tests.

On the other hand, the decrease of the average IBI value with respect to the baseline is often associated to a stress condition, showing that the subject is stimulated by an external and/or internal event [12]. This is what happens in some cases of our study, where the post-stimulus average IBI decrease is also present, mostly for the (c) *distorted music* (7 subjects out of 15), (e) *rain* (7 subjects out of 15) and (f) *snoring* (7 subjects out of 15) audio clips. These acoustic stimuli determine a reduction of the average IBI, so an increase of the subjects' average HR, even if, again, it does not always happen for the same subject. The maximum decrease of the average IBI is 0.05 s (found only for track (a) in subject S4), corresponding to an average increase of the HR of approximately 3 bpm. As expected, the stress condition is mostly moved by the sound tracks typically perceived as annoying ones. Generally, the sound of rain is associated to a relaxing condition [28], however both the storm and the thunder included in the (e) *rain* track may have modified the general user's emotional perception, activating the SNS and causing an increase of average HR in almost half of the subjects.

The same results may be looked at from the perspective of each subject, as given in Table 1.

Table 1. IBI variation (*Delta*) for each subject involved in tests, and for each audio track: (a) bees, (b) music, (c) distorted music, (d) white noise, (e) rain, and (f) snoring. Symbols: + means positive variation, − negative variation, and 0 no variation.

Subject \ Track	(a)	(b)	(c)	(d)	(e)	(f)
S1	+	+	+	0	+	+
S2	+	+	−	+	+	−
S3	−	+	+	+	+	−
S4	−	−	+	−	−	+
S5	+	+	+	+	−	+
S6	+	−	−	−	+	−
S7	+	+	−	+	−	+
S8	+	−	+	+	−	+
S9	+	+	−	−	+	−
S10	−	+	−	+	+	+
S11	−	+	−	+	−	+
S12	+	+	+	+	−	−
S13	−	+	−	−	−	−
S14	+	+	+	+	+	−
S15	+	−	+	+	+	+

From this point of view, it is evident as the S1 is an outlier with no variation between the baseline acquisition and the reaction to the (d) *white noise* stimulus. All the other subjects exhibit either positive or negative variations between the two acquisition time intervals. As an example, subjects S4, S6 and S13 show a prevalent decrease of the average IBI, so they exhibit an increase of their HR for at least 4 out of 6 audio tracks. The track (d) *white noise* is the only one which gives a reduction of the average IBI for all these three subjects.

Moreover, regarding the (a) *buzzing bees*, it can be noticed that all females (S1, S5, S7, S8, S9, S15) presented a positive *Delta*, while for males a few of them (S2, S6, S12, S14). Similarly, the majority of males (S2, S3, S6, S12, S13, S14) presented a decrease of average IBI value listening the *snoring* track, against only one female (S9) out of six.

During experiments, subjects were asked to fill in a paper-based evaluation of the perceived sound quality (CQS evaluation), joint with classification labels generated by using the standardized SAM scale, to identify themselves with five different pictographs (scoring from 1 to 9) over two dimensions, namely Valence and Arousal. The results obtained are shown in Fig. 5, for each audio track and for all the subjects involved in tests. As it is evident, the (c) *distorted music* sound track is mostly evaluated as bad or poor sound quality (dots color is red or orange) by 3 subjects (S4, S13 and S5) who scored an Arousal lower than 5 (corresponding to neutral score), while higher than 5 in 6 subjects. On the other hand, the Valence is perceived differently among the participants: the score is lower than 5 in 6 subjects, higher than 5 in other 6 subjects and equal to 5 in 3 subjects. Oppositely, the (b) *music* exhibits only positive (i.e., good or excellent) evaluation (dots color is blue or green) of the perceived sound quality, while (e) *rain* and (f) *snoring* exhibit mostly positive evaluation (with the exception of two fair evaluations -dots color is grey- given by S3 and S14, respectively). In particular, (b) and (e) show a very high Valence score (especially (b) for which all the subjects gave a score higher than 5, while in (e) two subjects - S2 and S9 - declared both low Valence and Arousal). Concerning the (a) and (d) tracks, the wide spread of dots, in terms of color and position in the plane, represents an obvious different perception of both the quality and evoked emotion by the participants.

Tracks associated to the lowest frequency of positive *Delta* values (see Fig. 4) were evaluated by all the participants as of good/excellent sound quality (i.e., (e) *rain* and (f) *snoring*) or bad/poor sound quality (i.e. (c) *distorted music*). This implies that sounds with a perceived good or bad quality are more likely to be associated to a decrease of average IBI, thus an increase of average HR, than sounds for which quality evaluation is blurred and diverges among the participants. However, the *Music* clip represents an exception. Indeed, although the sound quality was evaluated by all participants as good/excellent, 11 subjects out of 15 (highest frequency) presented positive *Delta* values. As mentioned above, a possible motivation is related to the emotional effects induced by the fame of the pop song proposed.

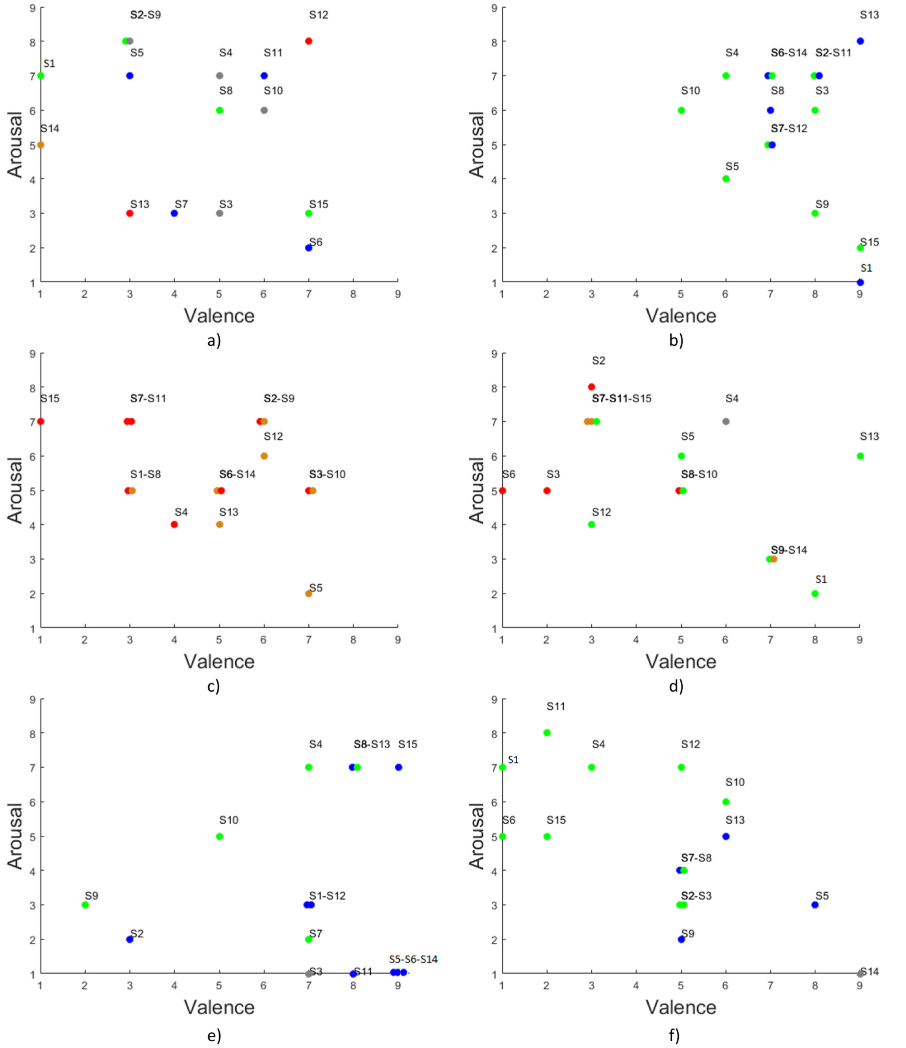

Fig. 5. Valence and Arousal assessment by SAM scale (values from 1 to 9), joint with CQS evaluation (dot color: red = bad (0–20), orange = poor (20–40), grey = fair (40–60), green = good (60–80), blue = excellent (80–100)), for all the subjects and the different audio tracks: (a) bees, (b) music, (c) distorted music, (d) white noise, (e) rain, and (f) snoring. (Color figure online)

5 Conclusion

This paper presented the preliminary results obtained on a population of 15 test listeners involved in the evaluation of the perceived sound quality of six different audio tracks. Such evaluation has been performed by measuring the changes in physiological parameters related to the cardiac activity of each listener, by means of a wearable and IoT-enabled device.

First of all, it is possible to say that listening to an audio track almost always generates a reaction in the listener: the *Delta* between the average IBI values measured following the stimulus, and those obtained before the stimulus, equals zero in just one case out of 90 tests run in total. Then, as a second remark, it is shown how some audio tracks are related to an increase of *Delta*, corresponding to a relaxing effect, and others are associated to a reduction of *Delta*, i.e., a stressing stimulation. It is of interest to observe how different natural sounds, such as buzzing *bees* and *rain*, exhibit opposite reactions from the listeners: relaxing the former, and stressing the latter. Probably, this trend is influenced by the nature of the two sound clips proposed. Indeed, concerning the (a) buzzing *bees* stimulus, this sound can be associated to constant variance in time, like the white noise, that is considered relaxing; on the other hand, during the (e) *rain* stimulus a thunderstorm, an event that generally scares and stresses individuals, arises suddenly.

Secondly, we investigated a possible relationship between the emotional reaction evoked by each audio track, and evaluated by the Valence-Arousal quantification through the SAM scale, and the corresponding CQS scoring, which is typically applied in sound quality tests according to specific technical recommendations. While it is not possible, at this stage, to obtain a general conclusion regarding the different audio tracks, we can observe how sounds with a commonly perceived good or bad quality are more likely to be associated to a decrease of average IBI, than sounds for which quality evaluation diverges, despite being associated to a quite different perception of the evoked emotions by the participants.

The importance of the investigated aspects is clear in the healthcare context. Music is quite often used to ensure the well-being in several daily settings (e.g., home, shops and hospitals), working as therapy or support to reduce stress, anxiety, patient's pain and improve the quality of sleep [7,8,20].

The preliminary results presented in this paper motivate the further development of this research, aimed at increasing the population of listeners participating in test sessions, to reinforce the findings and to achieve more general conclusions about the relationship between perceived sound quality and measurable changes in physiological parameters. Moreover, a multimodal physiological system (including, for example, skin conductance, heart rate variability and temperature) may help in improving the outcomes of the evaluation.

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