Effects of Physiology-Based Interaction on Collaborative Performance

A study using a tabletop system for sound generation and control.

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Abstract

Physiology-based systems have lead to implicit interaction models where signals coming from the human body are used to control devices and applications by means different to muscular movement or speech. However, most of these systems are focused on single-user modes, and its application in collaborative scenarios is still scarce. In this project we present a system for collaborative sound generation and control built from a Hybrid Brain-Computer Interface device (BCI) featuring Electroencephalogram (EEG) and Electrocardiogram (ECG), and the reactable, a music instrument based on a Tangible User Interface (TUI). We assessed collaborative performance and motivational variables in a task-oriented experiment based on the imitation of pre-recorded sound references. Measures were obtained through self-reported questionnaires. Teams of subjects with no previous experience on the reactable used two different methods for sound generation and control: implicit interaction, through physiological signals (EEG & ECG), and implicit interaction by means of physical manipulation.

The study has revealed four main effects of physiology-based interaction applied to a collaborative performance in a TUI. (1) Teams working with a combination of implicit and explicit models of interaction declared less difficulty and greater ease to solve the tasks. (2) They also shown higher levels of confidence during the performance. (3) The distribution of control and leadership was balance and didn't show significant difference between the two proposed interaction paradigms. (4) Teams have shown a significant correlation in key aspects for collaboration, such as confidence and motivation over time.

These findings suggest that the physiological signal extraction and processing implemented in this system could be linked to subtler descriptors related to affective states, emotional responses or music perception, allowing more advanced and stable methods for sound generation and control. We also propose to include previous training sessions, and carrying on experiments with musicians to test the expressiveness of the proposed system.

This work presents a friendly configuration for a collaborative sound composition experience. It encourages the development of Computer-Supported Collaborative Systems where subtle sources of information such as physiological states effectively support an explicit model of interaction, as in the case of tangible tabletops interfaces, by means of non-invasive, wireless devices that preserve adequate conditions for live performance.

Keywords: Physiology, Brain-Computer Interfaces (BCI), Computer-Supported Collaborative Work (CSCW), Tangible User Interfaces (TUI), tabletops, reactable, sound generation, sound control, sonification, biofeedback, interaction, music.

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1. INTRODUCTION

1.1 Problem Statement

In recent years, physiology-based systems have lead to implicit models of interaction where user's physiological signals, such as brainwave activity, skin response or heart rate, are monitored, mapped and transformed in commands to control devices and applications [39]. This interaction paradigm is based on internal states of the human body and has been explored by several disciplines such as cognitive psychology [37], neuroscience [60,28], affective and physiological computing [40,2], and Human Computer Interaction (HCI) [3,19].

However, most of the physiology-based interaction studies are focused in single-user modes, while its application in collaborative scenarios or in Computer-Supported Collaborative Work (CSCW) is still scarce. The use of BCI systems and other physiology devices for rehabilitation of motor-impaired subjects commonly requires individual conditions of use and isolation [60], but its application in healthy users as a mean for communication and control is still tested under similar scenarios [8].

In this project we propose the implementation of implicit interaction through a BCI device in a multi-user environment for collaboration. With this aim, we have developed an interactive tabletop system for real-time sound generation and control, which presents both implicit and explicit models of collaboration. The implicit model is based on a BCI that measures electroencephalogram (EEG) and electrocardiogram (ECG) for real-time sound generation and control. The explicit model, on its turn, uses the reactable [21] an interactive music instrument based on a tabletop surface and tangibles objects for music creation and live performance. The reactable has been widely tested in collaborative scenarios for music, education and entertainment purposes [45].

This Hybrid Interface, shaped by a BCI device and the reactable, presents a sound-processing model mainly dependent on physiological measures, which is the base of the implicit interaction we propose. The relation with the explicit interaction model is given by the dynamic linking and modular control of the reactable [19], which allow direct control and sound generation by manipulating tangible objects (pucks) on the surface of the table. Inspired by this, we have connected the physiological signals to new tangible objects that we have called the *physiopucks*. This method allows explicit representation of physiological states through both sound and physical objects, and also permits a collaborative musical experience with direct manipulation by multiple users, simultaneously.

To test the effect of physiology-based interaction in the collaborative music system, we carried on experiments based on collaborative tasks between pairs. The couples included a Standard User (sound generation and control through tangible manipulation) and a Physiology User (sound generation and control through physiological signals). The assessment method was based on declarative measures of performance and motivation during the collaborative music performance.

1.2 Physiology-based Interaction and Collaborative Performance. State of the Art.

a) Interaction and physiological states.

The monitoring of physiological states is commonly used in the study of cognitive processes such as affect [14], attention and decision-making, strategic planning, and learning.

Two key aspects of appraising human physiological signals are the sensing systems and the recognition techniques [16], which are used for adapting the system's response accordingly to specific states, or for providing a coherent feedback to the users. Several methods are applied for this kind of recognition. EEG, ECG, electro-oculogram (EOG), respiratory patterns and electro-dermal activity are widely used for physiology recognition [2], especially due to the recent improvements in sensing and monitoring systems.

Devices for physiological measure are becoming less invasive, unobtrusive, and apt for real-time operation, even in daily life environments [29]. Therefore, adding a physiological and implicit component to human computer interaction is possible through wearable devices that support skin-surface sensing and long-term monitoring [41]. This scenario has encouraged the use of physiological interfaces for rehabilitation treatments of motor-impaired patients [60], but also in healthy or temporal disabled subjects [3,13]. Physiological computing has been used with entertainment purposes, such as videogames [4,11], training systems for attention and relaxation [34], and control of brain rhythms trough biofeedback [42].

b) Physiology and collaboration.

Physiological states are multidimensional phenomena that involve the human nervous system and its relation with the surrounding environment. The importance of *real world scenarios* has been tackled by multimodal approaches in HCI [38] that highlighted the necessity of a context-sensitive analysis of human behavior. Certainly, collaborative experiences are one of those cases in which communication between participants is critical for a successful task achievement in order to reach optimal performance, synchronization and anticipation. In the same line, works on perceptual interfaces [57] aims to develop technologies based on the rules of human-human interaction and its physical and social context. This approach has lead to more intuitive models of group interaction, based on everyday knowledge.

But, what is the role of physiological states in collaborative experiences? Collaborative scenarios can be defined as activities organized among groups in which individuals interact with others in order to achieve a better productivity or performance [46], both factors being extreme sensitive to the information available in the collaborative environment. This dependence can be solved by means of different sources of information: explicit (factors such as the physical context of interaction and body gestures) and implicit (partner's internal states such as emotions, cognitive process, attention guidance, etc.). Whereas the former is represented in the physical world as a repertoire of information commonly accessed through the senses, the latter is guessed by perceiving (mostly through vision) physical and body cues, over which processes of anticipation, synchronization and decision-making are executed. Physiological states are a key part of this repertoire of implicit information of human behavior in collaborative experiences, and by means of wearable computers ready to transform physiological signals from the human body into real-time inputs, it is now possible to provide an explicit representation of such a subtle process (see figure 1).

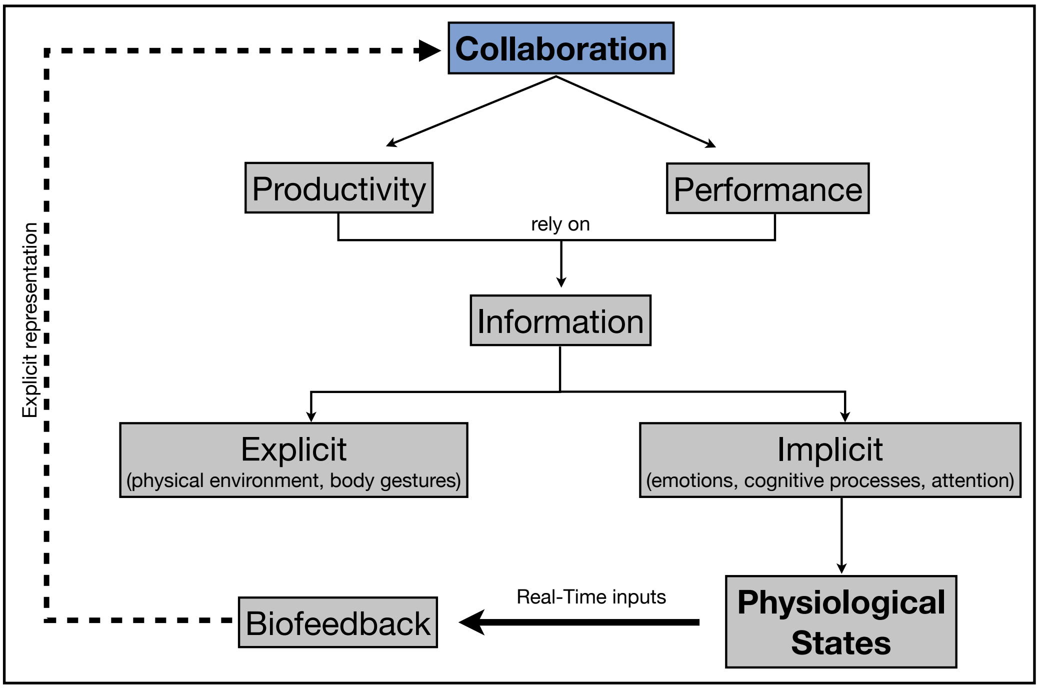

Figure 1: The role of physiological states in collaborative experiences.

c) Physiological Sonification.

Together with sensing and signal recognition, an expressive model is needed to properly map a specific physiological state to an explicit representation or biofeedback [2]. This expressivity can be achieved through auditory display techniques such as sonification, which generates a signal representation by means of sound [15]. This method allows subjects to perceive the complexity of subtle and emerging physiological processes by listening.

Researches on electronic music systems were pioneer in the implementation of devices based on bioelectric signals. Since the first biofeedback techniques implemented by Rosenboom during the mid-seventies for electronic music control [48], much work has been done in the field of music and physiological sensing. Some of the first experimental physiological devices for musical application include the *Music Activated Danced Directed Music* (MADDM)[12], which translated the movements of a dancer into synthesized sounds through myoelectric signals; or Biomuse [55], that was also based on synthesized music and offered different configurations for music and rehabilitation purposes using EMG, EEG and EOG (see figure 2).

Figure 2: Atau Tanaka performing with BioMuse at the Manca Festival (1995) [55:392]

1.3 Brain-Computer Interfaces for Music and Sonification. State of the Art.

a) Defining Brain-Computer Interfaces

A Brain-Computer Interface is a system that transforms signals originating from the human brain into commands that can control devices or applications [39]. It provides a nonmuscular communication channel that has been widely used in motor rehabilitation and in patients suffering other neurological injuries. While for disable subjects this represents a medium of action and communication with their physical environment, nowadays these devices also permit healthy people to change and enhance their experience of the everyday world by means different to speech and body gestures (see figure 3).

A BCI use a variety of electrophysiological signals as input data, such as cortical potentials, evoke and event related potentials (ERP) measured using skin-contact or implanted electrodes. Through signal processing, it is possible to extract specific features of EEG and use them to control computer devices. Audiovisual stimuli and motor imagery are sources of change in neural activity patterns that can be measure in real-time through EEG. Selective attention and concentration also alter different brain signals of evoked potentials that can be used as an input for a BCI. The most common applications of BCI systems are rehabilitation for motor-impaired subjects, control of neuroprosthesis, neurofeedback therapies, virtual reality [29] and videogames [11].

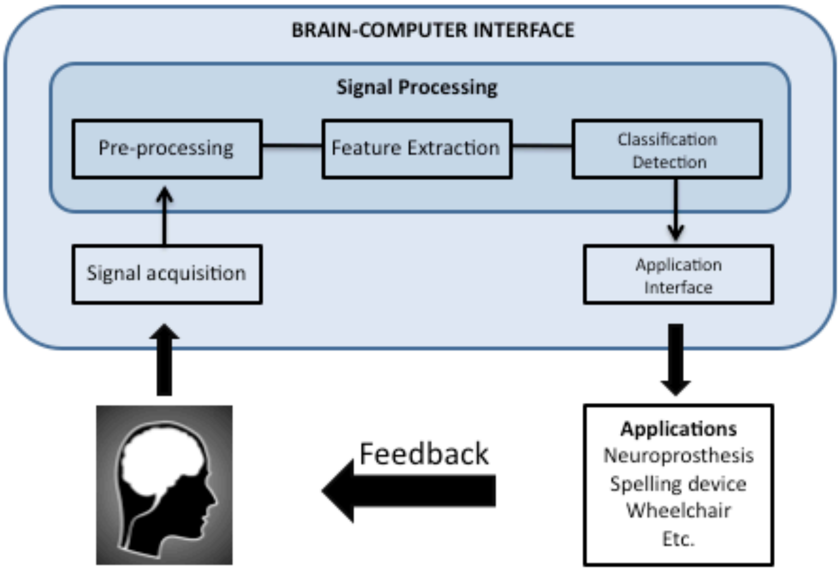

Figure 3: Diagram of a BCI system. Signals from the user's brain are captured and processed to extract specific features used for classification. The classified output is used as a device or application command, which also provides feedback to the user (Based on 39:369).

b) Historical account of BCI and music

The first measurement of human brainwaves was made in the 1920's by Hans Berger who termed it *Elektrenkephalogramm,* a brain electricity writing [5]. In the 1970's Jacques Vidal worked on the first attempt toward a BCI system [58] but it wasn't till the 1990's when the field started to make significant progress in the realm of human-computer interaction. At that time, Wolpaw et al. developed a BCI system, which allowed the control of a computer cursor using EEG's alpha levels [59].

Regarding BCIs for musical applications, a paper by Adrian & Matthews [1] from 1934 reporting a method for listening to the EEG, based on Berger's founding's, can be considered as one of the first references in the field. However, the first relevant achievement on BCI applied to music belongs to Alvin Lucier, who composed the first musical piece using EEG: *Music for Solo performer* in 1965 [30]. In [48] David Rosenboom -early pioneer on the field of musical interfaces with the human nervous system- considers Lucier's work as one of the first applications of physiological signals and biofeedback in the arts that achieved a direct mapping of a soloist's alpha rhythms onto the orchestrational palette of a percussion ensemble. On the other hand, Richard Teitelbaum's *Organ Music* and *In Tune*, both realized in 1968, added heart beat and breathing sounds to EEG signals in the creation of electronic music textures [56].

In the 1970's, Rosenboom began his own research on EEG for generating music content [48] under the hypothesis that it might be possible to detect certain aspects of the musical experience in the EEG signal. In his attempt to go beyond direct signification of EEG signals and, instead, use these to *create music*, he developed *The Performing Brain* [47] and *Portable gold and philosophers' stones (Music from Brains in Four* (figure 4)*,* in which he introduced a musical system whose parameters where driven by EEG believed to be associated with shifts of the performer's selective attention. From 1970 to 1971, Rosenboom worked on an audiovisual demonstration-participation-performance event entitled *Ecology of the Skin* [48] that involved biofeedback monitoring of brainwaves, and heart signals from performers and audience that were translated into musical textures.

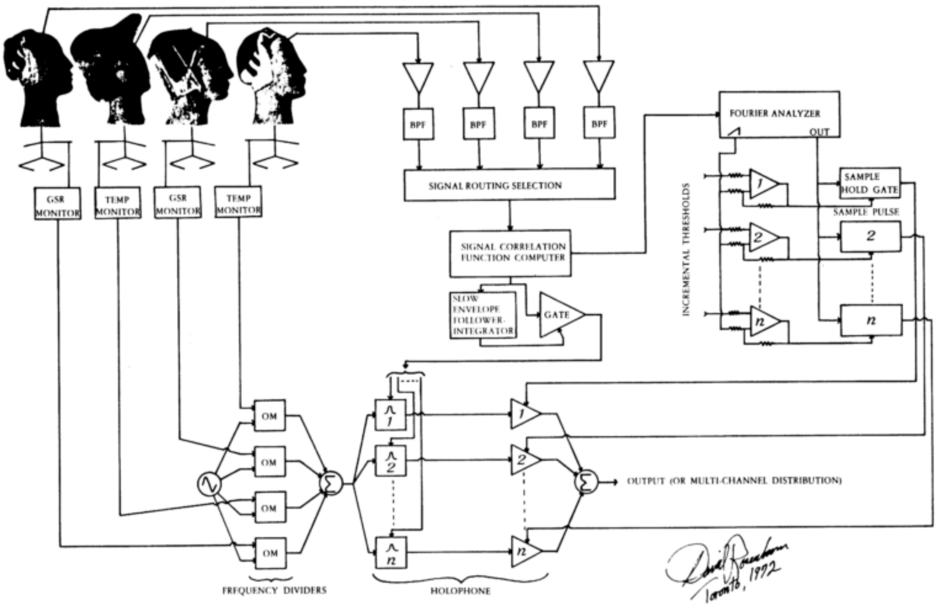

Figure 4: System diagram for Rosenboom's *Portable gold and philosophers' stones (Music from Brains in Four) (1972)*. Score of a musical composition that includes measurement and analysis of EEG signals, GSR and body temperature changes from a quartet of performers [48:24]

Recently, Miranda et al. have worked on protocols to associate EEG-acquired data with musical imagination [34], reporting new techniques and devices, such as the Brain-Computer Music Interface (BCMI) *Piano System* [32] that *trains* the computer to identify EEG patterns associated with specific cognitive musical tasks. Miranda and Soucaret also developed a BCMI to control a generative system for music mixing [32].

c) Categories of BCI systems

Authors agree on the existence of many well known and easily detectable neural events, such as visual evoked potentials, slow cortical potentials, P300 events and imagined movement [26,28,39]. However, researchers like Swift et al. [54] and Allison et al. [3] states that the neural events which form the basis of BCI communication often have very little to do with the goals or interaction metaphors of the interface itself (e.g. in selecting letters for text composition, participants may be required to repeatedly imagine moving their left or right feet [25]). Swift et al. call these types of interfaces *Artificial BCIs* [54]. At the other side of the BCI spectrum they locate those designs that presents a direct and intuitive relationship between the neural events to be detected and the purpose of the interface. According to Swift and colleagues, these *Natural BCIs* are based on more abstract measures of cognitive processes such as attention, emotion and creativity. Therefore, BCIs offer interesting possibilities for electronic music composition and performance, as measurements of neural activity can be used either to complement or to replace musical input devices such as MIDI controller or keyboards.

According to this line of analysis, most of the current musical BCI systems have primarily taken an artificial BCI approach: a participant is trained to perform standard artificial BCI “tricks”, and the resulting measures are used to control or modulate the output of a music generation engine.

Miranda, Durrant and Anders have proposed three main categories of BCI systems [33]:

1. *User oriented BCIs:* the computer adapt to the user by *learning* to associate specific EEG patterns to control a device (e.g. a wheelchair).

2. *Computer oriented BCIs:* the user adapts to the computer. Users learn to control specific aspects of the EEG signal acquisition, affording them the ability to control events on the environment (e.g. selecting letters for writing words).

3. *Mutually oriented BCIs:* combine the functionality of both previous categories: pattern classification and biofeedback (e.g. moving a pointer on a computer screen).

The authors states that the great majority of BCI projects applied to music controlling associate specific EEG characteristics (e.g alpha rhythms) to particular musical actions, which means computer oriented systems where the user needs to learn to control their brainwave generation.

d) Main challenges of BCI systems.

For those researchers working on BCI technologies *for the real world* [35,3], most of the existing BCI applications were designed largely for training and demonstration purposes. On [35] Moore et al. describe four main challenges inherent in employing BCI for real-world tasks:

- *Information transfer rate* (bandwidth): transfer rates for experienced subjects and well-tuned BCI systems are relatively low, in the vicinity of 24b (roughly three characters)/min.
- *High error rate*: a significant complicating factor in the slow information transfer rate of BCI users is the high probability of errors.
- *Autonomy*: BCI systems require extensive assistance from caretakers who need to apply electrodes or signal-receiving devices before a user can communicate. Furthermore, most BCI systems are system-initiated, meaning that the user cannot turn them on and off independently. This results in what is termed the *Midas touch problem*—the BCI system interprets all brain activity as input, so how can the user communicate the intent to control the system?
- *Cognitive load:* Most BCI systems are tested in quiet laboratory environments, where users are able to concentrate on the task at hand with minimal distractions. BCI users in the real world have to deal with much more complex situations, including the cognitive load of the task being performed, emotional responses, interactions with other people, and possibly even safety considerations.

Regarding BCI and music, Miranda et al. [33] strive for a new research area on BCMI that involve three major challenging problems:

- The extraction of meaningful information from signals emanating directly from the brain, to reach control beyond the standard EEG rhythms
- The design of generative music techniques that respond to such information.
- The training of subjects to use the system.

The authors states that this trend on BCI research for musical creation will satisfy the necessities of a wide range of users: people with special needs and disabilities (permanent or temporal by carrying on specific tasks), music performers, composers, among others.

1.4 BCI devices that inspired this project.

a) The BCMI-Piano System.

BCMI-Piano [34] is a BCI computer oriented system that looks for information in the EEG signal and match the findings with assigned generative music processes. It has four main modules (figure 5):

1. *Sensing*: 7 pairs of EEG electrodes (bipolar montage) that sense the whole surface of the cortex.

2. *Analysis*: generates 2 streams of control parameters: (1) Prominent frequency band in the signal, used by the music engine to generate the sound: two styles depending on whether the EEG indicates salient alpha levels (8-13Hz) or beta levels (14-33Hz) (2) Complexity of the signal, using Hjorth signal complexity analysis. The music engine uses this information to control the tempo and the loudness of the music.

3. *Music engine*: contains the generative music rules. Each rule produces a musical bar or half-bar.

4. *Performance module*: plays the music using a MIDI-enable acoustic piano.

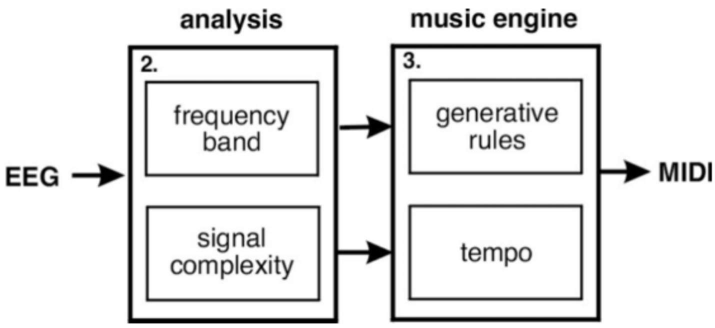

Figure 5: BCMI-Piano modules: (1) Spectral information is used to activate a music engine. (3) Generative music rules are applied to compose music on the fly, and the signal complexity is used to control the tempo of the music [34:3].

The software engine generates music using rules extracted from given examples (transition matrix of what-follows-what), which allow a simple method to generate musical phrases with a beginning and an end determined by EEG information.

Miranda also proposed a Generative Music System based on Constraints Programming [32]. A Constraint Satisfaction Problem (CSP) consists of a set of variables and mathematical relations between them, which usually presents a combinatorial problem; and a constraint solver may find one or more solutions. In the system proposed by Miranda, the user can define a wide range of musical CSPs, including rhythmic, harmonic, melodic and contrapuntal problems, like a set of "score objects". Hypothetically, the system receives the stream of pairs from EEG analysis data, which controls higher-level aspects of a forthcoming chord progression. The first value specifies whether a progression should form a cadence (cadence progression) or a chord sequence without any recognizable key (key-free progression). If the next progression is a cadence progression, then the key of the cadence is specified by the second value of the pair.

b) The Neural Music Software.

The Georgia State University BrainLab has developed *The Neural Music Software* [35] to translate brain signal and brain-signal patterns directly to Musical Instrument Device Interface (MIDI), allowing a tonal representation of the signal. The software has also been ported to Wadsworth's BCI2000.

c) Mind-Modulated Music.

The Mind-Modulated Music (MMM) [54] is a BCI system designed by Swift and colleagues, which attempts to harness the *natural* brain activity of musicians to mold and modulate music, as it is being composed and played. This computer music instrument is part of a system, the Mind Attention Interface, which provides an interface to a virtual reality theatre using measures of a participant's EEG, eye-gaze and head position. The theatre itself, and its spatialised sound system, closes a feedback loop through the participant.

In the MMM, the authors describe a different approach to the design of a music BCI system, which differs from other interfaces in the types of neural activity that is detected and how it is used to generate music. This approach is based on measurements of functional connectivity between brain regions.

Evidence of functional connectivity as an indicator of musical processing activity in the brain has been noted in [6], where musicians and non-musicians were monitored using an EEG system while listening to music. The results showed a statistically significant difference between the two groups, and give rise to the possibility to use real-time measures of functional connectivity as a feedback loop for music generation and control, which don't derivate directly from the neural activity of the subject.

In the MMM, The musical attention in the *biomusician's* brain can be used to inform the quality or characteristics of the generated music. The music engine can then generate music that varies along some dimension. A mapping between parameters in a particular time-window was used to govern the evolution of the generated music.

In the MMM, musical variation has been indexed using *Tonnetz*, a topological representation of the 12 different notes of the musical scale (Figure 6). Its structure provides a quantifiable relationship between different harmonic triads. Therefore, the MMM music engine generates music by taking biased random walks around the chord triads of the Tonnetz to generate chord progressions for improvisation in the marked progression region. As χ increases, the harmonic walk becomes more expansive. Once the walk strays outside the region, the current chord becomes the new root of the progression, and the scale for improvisation is redefined.

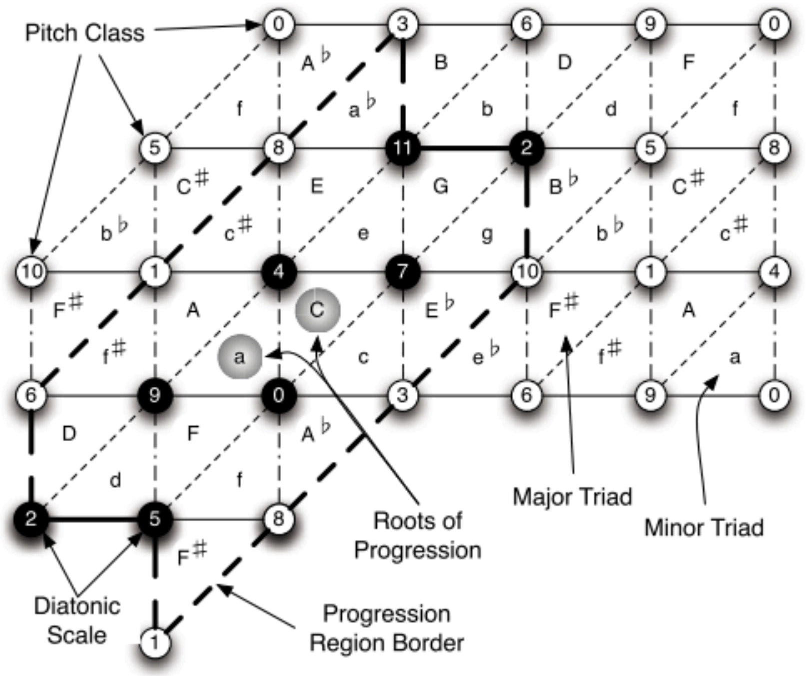

Figure 6: The Tonnetz. Visual representation [54:86]

Using this method, a *biomusician* can control a musical stimulus merely by attending to it, or concentrating on it. Through this mean, the natural musical sensibility and cognitive tools of the musician are responsible for the modulation of the music.

1.5 Interactive Tabletop Systems for Collaborative Experiences. State of the Art.

Several research studies have highlighted the potentials of tabletop devices as collaborative surfaces. The possibilities for co-located and co-present collaboration opened by this type of TUIs have been explored in several fields such as Computer-Supported Collaborative work (CSCW) [50], learning [43], collaborative design [23], interactive storytelling [52] and collaborative scenarios for children [51].

Although collaboration through physical representation is considered one of the most important characteristics of tangible and tabletop interfaces, some authors have noticed the lack of a framework for a *collaboration-sensitive design* on TUIs [31]. Evaluations and assessment methods often focus in individual use during task-oriented tests, without providing clear results regarding the success of tangible systems in multi-user and collaborative scenarios.

Several authors have proposed taxonomies for tabletop and tangible interface design [17,10], but these have been mostly descriptive and focused on system characteristics or functionality. Other researchers have analyzed collaborative experiences in tangible interaction, expanding the scope of TUIs through the interplay of physical and social experience [31]. Notions such as *shareable interfaces* propose interaction models centered in collocated groups of users and shared physical surfaces for collaboration [9]. These trends on tangible interface design represent a conceptual framework for collaborative learning and CSCW, encouraging the exploration of the collaborative potentials of tangible interfaces, compared to WIMP (Windows, Icons, Menus and Pointer) technologies and other traditional Graphic User Interfaces (GUI) based on single-user models.

Action-centered perspectives on tangible interaction, as an alternative to data-centered approaches, also put emphasis in the collaborative use of such interfaces, offering a framework for meaningful and control of digital data in shareable surfaces [9]. This model highlights the importance of the context and the physical settings in the definition of a tangible interface for collaborative activities. Following this line, several researchers are studying the potential of TUIs in the interplay of social, affective and collaborative activity [53].

1.6 Interactive Tabletop Systems for Music. An introduction to the reactable.

As has been noted by Jordà, music performance is one of the most archetypical group activities and one of the densest forms of human communication [21]. Under this perspective, TUIs such as tabletop systems, that physically represent digital information in graspable objects, have arisen as an exciting field for music performance. By combining low-level, sensitive control, with macro-structural control between user and system, tabletop interfaces allows multidimensional, continuous real-time interaction [21] and multi-user collaboration. On the other hand, the coupling of visual feedback and physical input control open a door for more intuitive models of interaction.

Music performance with digital instruments mainly relies on sharing control over computational processes rather than sharing data among users. This is directly linked with the aforementioned action-centered paradigm of tangible interaction [9], which offers a promising framework for digital music performance, especially for direct and shared control between performers and machine. Tangible interfaces also offer real-time interaction [41], allowing both time and space continuity as in a traditional music performance. This scenario strongly contrast with conventional WIMP-based and single-user computer applications, built from discrete and constrained sequences of events.

Aiming to explore the potential of tangible tabletop interfaces for live music performance, Alonso, Geiger, Jordà and Kaltenbrunner, researchers of the MTG in Universitat Pompeu Fabra in Barcelona, started in 2003 the reactable project. The goal of the project was to design an intuitive and non-intimidating musical instrument [21] appropriate for both single-user and collaborative performances (figure 7).

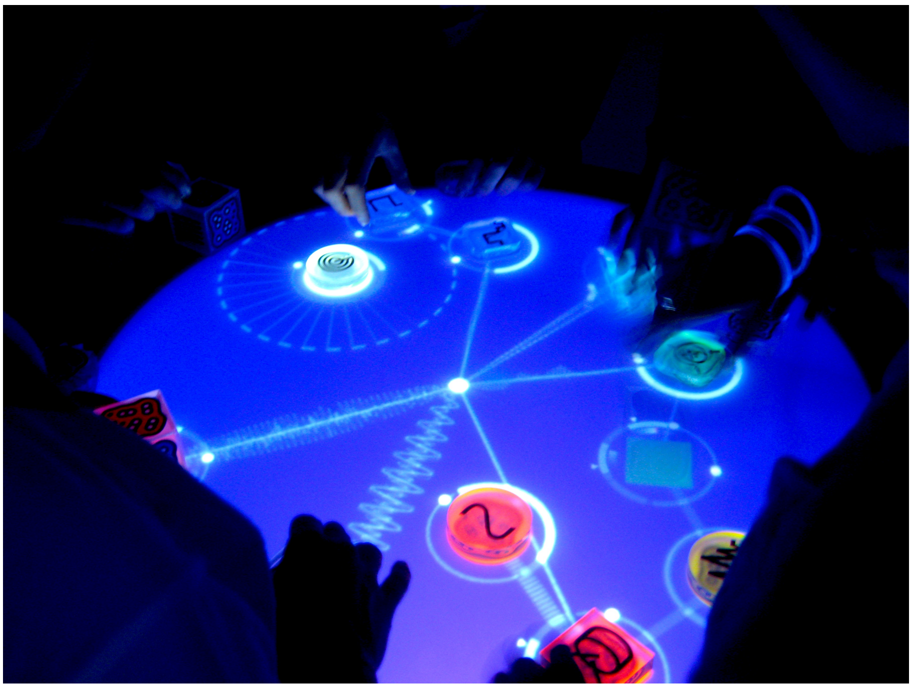

Figure 7: Collaborative performance using the reactable. Sónar A Coruña 2010.

Multi-user interaction is a natural feature of the reactable, as the shared control between performers and the system is part of its multi-dimensionality, combining the essential aspects of traditional instruments (i.e. direct, simultaneous and fine control of several parameters with two hands) with the potential of digital tools (i.e. shared control between user and instrument over simultaneous processes, quick monitoring and direct access to discrete events). An interactive tabletop surface was implemented to enhance control, monitoring and feedback information both for individual and collaborative performance. Starting for its circular design, the reactable seeks to maximize communication bandwidth in every direction: between human performers and the computer, between the computer and the performers, and between the performers themselves [21].

2. SYSTEM ARCHITECTURE

2.1 Physiology-Based Sonification in a Tabletop Interface for Collaborative Experiences.

In this report we present a hybrid interface for sound generation and control based in two devices: a wireless BCI and the reactable. While the former measures two physiological signals (EEG and ECG) from the users through a non-invasive setup, the latter represents the physical interface for music collaboration[1]. In the following section we describe the system architecture, starting from the physiological signal extraction and processing, the sound engine and its parameters for sound generation and control, and finishing with the mapping we have applied for a physiology-based sonification.

a) Physiological Signal Extraction and Processing.

For physiological signal extraction we used Starlab's *Enobio*, a wearable, modular and wireless electrophysiology sensor system for capture three biopotentials: EEG, ECG and EOG (Figure 8). The system features 4 channels connected to dry active electrodes using Carbon Nanotubes (CNT) [49] (figure 9) with a sample rate of 250hz, a resolution of 0.589μV, maximum Signal-to-Noise Ratio of 83db, a 16-bit Successive-Approximation Register (SAR) Analog-to-Digital Converter, and an automatic offset compensation for each channel. The data captured by the electrodes is amplified and then streamed via IEEE802.15.4 PHY to a server application running in a local host for data recording, display and transmission to the sound engine (client) via TCP/IP (figure 10).

Figure 8: Starlab Enobio. Wireless BCI device (www.starlab.es)

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[1] video available in: http://www.vimeo.com/14675468

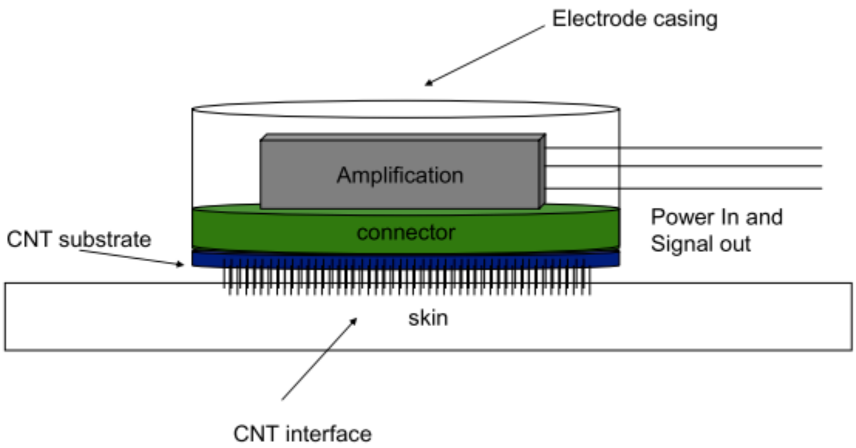


Figure 9: Dry electrode sensor for biopotential applications. The tip of the electrode is covered with multi-walled Carbon Nanotubes (CNT). Its brush-like structure penetrates the outer layers of the skin improving electrical contact [49:2]

Figure 10: Starlab's Enobio interface for reception, calibration and monitoring of physiological signals (EEG and ECG). The software features a control panel to check synchronization for each of the 4 channels available, a TCP server for data streaming and a file writer to save the values obtained during the measures.

This system permits real-time EEG and ECG signal acquisition, without the need of any skin preparation or application of electrolytic gel, as it is commonly used for the extraction of low amplitude signals such as the case of EEG. By implementing dry CNT electrodes, we have avoided long preparation, application and stabilization times for each electrode. This is a common procedure when working with electrophysiology electrodes, but might present serious constraints for real-time and *out-of-the-lab* performances, such as the collaborative music performance we propose. Enobio is also a fast setup wireless device. It has to be placed in the forehead (frontal lobe), and electrodes can be easily adjusted using a headband.

- EEG Placement: one dry CNT electrode placed in the Frontal midline (Fz) lobe, according to the 10-20 International System [26].
- ECG Placement: one dry CNT electrode placed in the wrist using a wristband.

Both signals are streamed to a server application for calibration, transmission and reception monitoring, and raw data visualization (Figure 11).

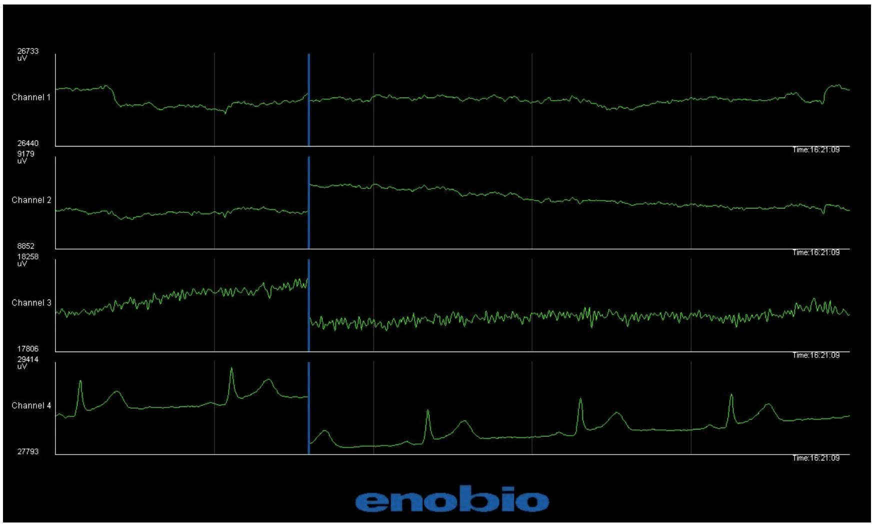


Figure 11: Enobio interface. Monitoring of calibrated signals (in green) for EEG (channels 1,2 and 3) and ECG (channel 4).

At this stage, we apply a digital filter to reduce environmental noise (usually centered between 50 and 60hz). Once the physiological signals are acquired, amplified and synchronized, the application enables a TCP/IP data port. The music engine thus connects to the TCP/IP server to process the EEG and ECG measures (see figure 12).

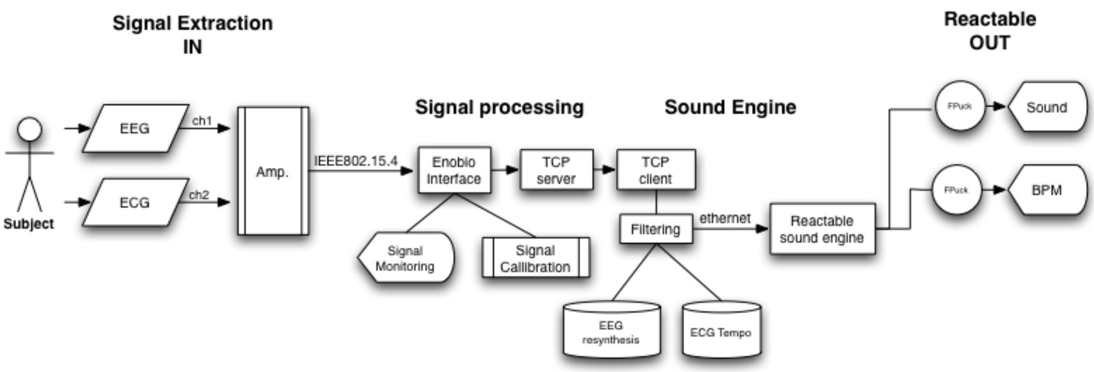


Figure 12: System architecture. Signal extraction, processing and filtering. Sound engine and implementation for the reactable hardware.

b) Physiology-Based Sound Engine

We decided to create a direct mapping between EEG spectral bands and the audible sound frequency spectrum. This EEG analysis and resynthesis as an audio signal appears as a sound generator puck in the reactable application. At the same time, ECG has been mapped to a puck to control tempo (BPM) in the reactable music engine (figure 13).

To perform the real-time signal analysis and sound synthesis we opted for the use of the Pure Data computer music system [44] due to its openness and suitability for the task of real-time spectral analysis and resynthesis, and for its flexibility when defining mapping.

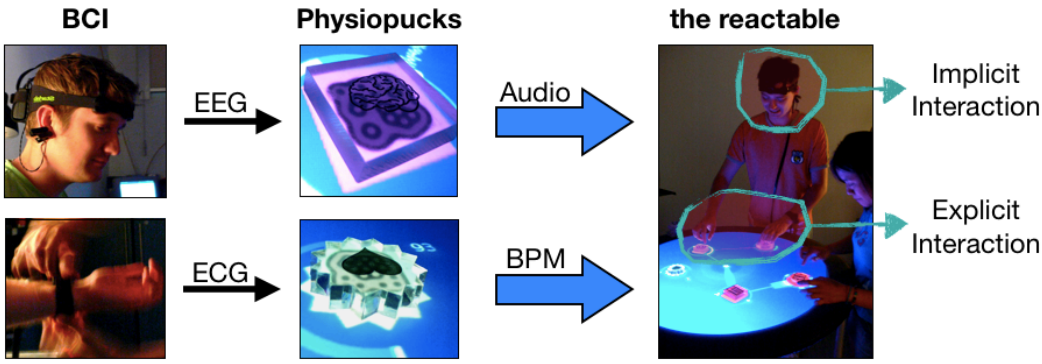


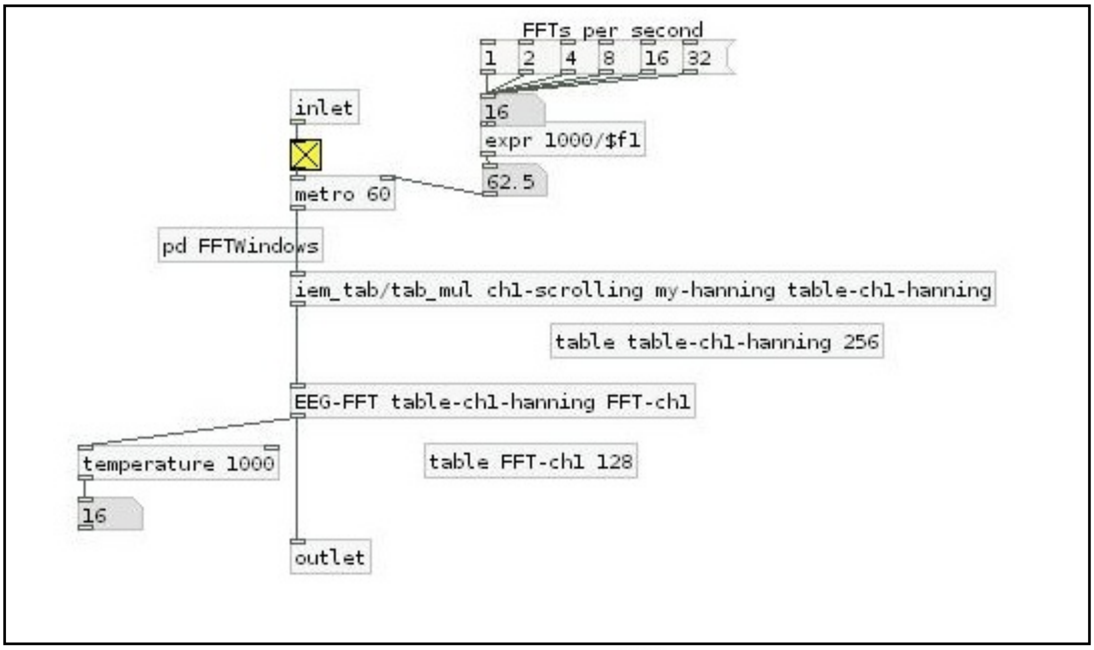
Figure 13: Computer-Supported Collaborative System. Physiological signal extraction (EEG and ECG) through a BCI device. Physiopucks for audio generation and control using EEG and ECG measures. The reactable as a shareable surface for collaboration.

c) EEG Signal Sonification (EEG Resynthesis)

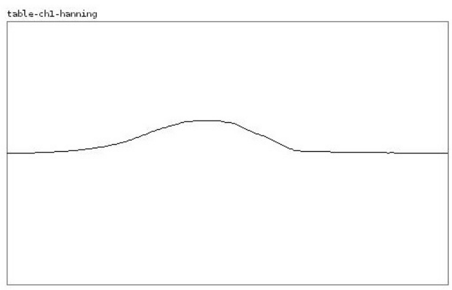
The Enobio device samples the EEG signal at a rate of 250hz. We process the signal coming from the BCI by first applying a DC block filter to contrast the signal drift and by then performing a frequency magnitude analysis (figure 14). The signal is processed in blocks of 256 samples with a hop-size of 15 samples, corresponding to about 16 processed blocks per second.

Each block is multiplied by a Hann window function of the same size. An FFT with a size of 256 samples is then performed, leading to a spectral resolution of about 0.97hz per frequency bin (figure 14).

(1)



(2)



(3)

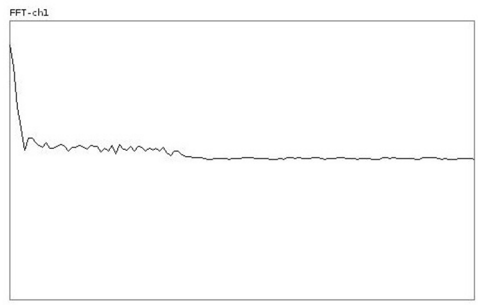


Figure 14: Frequency magnitude analysis in Pure Data (1): blocks of 256 samples (16 processed blocks per second) are multiplied by a Hann window (2). Then, an FFT analysis is performed, resulting in a spectral resolution of 0.97hz per frequency (3).

The computed magnitude spectrum for each frame is then used to shape the spectrum of a white noise signal (Figure 15). Each frequency bin of the EEG is used to weight the first 128 frequency bins of a 256 bins white noise FFT. Working at 44.1khz for audio synthesis, we have a covered frequency range going from 0Hz to the 11025hz, with each frequency bin covering about 86Hz. The spectral magnitudes have been equalized by mean of weighting the chosen curve in order to emphasize the weaker higher frequencies (Figure 16). The sound resynthesis phase consists of an overlap-add of the inverse FFT of the weighted and equalized magnitude spectrum of each consecutive processed EEG signal block and is entirely handled by the Pure Data synthesis engine.

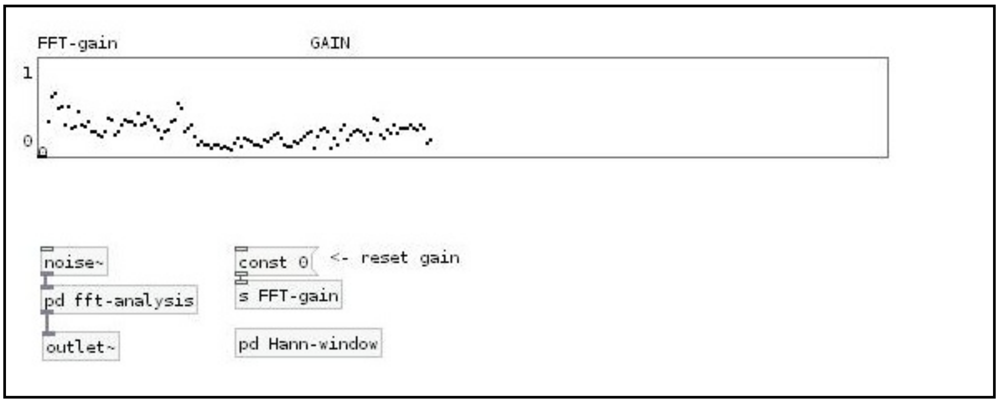


Figure 15: Sound resynthesis of EEG signal in Pure Data: the spectral magnitude of the EEG measure is used to shape a white noise signal. The sound synthesis consist of an overlap-add of the inverse FFT of the magnitude spectrum of each EEG signal block.

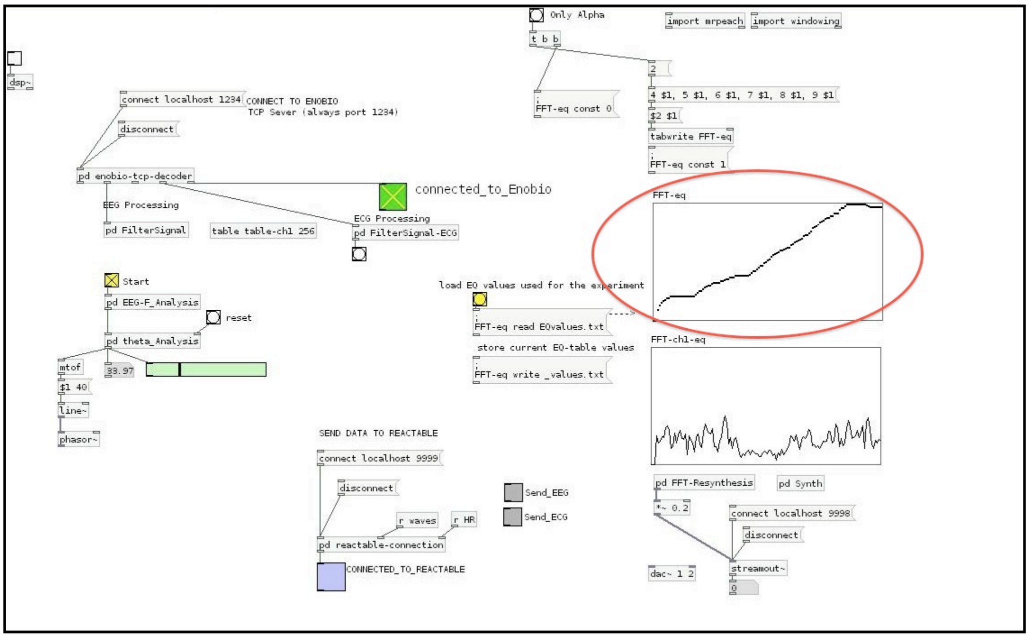


Figure 16: Physiology-based sound engine for EEG and ECG signals. The spectral magnitudes have been equalized (red circle) by mean of weighting the chosen curve in order to emphasize the weaker higher frequencies.

This resynthesized audio signal is finally streamed over a TCP-IP/LAN connection to the server running the Reactable software to be injected into its synthesis engine.

d) ECG Signal Processing for Tempo Tracking (ECG Tempo)

We process the ECG signal by first applying an adaptive rescaling to the system. We look at a 2 seconds sliding window (500 samples) checking for the minimum and maximum values and we normalize the signal depending on that range (Figure 17).

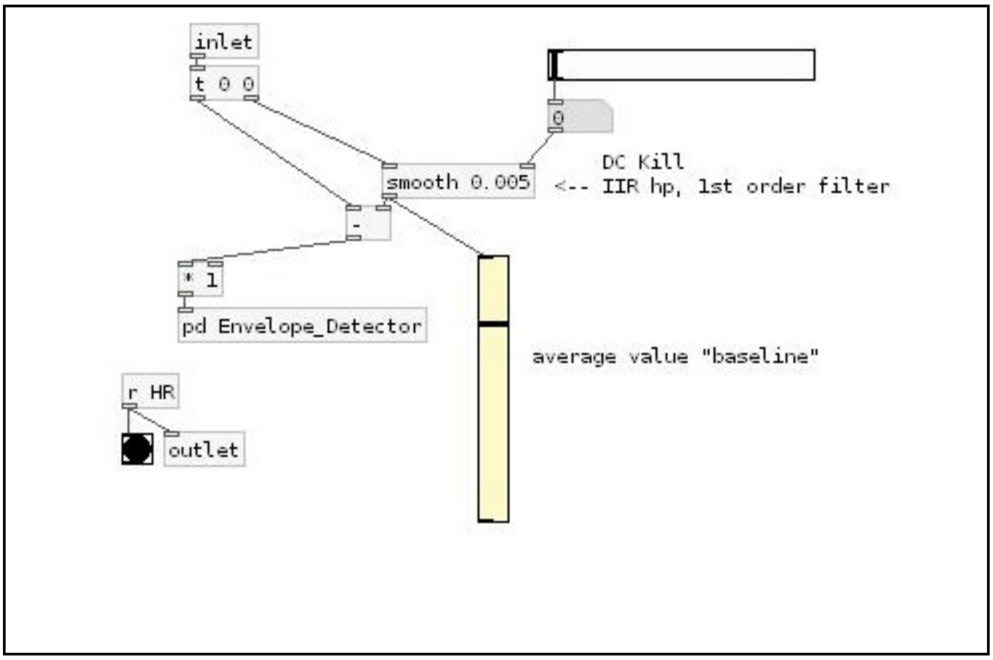


Figure 17: ECG signal processing for tempo tracking based on ECG signals. Signal reception from BCI, DC control filter to contrast the signal drift and measure the average baseline value. Then, signal is sent to and adaptive rescaling module for ECG peak detection.

We choose this adaptive rescaling system in order to compensate for the signal while at the same time not loosing peak resolution.

Peaks in the ECG are detected by applying a simple threshold function. A heartbeat is detected if the normalized signal is above the 40% of the normalized range. A new heartbeat is then detected only if this signal falls below 30% (Figure 18).

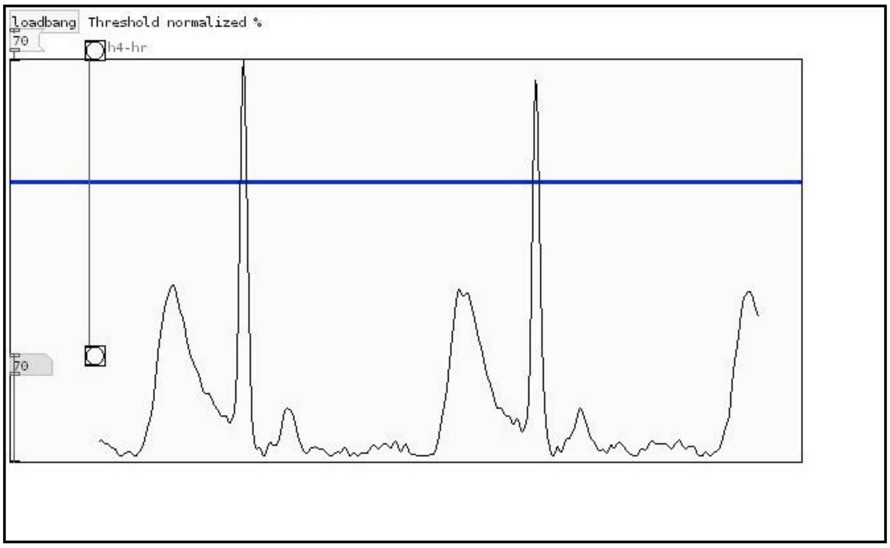


Figure 18: Threshold function for ECG peak detection in Pure Data. An adaptive rescaling compensates the signal without loosing peak resolution. A heartbeat is detected when the normalized signal is above the 40% of the range. A new heartbeat is detected only if the signal falls below 30% of the normalized range.

Figure 19 shows a complete diagram of the sound engine, the EEG and ECG signal processing.

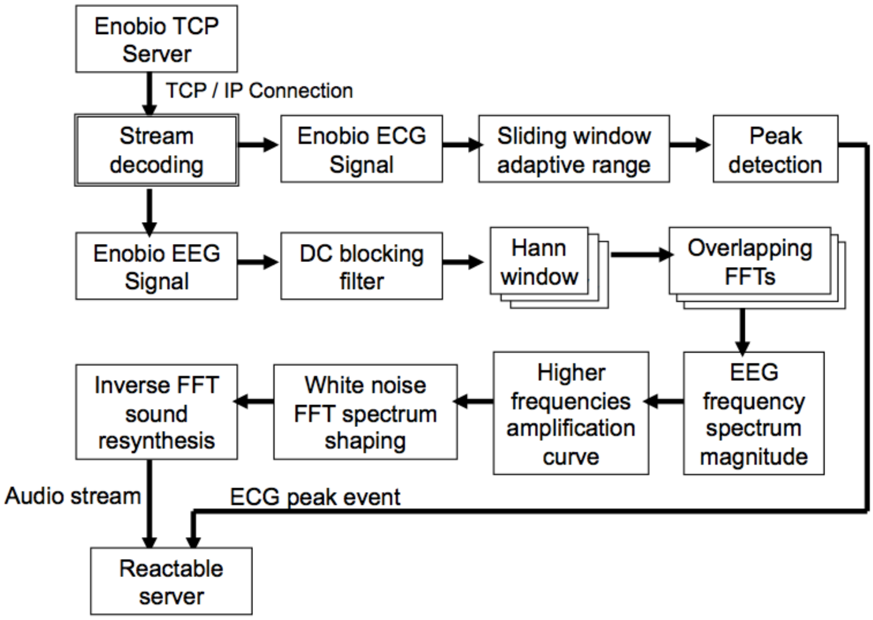


Figure 19: Physiology based sound engine, block diagram. Signal processing and sonification.

e) Integration into the Reactable Software.

The reactable's sound synthesis and control methods follow a modular approach, a prevalent model in electronic music, which is based on the interconnection of sound generators and sound processors units. In the reactable this is achieved by relating pucks on the table surface, where each puck has a dedicated function for the generation, modification or control of sound. Reactable's objects can be categorized into severeal functional groups such as audio generators, audiofilter, controllers (which provide additional variable control to any other object) or global objects (which affect the behavior of all objects within their area of influence). Each of this families is associated with a different puck shape and can have many different members, each with a disctint (human-readable) symbol in the surface. Because of this modular paradigm, the integration of our system into the standard reactable was straighforward. Two new pucks (*physiopucks)* were created, one as a sound generator (EEG resynthesis) and one as global object for controlling the tempo (BPM) of the whole table, based on the ECG rate (see table 1 and figure 20).

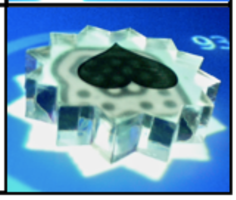
Type	Subtype	Connection	quantity	Shape
Generator	EEG resynthesis	1 audio out N control in	1	
Global	ECG Tempo	N control out	1	

Table 1: Description of the physiopucks

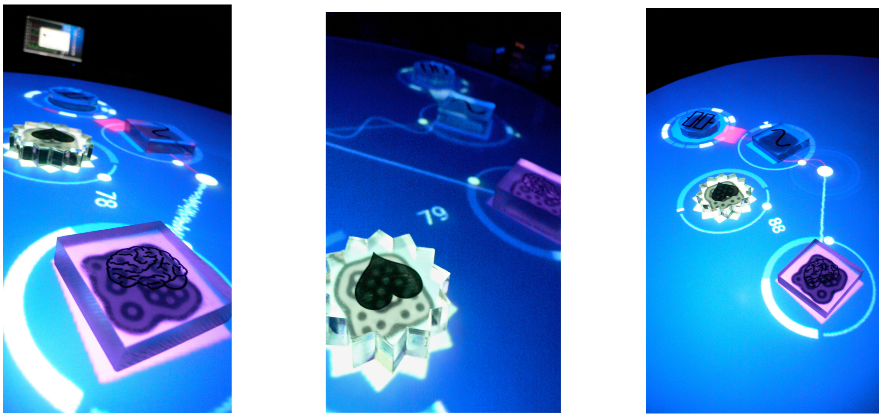


Figure 20: the *physiopucks* during a performance. EEG (square object with brain icon) and ECG (star object with heart icon) interacting with standard objects in the reactable.

3. METHODS

The following experiment has been created to assess *performance* and *motivation* in the proposed collaborative system using self-reported measures. As mentioned, the system introduces two different interaction models: explicit interaction through TUIs, and implicit interaction through a wireless BCI. The experiment in based on a collaborative music performance between two subjects using the tabletop system, and aims to answer the following research questions:

RQ1: Can real-time feedback of physiological signals be perceived by users collaborating in a music performance?

RQ2: How does physiology-based interaction affects a collaborative music experience in terms of motivation and performance?

3.1 Experiment Setup and Protocol

The experiment involved groups of 2 subjects with specific roles: one *standard* user (explicit interaction), that manipulates all the reactable pucks with its hands; and one *physiology* user (implicit interaction) that provides the physiological signals for the *physiopucks* (EEG and ECG measures through a BCI) (figure 21).

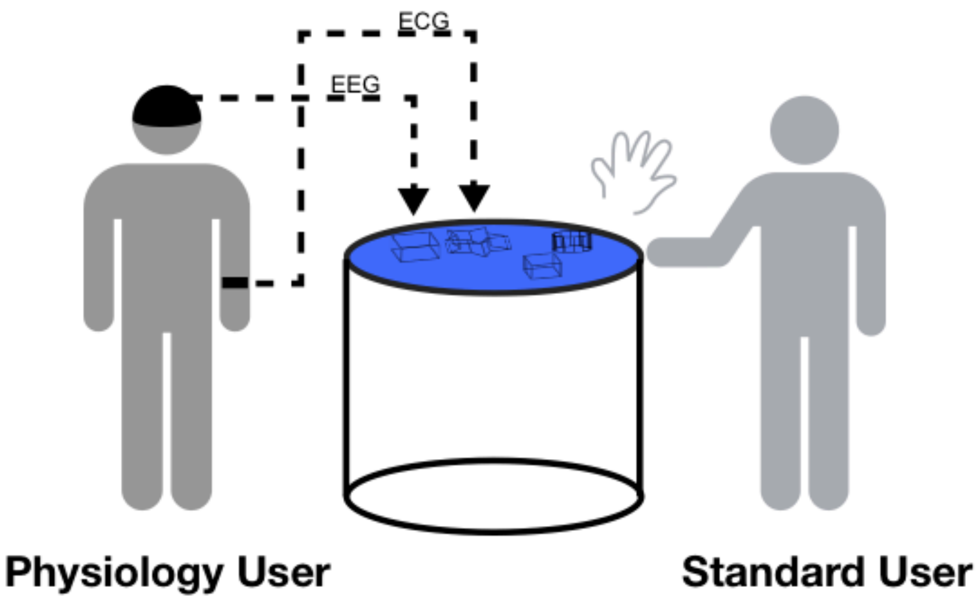


Figure 21: Types of user collaborating during the tasks. A *Physiology User* provides the physiological signals (EEG and ECG) to the physiopucks. A *Standard User* participates in the sound generation and control by means of physical manipulation of the pucks.

The groups worked with a set of six standard reactable pucks plus the two *physiopucks* (see table 1 and figure 20). After a first explorative phase, the group listened to two audio samples specially recorded from physiological signals and using the same set of pucks. Then, they were asked to mimic the sounds with the pucks.

Average time for each experiment was 40 minutes. The stages of the experiment were the following:

- Subjects were received and guided to a desk. Once there, they were asked to sign a consent form and authorization for the academic use of the data generated during the experiment (duration: 3 min)
- The physiology user was guided to a sector prepared for BCI setup and calibration (duration: 5min).
- Subjects filled out a pre-test questionnaire (duration: 5min).
- Explorative phase: Subjects received information about the reactable and the set of available pucks. Next, the subjects had a period for testing and exploration before the beginning of the tasks (duration: 8min).
- Task execution: the subjects listened a sound sample of 20 seconds length. Then, the group had up to 5 minutes to mimic the sound sample. During the task, the standard user controlled the pucks with its hands, while the physiology user provided sound generation and control through the BCI. The subjects were able to ask for a replay of the sound of reference at anytime. There were 2 tasks in total (duration: 12min).
- The subjects were asked to leave the reactable.
- The physiology user was guided to an specific sector of the room to unmount the BCI device (duration: 3min)
- The subjects filled out a post-test questionnaire (duration: 5min).

3.2 Sample

A total of 32 subjects, mean age of 28.09 y/old, 15 females and 17 males, with no experience using the reactable, participated in the experiment. They were distributed in two groups (Figure 22):

- Real-time Group: 22 subjects. Signals from the physiology user were mapped in real-time to the *physiopucks*.
- Sham Group (control group): 10 subjects. Physiopucks respond to pre-recorded signals, thus no real feedback is provided to the users.

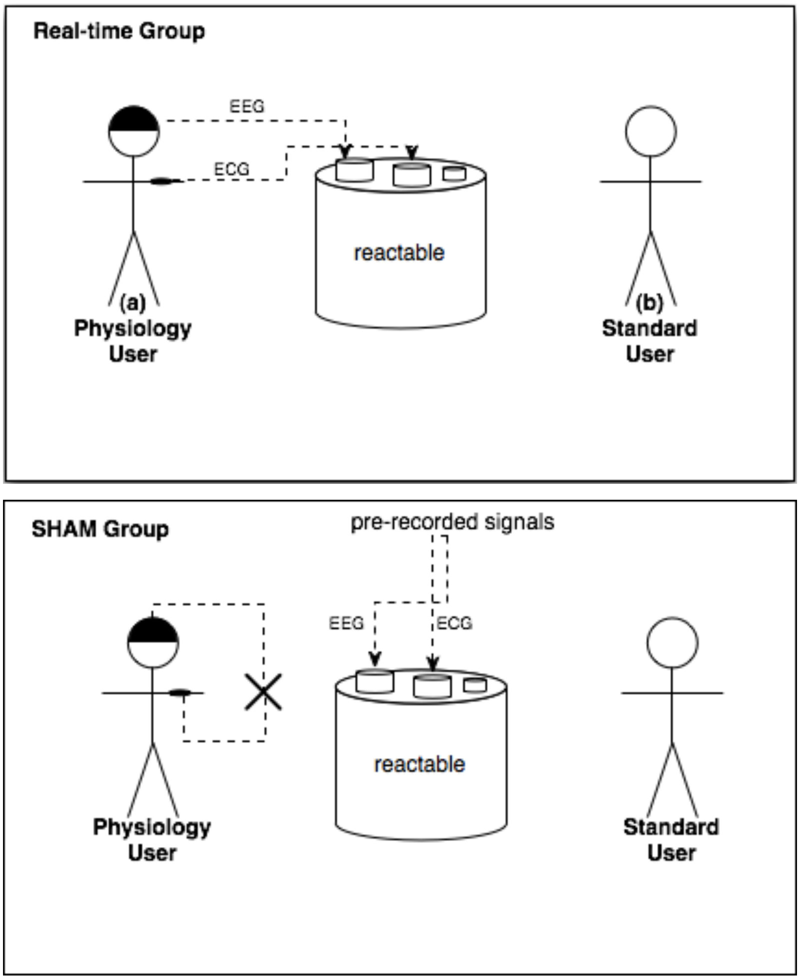


Figure 22: Experimental setup and groups. In the Real-time Group (up) physiology user's signals (EEG & ECG) are mapped to the physiopucks. In the Sham Group (down), real-time physiological signals are replaced by pre-recorded measures.

3.3 Task Design

The task entailed to replicate a pre-recorded sound sample created with the same objects that the users had available during the test. After the sample was played, the group had up to 5 minutes to mimic the sound. The subjects were able to replay the sample of reference at any time by asking the supervisor.

There were specific roles for each user during the tasks. The standard user manipulated the pucks in the surface of the reactable (explicit interaction) whereas the physiology user performed through her own physiological signals mapped to the physiopucks. These pucks, which allow filtering and transformation, could use by both user, in combination with any other objects (figure 23 and 24).

A tasks oriented design were applied to engage the groups in a composition process, encouraging collaboration between subjects in order to achieve a common goal (imitation of reference) and exploration of the tools available for both standard and physiology users.

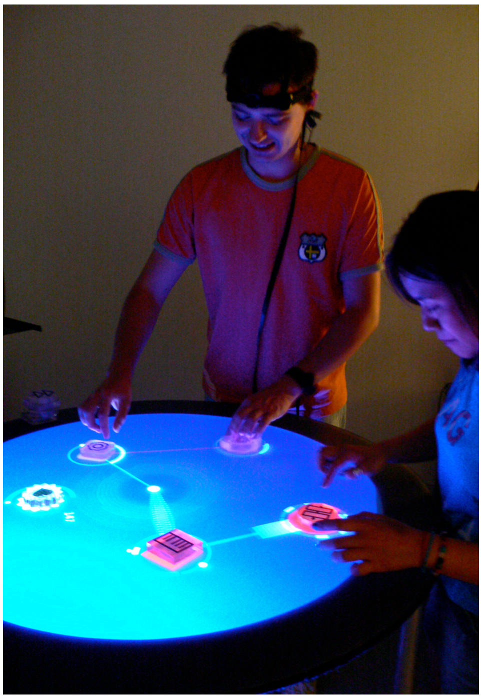


Figure 23: pair of participants performing task 1 during the experiment. Physiology user located in the center, Standard user in the right.

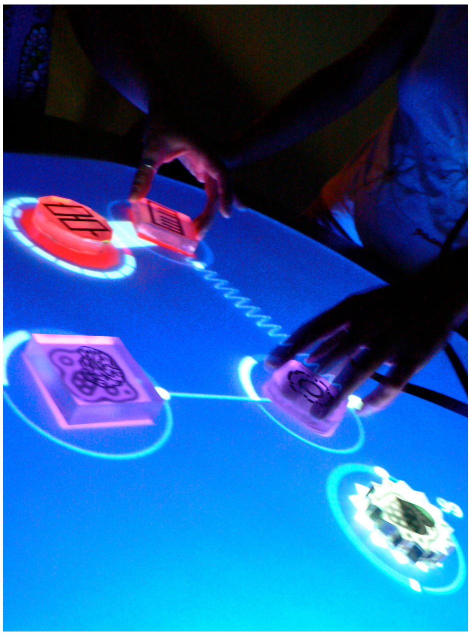


Figure 24: pair of participants exploring combinations of pucks and *physiopucks* during the explorative phase of the experiment.

3.4 Measures

- Pre-test questionnaire: demographics, general music knowledge, electronic music skills and Reactable knowledge (see Appendix, Section 2).
- Post-test questionnaire: Motivation, Enjoyment and Performance, based on a Likert-scale of 5 point ranging from "strongly agree" to "strongly disagree", except where noted or implied (see Appendix, Section 2).
- 9-point Bidimensional Self-Assessment Manikin pictorial scale (SAM) for valence and arousal, developed by Lang [27].

In the experiment we assessed nine different factors concerning motivation and performance. The proposed model for Collaborative Performance was based on [18] and [20] and involves the following measures:

1- *Feedback*: does the provided feedback (visual, sound, language) facilitates the collaboration between partners and motivates the interaction? (Example of statement: The visual interface of the reactable helped me to understand how to create sound compositions).

2- *Leadership and distribution of control*: balance of control among subjects (Example of statement: I feel I was leading most of the work in every task).

3- *Social Affinity between partners*: willingness to work together and collaborate (Example of statement: I have a relation of friendship with my partner).

4- *Nature of task*: can the task be sub-divided and distributed among subjects? Does the subject lose the feeling of ownership on specific parts of the task? (Example of statement: Collaboration with my partner was difficult to carry on).

The assessment of motivational aspects is based on [18]. The variable of *Curiosity* has been complemented with the Attitude scale of Eagly & Chaiken [7].

5- *Curiosity*: Does the user find the activity *strange* or unusual? (Example of statement: Performing with the reactable was an unusual experience).

6- *Difficulty*: too easy / too difficult. Rates the difficulty level of the experience (Example of statement: The tasks were too difficult to be accomplished).

7- *Confidence*: self-efficacy on achieving the tasks (Example of statement: I've accomplished the tasks with efficacy).

8- *Control*: freedom to negotiate own paths to accomplish the task and the self-perception of being in control of the experience (Example of statement: I was in control of the reactable).

9- *Motivation and perception of time*: How does the nature of the experience change over time? Does the subject lose interest as time pass by? (Example of statement: The first tasks were more compelling and interesting than the latter).

4. RESULTS

We have compared the ratings for nine motivation and performance measures, and SAM ratings according to 4 groups of subjects: Real-time, Standard User (RT-S); Real-time, Physiology Users (RT-P); Sham, Standard User (SH-S); and Sham, Physiology Users (SH-P) (see figure 25). The data was collected through computer-based questionnaires.

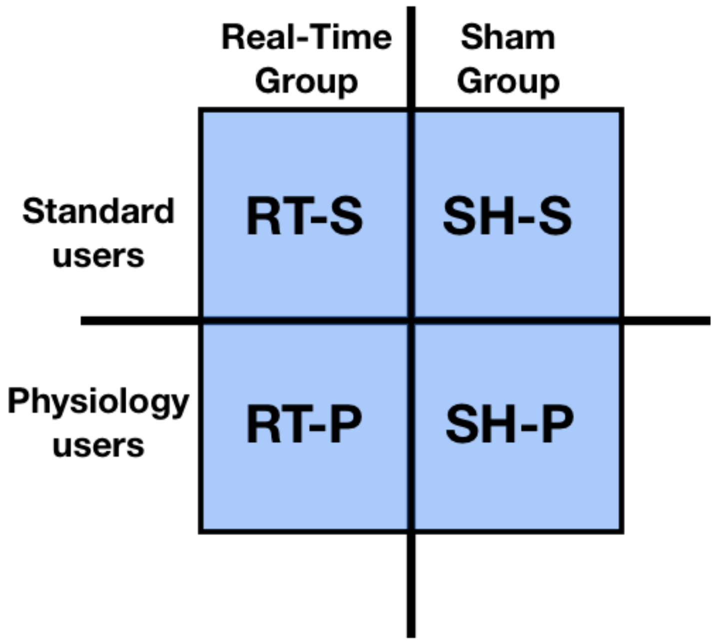


Figure 25: Groups of analysis defined by type of user (Standard / Physiology) and type of group during task (Real-time / Sham).

The ratings were processed using SPSS for the statistical analysis of each of the nine variables implemented in the performance/motivation assessment. Firstly, an independent-samples t-test was applied to compare the means of the dependent variables between sample groups, showing significance in three variables: difficulty, confidence and leadership. The analysis didn't show any other significance for the rest of the variables. Secondly, the variation of measures by couples was evaluated by applying a Pearson correlation analysis.

4.1 Motivation: Difficulty

Two significances were found in the analysis of difficulty measures (see figure 26). First, within the Sham Group, Physiology Users declared higher difficulty than Standard Users ($t(9)= -3.57$, $p<0.01$) (see Appendix, table 5). Second, in a inter-grupal analysis, Physiology Users in the Sham Group also declared greater diffculty than Physiology Users in the Real-time Group (t(15)= -2.37, p<0.05) (see Appendix, Table 12).

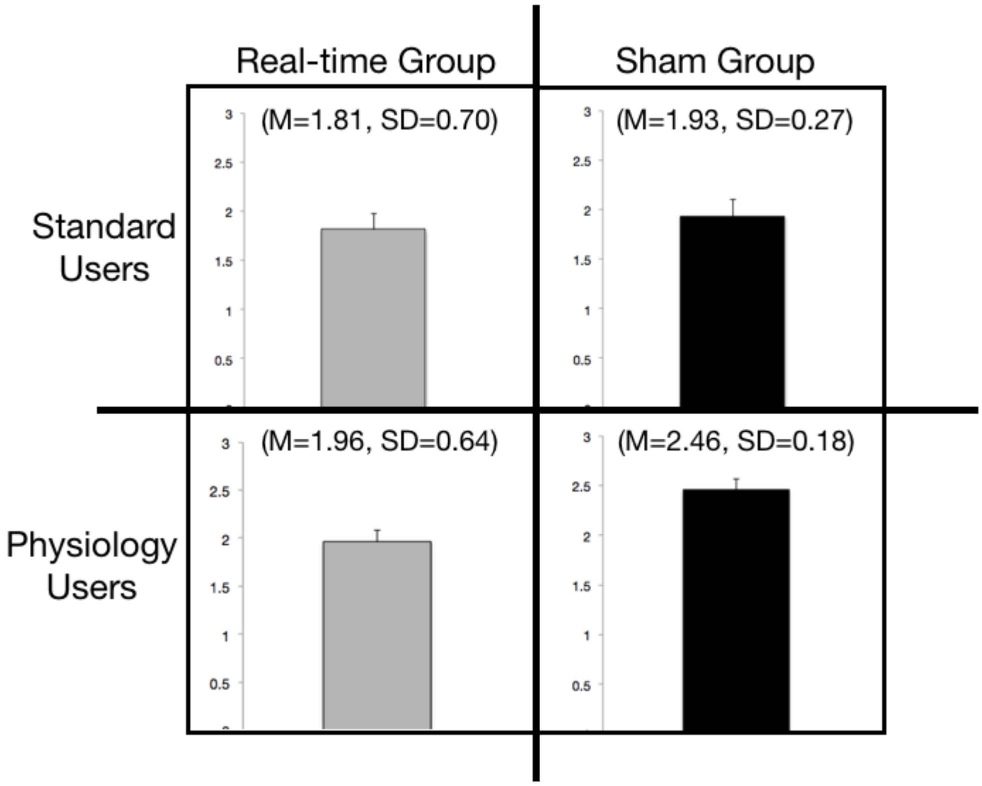


Figure 26: Difficulty measures for the four groups of analysis (scale from 0 to 5). A significant difference was found in the comparison between users within the Sham Group (t(9)= -3.57, p<0.01), with Physiology Users declaring higher difficulty (M=2.46, SD=0.18) than Standard users (M=1.93, SD=0.27). The difference between Physiology User in both groups was also significant (t(15)= -2.37, p<0.05) as Physiology users in the Real-time Group declared less difficulty (M=1.96, SD=0.64) than the same type of user collaborating in the Sham Group.

4.2 Motivation: Confidence

The analysis of confidence (see figure 27) shown a significant difference between Standard Users in both Real-time and Sham Group (t(15)=2.03, p<0.05) (see Appendix, table 10). Standard Users in the Real-time Group declared higher confidence (M=5.06, SD=1.45) than Standard Users in the Sham Group (M=3.55, SD=1.19). On the other hand, the confidence comparison between Physiology Users in the two groups also reached significance (t(15)=2.24, p<0.05). Physiology Users in the Real-time Group declared greater confidence levels (M=4.90, SD=1.06) than the same type of users within the Sham Group (M=3.65, SD=0.96). Finally, significance was also found in the confidence comparison between Real-time and Sham groups (f=2.98, p<0.05) (see Appendix, table 8 and 9).

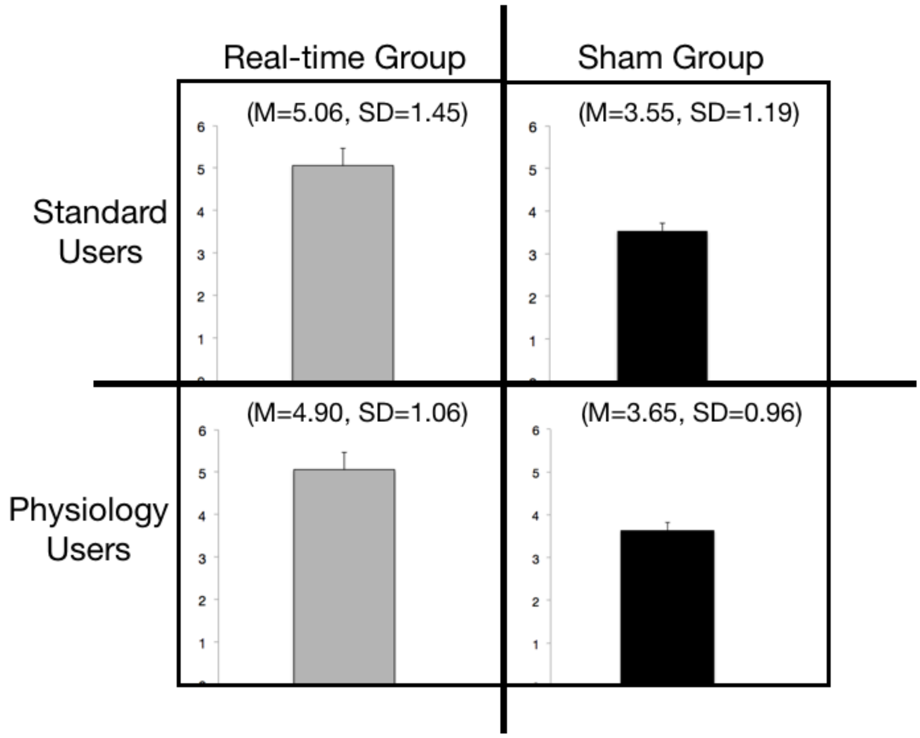


Figure 27: Confidence measures for the four groups of analysis (scale from 0 to 9). A significant difference was found in the comparison between Standard Users in both Real-time and Sham Group (t(15)=2.03, *p*<0.05). The comparison for Physiology users in both Real-time and Sham group also shown a signifcance (t(15)=2.24, *p*<0.05).

4.3 Performance: Leadership

Regarding leadership analysis (see figure 28), we found significance in the comparison of ratings of Standard and Physiology users within the Sham Group (t(9)=-2.35, *p*<0.05) (see Appendix, table 6). In this case, Physiology Users declared higher leadership (M=2.80, SD=0.44) than Standard Users (M=1.80, SD=0.83). We also detected a significant difference of leadership when comparing Standard Users in Real-time and Sham Groups (t(15)=2.60, *p*<0.05) (see Appendix, table 11). The analysis shown that Standard Users in the Real-time group declared more leadership (M=3.00, SD=0.89) than the same type of users in the Sham Group.

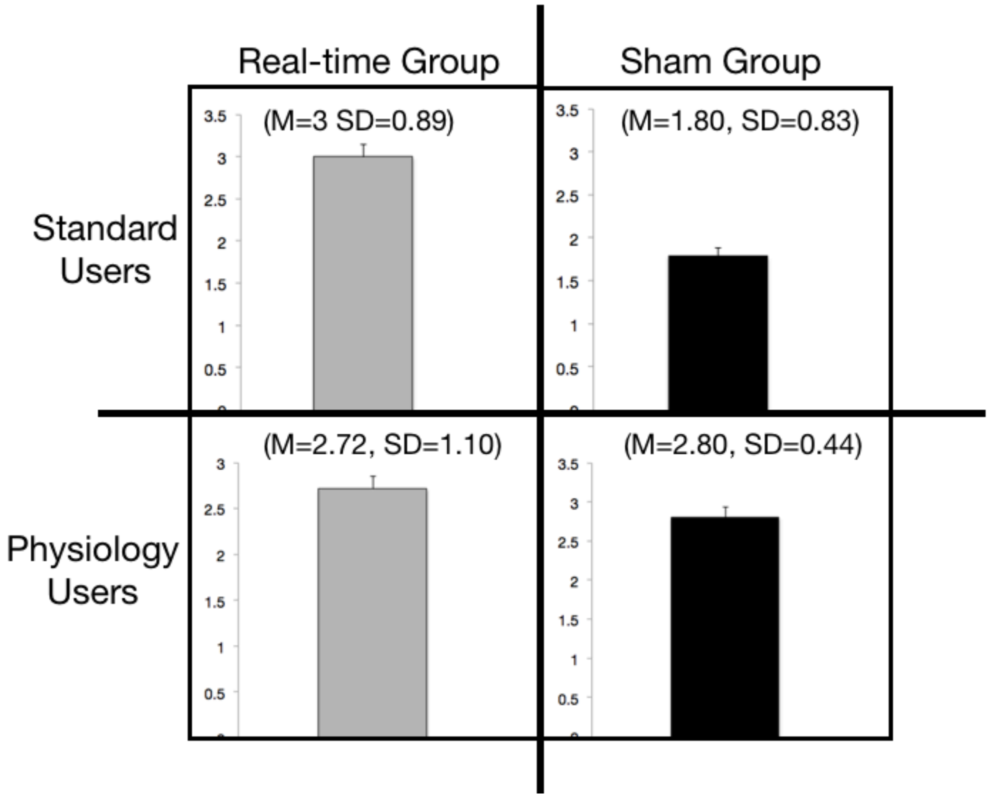


Figure 28: Leadership measures for the four groups of analysis (scale from 0 to 5). A significance difference was found between Standard and Physiology users within the Sham Group (t(9)=2.35, *p*<0.05). The comparison of leadership ratings for Standard Users in both groups also reached significance, with the Real-time Standard Users showing greater leadership (t(15)=2.60, *p*<0.05).

4.4 Correlations between team member’s ratings.

Couples of users collaborating during the tasks has shown different levels of correlations among variables, specially for those reflecting the collaborative design of the experimental setup. Couples collaborating in the Real-time Group reflected a strong correlation for measures of confidence (Pearson's correlation r=0.91, p<0.01) that assessed self-efficacy on achieving the tasks and releabilty of partners (figure 29). For the same group, we also found a significant correlation for visual feedback coming from the system's interface (Pearson’s correlation r=0.67, p<0.05).

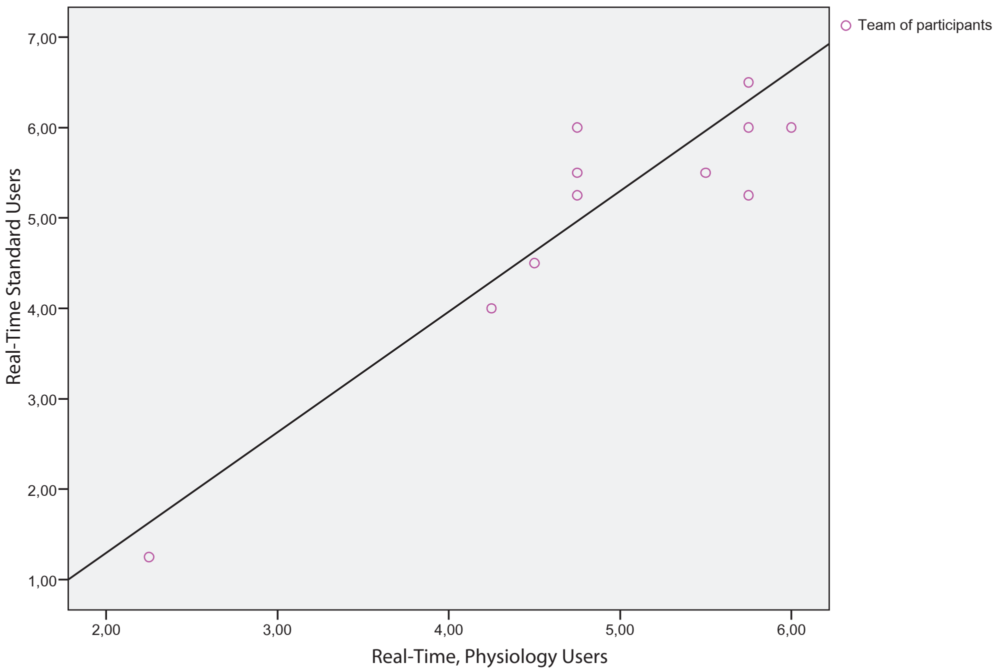


Figure 29: Pearson's Correlation between confidence ratings given by the team memebers collaborating in the Real-Time Group (Standard Users and Physiology Users). Rating scale from 1 to 10.

Regarding couples in the Sham Group, one variable strongly linked with the collaborative aspect of the experiment have shown significance in the correlation analysis. The measures of curiosity (does the subject finds the tasks attractive? Is the participant interested in perform more time?) reach strong correlation between pairs ($p<0.05$, coefficient=0.92). This shows that the curiosity of the users and their will to perform more time in order to find other sound combinations declined in a sistematic manner for both users collaborating.

5. DISCUSSION & FUTURE WORK

5.1 Discussion

In this report we have presented an interactive tabletop system, based on a hybrid interface shaped by a BCI and a TUI. Through this design, we wanted to assess the effect of physiology-based interaction in collaborative performances, and the perception of the real-time feedback of physiological signals during such an experience.

The study has revealed three main effects of physiology-based interaction applied to a collaborative performance in a TUI. First, teams on the Real-time group (with physiological signals connected to the *physiopucks*) declared less difficulty and greater ease to solve the tasks, with similar levels for both Standard and Physiology users. In the Sham Group, on the other hand, Standard Users also shown low ratings of difficulty, but Physiology Users (whose physiological signals were pre-recorded, not streamed in real-time from the BCI) declared highest challenge levels.

Secondly, and also related with the difficulty measures, users collaborating in the Real-time group have shown higher levels of confidence during the tasks, describing the system as responsive and controllable during explicit interaction (using both hands) and implicit interaction modes (by means of EEG and ECG measures). Some statements of the participants collected after the experiment also reinforce these measures:

"I could see how the reactable responded to my BCI (...) and the visual feedback of the tempo controlled by my heart didn't look delayed compared to the audio output. After a few minutes, I could start to control aspects of the BCI, and take out the heart rate puck if I wanted to define a different tempo (Physiology User, code ED03, see appendix, section 3).

"One aspect I would highlight is the fact that you can control the objects (physiopucks) by exploring your brain activity or your heart rate, but also linking these with other reactable's objects, or just taking it out of the surface of the table (...) Also it allow me to control the (physiology) signals of my partner using my hands and combining it with more traditional tools like filters, controllers or virtual instruments (Standard User, code ES09, see appendix, section 3)."

As opposite, those subjects participating in the Sham Group declared:

"I was able to recognize the audiovisual feedback coming from my BCI, but it didn't look responsive to what I wanted to generate in the reactable (...) In sum, I think the system is difficult to control using the BCI (Physiology User, code CD01, see appendix, section 3)."

"For me, the interaction was pretty straight forward, regardless I didn't have any previous experience using the reactable. However, the collaboration with my partner was difficult to carry on and predict, as she couldn't manage to control de BCI (...) We could combine normal reactable's objects with the brain and heart (physiopucks) in

order to solve the tasks, but it was just too difficult to sustain any kind of sound for more that a couple of minutes (Standard User, code CS04, see appendix, section 3"

In a third place, the distribution of control and leadership during the collaborative performance in the Real-Time Group was balance and didn't show significant difference between the two proposed interaction paradigms (explicit through physical manipulation, and implicit through physiological measures). On the contrary, the Sham Group revealed significant differences in terms of leadership betwen the two types of users, as has been explained in Figure 28

Regardling feedback perception, the significance detected in both difficulty and confidence measures lead us to confirm that physiology users were able to perceive whether the audiovisual feedback was linked to her physiological signals or not.

Finally, the analysis by teams of participants has shown different levels of correlation between variables, which strenght the collaborative aspect of our experiemental setup. Teams interacting in the Real-time group shown a significant correlation in key aspects for collaboration, such as confidence in accomplish the tasks with efficacy and confidence in his/her partner. The correlation for the motivation measures also show how the collaborative performance was sostainend in terms of interest over time.

On the contraty, users performing in the Sham Group revealed several flaws duirng the collaborative task. The analysis of correlations shown that the curiosity of the users and their will to perform more time in order to find more possible combinations declined in a sistematic manner for both users collaborating.

5.2 Faced Problems and Future Work

During the evaluation process, we have detected some challenges that might guide future works in the field of research. To start, we have applied a signal analysis and processing that allow a direct mapping between EEG spectral bands and the audible sound frequency spectrum. This process transforms the EEG signal in a resynthesis that appear as a sound generator puck in the reactable application. On the other hand, ECG patterns have been mapped to control tempo (BPM) in the reactable music engine. This paradigm for sonification allowed us to assess the effects of explicit and implicit interaction in a collaborative scenario and feedback perception. But considering the current findings, the physiological signal processing could be refined in order to find more subtle descriptors that describe the physiological substrate of phenomena such as affective states, emotional responses or music perception. This process will lead to more advanced methods for sound generation and control.

We have also detected specific limitations in *Enobio*, the BCI device we used to design the Computer-Supported Collaborative System. The noise generated by muscular movements and body displacement produced an unstable signal during the music performance. Also, the device limits the electrode placement to the frontal cortex (Fz, Fp1 and Fp2 of the International 10-20 System of Electrode Placement), as it uses CNT dry electrodes that require direct skin contact. In order to improve signal acquisition and cover other regions of the brain we suggest to test other BCI devices, even those that require electrolytic gel or special preparation, as these might allow a more stable signal extraction and a deeper monitoring of processes distributed in different brain regions (e.g. emotional states associated with alpha brainwaves, attention and metal tasks associated with alpha-theta rhythms).

Regarding the experimental design and methods, we propose to complement the current self-reported assessment tools (questionnaires and SAM scale) with physiology-based techniques and sound analysis. The first feature will allow real-time monitoring of physiological states of multiple subjects during a collaborative performance, without affecting sound control and generation by means of BCI devices. A sound analysis method such a similarity tests on timber, frequency and tonality, will optimize the assessment of musical performance, making it quantifiable by comparing, for example, the sound references and the measures generated by the groups during each task. Other options to strength the current experimental design would be to measure EEG and ECG from both participants, including a second BCI device. This will make the implicit interaction model available for multiple users. Finally, in order to explore the musical possibilities of our design, we suggest carrying on experiments with professional musicians and including previous training phases to test the expressiveness of the proposed CSCS.

6. CONCLUSION

In this project we have presented two different models of interaction for collaborative performances: explicit interaction using physical manipulation, and implicit interaction by means of physiological signals.

The analysis of measures has shown that the combination of these models doesn't represent a high challenge for novel participants collaborating in a sound composition experience; it also tends to preserve a balanced distribution of control between subjects and encourage collaboration by means of a sustained confidence during tasks, for both types of interaction models.

These results encourage the development of computer-supported collaborative systems where subtle sources of information such as affective and physiological states effectively support a more direct and explicit model of interaction, as in the case of tangible tabletops interfaces. This paradigm opens an exiting field to explore the expressiveness of sound generation and control based on the internal states of the human body, monitored with non-invasive, wireless devices that tend to preserve adequate conditions for live performance.

The confidence levels reached by real-time users (both standard and physiology) is a clear sign of how the combination of explicit and implicit interaction can enhance a collaborative experience that take place in a common tabletop surface. We consider this work as a first exploration in the path for a most robust and expressive collaborative music system. More work can be done regarding pattern extraction and signal processing of the physiological measures. Such research will allow for more complex and accurate descriptors for sound generation and control.

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APPENDIX

1. Tables of Results

Real-time Group					
	User	N	Mean	Std. Deviation	Std. Error Mean
Motivation / Time	Standard	11	1.5909	.66401	.20021
	Physiology	11	2.1818	.78335	.23619

Table 2: Motivation along time for Standard and Physiology users in the Real-time Group. Means and SD.

Real-time Group: Standard vs. Physiology Users										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Diff.	95% Conf. Int. of the Diff. Lower	95% Conf. Int. of the Diff. Upper
Motivation / Time	Equal variances assumed	.468	.502	-1.908	20	.071	-.59091	.30963	-1.23678	.05496
	Equal variances not assumed			-1.908	19.477	.071	-.59091	.30963	-1.23789	.05607

Table 3: Motivation along time for Standard and Physiology users in the Real-time Group. Independent samples t-test.

Motivation / Time								
					95% Confidence Interval for Mean			
User	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Min	Max
RT-Standard	11	1.5909	.66401	.20021	1.1448	2.0370	1.00	3.00
RT-Physiology	11	2.1818	.78335	.23619	1.6556	2.7081	1.00	3.50
SHAM-Standard	5	2.1000	1.08397	.48477	.7541	3.4459	1.50	4.00
SHAM - Physiology	5	1.7000	.44721	.20000	1.1447	2.2553	1.00	2.00
Total	32	1.8906	.76973	.13607	1.6131	2.1681	1.00	4.00

Table 4: Motivation along time for all group of users. Description of Means, Standard Deviation and Standard Error.

SHAM Group: Standard Users vs. Physiology Users.										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Conf. Int. of the Difference	
									Lower	Upper
Difficulty / Challenge	Equal variances assumed	.640	.447	-3.578	8	.007	-.53333	.14907	-.87709	-.18957
	Equal variances not assumed			-3.578	6.897	.009	-.53333	.14907	-.88691	-.17976

Table 5: Difficulty level for Standard and Physiology users in the SHAM Group. Independent Samples t-test.

SHAM Gorup: Standard vs. Physiology Users.										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Conf. Interval of the Dif.	
									Lower	Upper
Leadership	Equal variances assumed	1.969	.198	-2.357	8	.046	-1.00000	.42426	-1.97835	-.02165
	Equal variances not assumed			-2.357	6.113	.056	-1.00000	.42426	-2.03349	.03349

Table 6: Leadership level for Standard and Physiology users in the SHAM Group. Independent Samples t-test.

Confidence

A					95% Confidence Interval for Mean			
Groups	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
RT- STD	11	5.0682	1.45384	.43835	4.0915	6.0449	1.25	6.50
RT-PHY	11	4.9091	1.06813	.32205	4.1915	5.6267	2.25	6.00
SHAM-STD	5	3.5500	1.19111	.53268	2.0710	5.0290	1.75	4.75
SHAM-PHY	5	3.6500	.96177	.43012	2.4558	4.8442	2.50	5.00
Total	32	4.5547	1.33612	.23620	4.0730	5.0364	1.25	6.50

Table 7: Confidence Levels for all groups. Description of means, Standard Error and Standard Deviation.

Confidence

B	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	13.421	3	4.474	2.988	.048
Within Groups	41.920	28	1.497		
Total	55.342	31			

Table 8: Confidence level analysis between groups.

Physiology Users: Real-time vs. SHAM Group.									
Confidence	Levene's Test for Equality of Variances		t-test for Equality of Means						
								95% Confidence Interval of the Difference	
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Equal variances assumed	.016	.902	2.247	14	.041	1.25909	.56032	.05733	2.46085
Equal variances not assumed			2.343	8.654	.045	1.25909	.53733	.03613	2.48205

Table 9: Confidence levels for Physiology users in Real-time and SHAM Group. Independet Sample t-test.

Standard Users: Real-time vs. SHAM Group									
Confidence	Levene's Test for Equality of Variances		t-test for Equality of Means						
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Conf. Interval of the Diff. Lower	Upper
Equal variances assumed	.011	.917	2.034	14	.061	1.51818	.74640	-.08270	3.11906
Equal variances not assumed			2.201	9.508	.054	1.51818	.68985	-.02977	3.06613

Table 10: Confidence levels for Standard users in the Real-time and SHAM Group. Idenpendent Sample t-test.

Standard Users: Real-time vs. SHAM Group									
Leadership	Levene's Test for Equality of Variances		t-test for Equality of Means						
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
Equal variances assumed	.125	.729	2.533	14	.024	1.20000	.47373	.18396	2.21604
Equal variances not assumed			2.602	8.336	.030	1.20000	.46122	.14382	2.25618

Table 11: Leadership levels for Standard users in the Real-time and SHAM Group. Independet Samples t-test.

Physiology Users: Real-time vs. SHAM group.									
Difficulty	Levene's Test for Equality of Variances		t-test for Equality of Means						
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
Equal variances assumed	4.906	.044	-1.675	14	.116	-.49697	.29662	-1.13317	.13923
Equal variances not assumed			-2.371	12.867	.034	-.49697	.20964	-.95034	-.04360

Table 12: Difficulty levels for Physiology users in the Real-time and SHAM group. Independet Samples t-test.

2. Questionnaire for assessing performance and motivation in computer-supported collaborative experiences

Subjective ratings of performance and motivation were gathered by a two-part questionnaire. The constructs were created by grouping several questions (2 to 4 questions for each variable) in order to provide a statistically significant result. The questionnaire presents a Likert-scale of 5 point ranging from "strongly agree" to "strongly disagree", except where noted or implied, and is based on user evaluation techniques; as well as constructs created specifically for the proposed research.

A pre-test questionnaire was created to assess demographics (box 1.a), general music knowledge (box 1.b) and electronic music skills (box 1.c). The more general variables regarding demographics were taken from the System Usability Scale (SUS), which has been widely used as a general high-level evaluation tool for computer systems. The *Internet Self-Efficacy Scale* (Eastin and LaRose, 2000) was adapted to assess user's previous knowledge about general and electronic music.

A post-test questionnaire was designed to assess declarative ratings of motivation and performance. The former is based on Keller (1987), a two-dimensional model of motivation, featuring *curiosity* and *challenge* (box 2.a and 2.b). It has been complemented with the attitude scale of Eagly & Chaiken (1993) to determine the user's emotional response to the experience (box 2.a); and involvement (Zaichowsky, 1987), which focuses on how involved the participant was during the experiment (box 2.b).

The assessment of Performance is based on Issroff & del Soldato (1996) and Jones & Issroff (2005). The questions were specially designed to address the specific variables of this model: control (box 3.a); social affinity between partners (box 3.b); cognitive abilities (box 3.c); GUI feedback and its importance for (box 3.d); motivation over time (box 3.e); level of general satisfaction and enjoyment (box 3.f); and subjective rating of communication resources, named verbal, visual, sound and gesture communication (box 3.g).

a) Pre Test Questionnaire (PT)

Box 1

DEMOGRAPHICS AND MUSIC KNOWLEDGE

a) Demographics
- Age: - Genre: - Nationality:

b) General Music knowledge
Please describe the extent to which you agree or disagree with the following statements: 1- I can play music. 2- I can compose music.

c) Electronic Music knowledge
Please describe the extent to which you agree or disagree with the following statements: 1- I can play an electronic instrument. 2- I understand how an electronic instrument works.

b) Post Test Questionnaire

Box 2

MOTIVATION (MOT)

a) Curiosity and Attitude
Please describe the extent to which you agree or disagree with the following statements: 1- Performing with the reactable was an unusual experience 2- I would like to perform more time in order to find more possible combinations and compositions. 3- I want to know more about the reactable.

b) Challenge and Involvement
Please describe the extent to which you agree or disagree with the following statements: 1- The tasks were too difficult to be accomplished 2- Collaboration with my partner was difficult to carry on. 3 - My partner looked surpassed during the tasks.

c) Confidence
Please describe the extent to which you agree or disagree with the following statements: 1- I've accomplished the tasks with efficacy. 2 - My partner looked confident while performing the tasks From 0 to 10, please rate the level you think you achieve in the task. 3- Task 1: 4- Task 2:

Box 3

PERFORMANCE (PER)

a) Control and Distribution of Control
Please describe the extent to which you agree or disagree with the following statements: 1- I was in control of the reactable 2- The reactable was responsive to my actions. 3- I was capable to negotiate different paths and options with my partner in order to achieve the tasks. 4- I didn't feel the necessity of guiding instructions in order to make my choices. 5 - I feel I was leading most of the work in every task.

b) Social Affinity between partners
Please describe the extent to which you agree or disagree with the following statements: 1- I have a relation of friendship with my partner. (maybe can be a Yes/No question) 2- I could communicate with my partner using the tools available for sound composition

d) Feedback
Please describe the extent to which you agree or disagree with the following statements: 1- The visual interface of the reactable help me to understand how to create sound compositions. 2- The interface of the reactable is more adequate for single-user modes.

e) Time
Please describe the extent to which you agree or disagree with the following statements: 1- I felt bored or demotivated as time pass by. 2- The first tasks were more compelling and interesting than the latter.

f) Satisfaction
Please describe the extent to which you agree or disagree with the following statements: 1- I enjoyed the experience using the reactable 2- Playing with my partner was a positive experience 3- I can achieve better results performing the tasks by my own.

g) Nature of the communication
From 1 to 10, please rate the following resources according to the importance you think they had during the tasks: 1- Verbal communication: 2- Visual Feedback from the reactable: 3- Body gestures from your partner: