Neurophysiological Experimental Facility for Quality of Experience (QoE) Assessment

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***Abstract*—The human brain is the epicenter of every human action, thus neurophysiology will pave the way for understanding human behavior and cognition and their interplay with Quality of Experience (QoE). Recent advances in neurophysiological monitoring tools have allowed useful QoE constructs to be measured in real-time, such as human cognition, attention, emotion, fatigue, perception and task performance. In this paper, we describe a multimodal neurophysiological experimental facility recently implemented for QoE evaluation. A description of the facility and the available equipment is presented. Results of three recent studies are also presented, thus showing that neurophysiological correlates can be obtained for i) natural speech and ii) synthesized speech QoE perception, as well as iii) image preference characterization for multimedia QoE evaluation.**

I. Introduction

Quality of Experience (QoE) is a fast emerging multidisciplinary field based on social psychology, cognitive science, economics, and engineering science, focused on understanding overall human quality requirements [1]. Some of the examples of its different sub-factors or constructs are perception, cognition, emotion, judgement, satisfaction, happiness and acceptability. ITU-T defines QoE as "the overall acceptability of an application or service, as perceived subjectively by the end-user" [2]. Normally users manifest their subjectivity through their comments, opinions and thoughts. And that is normally quantified into numerical and interpretable values by conducting user studies, surveys and interviews. In addition to subjective assessment of QoE, there is an emerging trend to objectify QoE by capturing human physiological and cognitive information. The objective QoE factors are based on human physiology, psychophysics and cognitive systems [1], [3] which provide precise information about human cognition and neuronal activities. QoE factors can further be divided into different sub levels for instance level of service (ease of use, joy, feeling), level of interaction (communication efficiency, naturalness), level of direct perception(involvement, localization,distortion), and the level of the usage situation (accessability and the stability) [4]. These different constructs are the result of neuronal activity exhibited at low level sensory processing and/or high-level cognitive processing [4].

The human brain produces thoughts, feelings, memory, perception and experience of the world around us. To demystify the complexities of human brain, neurophysiological insights may be obtained via neuroimaging techniques, such as electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and near-infrared spectroscopy (NIRS), as well as body area sensors and networks. EEG/MEG relies on measuring the electrical/magnetic activity in the brain, whereas fMRI and NIRS are based on tracking blood flow (and correlates) that accompanies neuronal activity. Additionally biosensors could also be used to extract information about the human peripheral autonomic nervous system (PANS), responsible for regulating heart and respiration rates, body temperature, and sweat, to name a few. These insights can shed light into human affective and cognitive states.

With the advances in neurophysiological signal acquisition technologies, there is growing interest in investigating the neurophysiological correlates of human quality perception. The goal of this paper is to provide first hand information on existing techniques and their importance for QoE assessment. We then describe an experimental facility developed at the Institut National de la recherche Scientifique (INRS) in Montreal, Quebec, Canada for QoE assessment. We conclude the paper by presenting results of three recent studies aimed at objectively characterizing human preference, affective states, and attention and their relationship to multimedia QoE perception.

II. Background

In this section, we present an overview of existing neurophysiological signal acquisition technologies, along with their features, strengths, and limitations.

A. *Electroencephalography (EEG)*

The brain's activity is maintained by billions of neurons which are responsible for gathering and transmitting electrochemical signals. Each neuron acts as a dynamically oscillating battery that is continually being recharged [5], thus producing currents which spread throughout the head. These currents can reach the scalp surface, thus generating an electric field potential on the scalp that can be measured by an electroencephalogram (EEG). The EEG is recorded by placing electrodes on the heads surface. These electrodes are often arranged in the so-called 10-20 standard system and are referenced towards an electrode on the tip of the nose or the mastoids (located on the bone behind the ear). EEG data can be characterized by different features, such as amplitudes, latencies, frequencies, and the sites on the scalp at which they were recorded. More details about EEG features will be given next.

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Name	Frequency(Hz)	Detection Area	Functions
Delta	0.5-3.5	Frontal brain area in adults, posterior in children	Deep, restful sleep and unconsciousness state of mind
Theta	3.5-7.5	Mid-temporal region	State of light sleep and drowsiness, visual imagery prominent during infancy and childhood
Alpha	7.5-12.5	Posterior region but with high voltage at occipital region	Drowsy, closing of eyes, relaxed, awake
Beta	12.5-30	Frontal and central regions	Alert, focused attention
Gamma	30-60	Somatosensory cortex	Formation of perceptual functions, memory, linguistic processing, associative learning

TABLE I: Characteristics and function of five common EEG subbands

1) EEG Features: One of the most common EEG components is the event-related potential (ERP), which is a change in the EEG time series in response to a discrete event or stimuli, such as a beep or a flashing light. Event-related potentials can be elicited by a wide variety of sensory, cognitive or motor events, thus providing a safe and noninvasive approach to study psychophysiological correlates of mental processes [6]. The most well known ERP component is the so-called *P300*, which is a positive peaks in the EE time series occurring approximately 300 ms post stimulus onset. An oddball paradigm is the m ost utilized method to elicit P300s; in the oddball paradigm, rare "target" stimuli are presented to subjects amongst a series of more common stimuli. For example, it has been reported in [7] that the amplitude of the *P300* component may change due to stimulus quality, attention level, and task relevance of the stimulus. The *P300* component has also been used for QoE assessment of multimedia services. For example, [8], [9] showed that simple degradations in the speech signal could be processed by humans at a non-conscious level. It was found that increased degradation in a stimulus quality causes increase in *P300* amplitude.

Another common EEG feature is the subband power of five common frequency bands, namely: delta, theta, alpha, beta and gamma. Table I described the frequency range of each band, as well as their most prominent detection areas in the scalp and their functions [10]–[12]. Subband frequency powers, as well as cross-frequency coupling have been used to characterize human mental activation status, cognition, as well as emotions and memory performance [13]. An additional feature commonly used in EEG studies is that of inter-electrode *coherence*. This feature provides a measure of functional association or synchrony between two brain regions, based on the cross-spectral analysis of EEG signals measured by different electrodes [14]. EEG coherence has been applied to studies of cognition [15], emotion [16], and intelligence [17].

2) EEG Limitations: As can be seen above, EEG features can provide useful insights for QoE characterization. There are some limiting factors with the technology, however, which must be taken into account in neurophysiological studies. Representative examples include:

- Poor spatial resolution: Despite having high temporal resolution (brain activation can be detected within a few milliseconds), EEGs suffer from poor spatial resolution as it is impossible to determine the exact location of neuronal activity from the signals measured on the scalp surface due to the ambiguity of the underlying static electromagnetic inverse problem [18]. Notwithstading, advanced source localization methods, such as Laplacian weighted minimum norm (LORETA), local autoregressive average (LAURA), beamformer, and Bayesian approaches [18] have been developed to mitigate this limitation.
- Sensitivity to artefacts: EEG signals are extremely sensitive to various physiological and environmental reasons. The most common physiological artifacts include eye blinks, eye movements, cranial muscle activity, and heart beats. Environmental artifacts, in turn, can be related to power line noise, poor electrode placement, movement, and abnormal electrode impedances. Common methods of artifact rejection include visual inspection and manual rejection, filtering [19], and principal component analysis [20]. While these methods help remove unwanted artefacts, they may also remove useful perceptual/cognitive information.
- Signal quality: EEG electrodes can be classified as wet or dry. Wet electrodes require the use of gel to facilitate direct scalp coupling. They are the most common type to date and are found in research laboratories and in clinical settings. Wet electrodes are the most expensive but provide signals of high quality. Dry electrodes technologies, on the other hand, do not require the use of gels and are quicker and simpler to put on, as well as cheaper to purchase. The drawback is that the quality of the signals are not high, although recent studies in the brain-computer interface (BCI) field have shown dry electrodes to be useful [21].

B. Near-Infrared Spectroscopy (NIRS)

Near-infrared spectroscopy (NIRS) utilizes low intensity near-infrared electromagnetic radiation (650–950 nm wavelengths) through the skull to measure changes in blood oxygenation [22], a direct measure of neuronal activation of the brain [23]. During neural activation, neurons undergo changes in metabolic demand which leads to corresponding increases in oxygen consumption [23]. In order to meet this increase in oxygen consumption, there is an increase in local cerebral blood flow and cerebral blood volume resulting from vasodilation of local arterioles [24]. This regional increase in blood flow results in changes in concentrations of two chromophores, more specifically, an increase of oxygenated hemoglobins and a decrease in deoxygenated hemoglobins. NIRS utilizes a near-infrared transmitter and a receiver to characterize blood flow oxygenation by comparing the intensities of the returning and incident light. This can be achieved as the fraction of light absorbed versus the fraction transmitted is dependent on the concentrations of the two above mentioned chromophores. While NIRS has poor temporal resolution (blood flow changes can take up to 10 seconds to be detected [22]), it provides better spatial resolution than EEG.

1) NIRS Features: Via the so-called modified Beer-Lambert Law, light intensities can be converted into concentration values of oxygenated and deoxygenated hemoglobins. Since NIRS signals are inherently slow, they provide a smaller number of time-domain features for automated analysis. Commonly, changes in oxygenated, deoxygenated and total hemoglobin concentrations (given by the sum of the two) from a baseline state to a mental activity state are used as features [25]. Other temporal features include the latency to achieve a peak concentration post mental activity and the slope of the change. Alternately, spatial synchrony/lateralization features have shown to be useful. For example, the ratio of the right to left hemisphere slopes and the absolute mean difference of the left/right hemispheric slopes was shown to be useful in characterizing the emotional content of music [26], an important aspect of QoE perception.

2) NIRS Limitations: Using NIRS as a neuroimaging tool has been a relatively new endeavour, thus several limitations still exist. Despite being more robust to movement artefacts than EEG, NIRS signals are still sensitive to movement if optodes are not placed correctly. Moreover, NIRS signals are contaminated by several physiological artifacts, such as heart pulsation (1-1.2 Hz), respiration (0.5 Hz), and the so-called Mayer waves (0.1 Hz) which represent blood pressure effects [27]. While many ad-hoc approaches have been proposed to mitigate these effects (e.g., band-pass filtering), standardized procedures have yet to be developed. Moreover, compared to magnetic resonance imaging, NIRS provides a relatively low depth resolution. Using Monte Carlo simulations, a recent study showed that the maximum depth penetration achieved by NIRS was approximately 23 mm [28]. This limits the use of NIRS to gather insight into deeper brain regions, such as the hippocampus.

C. Peripheral Autonomic Nervous System (PANS) Signal Acquisition

The peripheral autonomic nervous system (PANS) is responsible for the communication between the central nervous system and the rest of the body. It mediates physiological actions such as respiration, heart rate, skin conductance, and skin temperature, factors which have been shown useful in characterizing fatigue, affective states, and attention.

1) PANS Signal Features: Skin conductance (also known as galvanic skin response or electrodermal activity) is a measure of sweat present in the skin and is often used to characterize arousal levels, due to increased activity in the sweat glands, as well as attention, habituation, and cognitive effort [29], [30]. Commonly, amplitude changes in skin conductance, number of electrodermal activations (defined as an instance in which the skin conductance surpassed a pre-specified threshold), or skin conductance variability are used as common features [31]. Directly related to sweat characterization is the use of skin temperature signals to characterize human affective states.

Signals related to the cardio-respiratory function have also shown useful in characterizing human affective states. Features such as heart rate (HR), heart rate variability (HRV), and blood pressure have been used as indicators of emotional experience [32], [33]. Similarly, respiration features such an inhalation/exhalation duration have been used to characterize emotional arousal state [34]. While HR and HRV can be measured using a photoplethysmograph sensor or an electrocardiogram, respiration signals are commonly measured using a piezoelectric belt placed around the thoracic area, with which stretching due to expansion and contraction of the chest is converted into voltage changes.

2) PANS Signal Limitations: PANS signals have been used in numerous applications ranging from biofeedback to lie detection. While existing biosensors are fairly robust to movement artefacts if placed correctly, many are cumbersome to wear and are not portable/wireless. Commonly, PANS biosensors are placed on fingers in the non-dominant hand, thus limit their use in moving "living lab" studies. Advances in signal acquisition technologies, however, have allowed for wireless multimodal devices to be developed.

D. Multimodal Integration

As seen above, each of the three technologies carries its own strengths and weaknesses. By integrating the technologies in a clever manner, it is expected that a richer pool of information will be made available, thus allowing us to better understand human QoE perception. As examples, by integrating NIRS and EEG, we can take advantage of the EEG temporal resolution and the NIRS spatial resolution to gather insight into neuromuscular coupling and its role in QoE perception. Moreover, by measuring NIRS, EEG and PANS signals concurrently, physiological artefacts can be removed more reliably. Moreover, data segments contaminated by movement artefacts can be detect more accurately.

III. Implementation of a Neurophysiological Experimental Facility for QoE Assessment

Quality of Experience perception is dependent on several human influential factors [4], which can be inferred by intelligent signal processing of neurophysiological signals. As such, an experimental facility has been implemented at the Institut National de la Recherche Scientifique in Montreal, Quebec, Canada. The facility features an integrated NIRS-EEG-PANS system, as well as portable multimodal system for QoE assessment studies, both in controlled and in "living

Fig. 1: Combined EEG and NIRS setup

lab" scenarios. The multimodal integrated setup includes a 64-Channel ActiveTwo EEG system from BioSemi, a 384-channel NIRS system from NIRx, a head-mounted eye-tracking system, and a suite of PANS biosensors. All systems are integrated and time-aligned signals can be obtained for multimodal analyses. Figure 1 depicts a participant wearing the customized NIRS-EEG headset. For particular studies (see Section IV.B), NIRS optodes are placed in the pre-frontal cortex region (forehead), in order to closely monitor cognitive and affective states. EEG electrodes, in turn, are placed in a full-head configuration, such that multiple brain networks can be investigated.

Customized integrated portable systems are currently being developed by integrating a portable EEG system (EMOTIV EPOC and InteraXon Muse headsets), a portable NIRS system (32-channel NIRSport from NIRx), and portable PANS bion-sensors (Biopeak Biofusion bioimpedance monitor, Affectiva Q Sensor). These wireless devices will be integrated via Bluetooth to portable iOS and/or Android devices. Moreover, in order to process the high dimensionality of the recorded data, multi-core computers are available with 100Gb of available RAM. ITU-T (International Telecommunications Union) standardized rooms are also available to conduct user studies. Large-, medium-, and small-sized screens (i.e., 30-inch monitors, tablets, smartphones, respectively) are available for multimedia QoE studies, as well as 32-channel microphone and speaker arrays are available for speech/audio QoE assessment.

IV. Pilot Experimental Results

Three pilot experiments have been performed with the recently-implemented experimental facility. Two of the experiments have focused on speech QoE perception, while the third has focused on multimedia QoE perception. More details about the three studies are given below and in the references therein [9], [35], [36].

A. QoE Perception of Hands-free Speech Communication

Hand-free speech communications is often corrupted by room reverberations which can compromise communications and affect QoE perception. In the first pilot study, we used electroencephalography (EEG) and self-assessment tools to investigate the neural and affective correlates of reverberant speech QoE perception. Room impulse responses recorded in a typical home living room environment (reverberation time of 400ms) and in an auditorium (reverberation time of 1500ms) were convolved with the clean speech signals to generate the reverberant stimuli. We found significant correlations between the P300 ERP component and reverberation time, as well as between the P300 peak amplitude and emotional self-assessment ratings. Moreover, negative correlations between P300 peak amplitudes and subjective quality ratings were obtained, thus suggesting that cognitive neural networks were involved in order to comprehend low-quality speech stimuli. Additionally, human reaction time in the P300 oddball task was computed for each presented stimulus, and a significant main effect with reverberation time was also observed for *reaction time*. These insights could lead to more effective ways of characterizing room acoustics.

B. QoE Perception of Text-to-Speech (TTS) Synthesis

Text-to-speech (TTS) synthesis systems have evolved drastically over the last decade, but despite these advances synthesized speech quality and intelligibility is still far from what is achieved with natural speech. In this study, we explored the use of NIRS and EEG correlates of human affective states, comprehension, and pleasantness perception.

Synthesized speech stimuli from the international TTS Blizzard Challenge [37] were used and consisted of 10-second sentences generated by a low-, medium- and high-quality TTS systems. Experimental results showed a statistically significant relationship between EEG alpha, beta and gamma powers and arousal and valence levels. Moreover, a significant (inverse) main effect between TTS low- and high-quality stimuli on P300 peak amplitude was also observed as depicted in Figure 2 [35]. NIRS oxygenated and deoxygenated concentration values showed significant correlations with both affective and quality constructs, suggesting that NIRS and EEG can be used to characterize speech QoE perception.

C. Image Preference Characterization

When characterizing multimedia QoE, content and content *preference* play an important role. In this pilot study, we explored the use of NIRS lateralization features and PANS signals to automatically classify mental states according to three different classes: when a preferred image was shown, when a non-preferred image was shown, or a neutral baseline mental state. An accuracy rate as high as 72% could be obtained when insights from the NIRs and PANS modalities were fused at the classification stage [36].

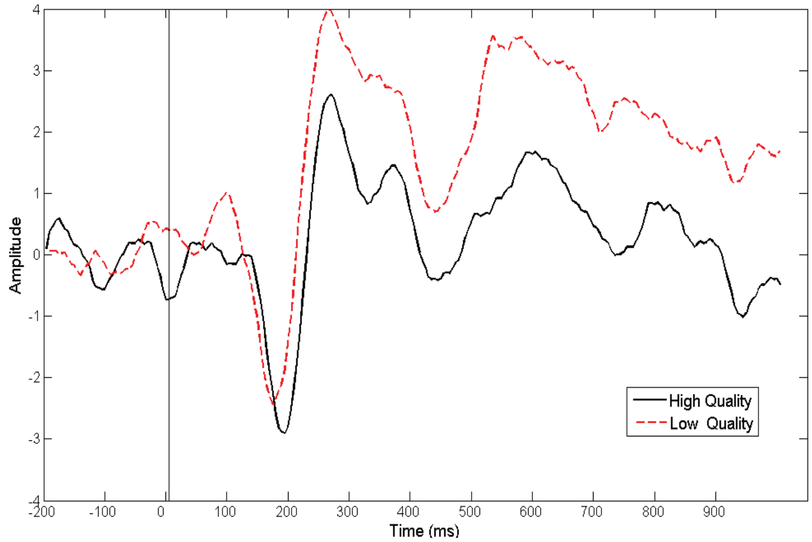

Fig. 2: P300 potentials elicited by low- and high-quality TTS stimuli

V. Conclusions

Quality of experience (QoE) characterization requires multi-disciplinary insights into human perceptions, feelings, and expectations, to name a few human influential factors. These factors are subjective and vary between users, thus making it hard to accurately quantify and measure QoE objectively [38]. Notwithstanding, advances in neuroimaging and physiological signal acquisition tools have opened doors for these subjective insights to be quantified and characterized in real-time. This paper has described our efforts of developing an experimental facility that will allow for such human influential factors to be automatically characterized. Promising results from three pilot experiments suggest that complex human neurophysiological processes may be characterized, such as arousal, valence, attention, and preference.

More work is still needed, however, in order to better align our developed experimental protocols with those standardized by e.g., ITU-T. For example, in EEG experiments in general, short-duration stimuli are commonly presented (in the order of 100-1000 ms), content variability is kept to a minimum, and users are instructed to stay as still as possible, as to minimize artifacts in the collected data. Alternately, conventional ITU-T subjective tests usually involve audio-visual stimuli of 8-12 seconds in duration and varying content; furthermore, users are normally free to move around their chair during the experimental protocol. Moreover, in EEG ERP-based studies, multiple repetitions of a test are needed in order to improve the signal-to-noise ratio of the P300 curves; this repetition may cause fatigue and compromise subjective results. Ultimately, it is hoped that the experimental facility will allow for a better understanding of the human internal processes behind QoE perception, thus leading to improved subjective testing protocols, objective quality models, and multimedia technologies.

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