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An apparatus to investigate western opera singing skill learning using performance and result biofeedback, and measuring its neural correlates

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Abstract

We present our preliminary developments on a biofeedback interface for Western operatic style training, combining performance and result biofeedback. Electromyographic performance feedbacks, as well as formant-tuning result feedbacks are displayed visually, using continuously scrolling displays, or discrete post-trial evaluations. Our final aim is to investigate electroencephalographic (EEG) measurements in order to identify neural correlates of feedback-based skill learning.

Index Terms: western opera singing, face muscle activity, singing power ratio, feedback-learning, neural correlates

1. Introduction

The skill learning mechanisms involved in biofeedback should be thoroughly investigated, as the existing literature is largely insufficient to understand biofeedback and explain how it works [1]. We present an experimental apparatus designed to measure neural correlates of biofeedback-based skill learning in western opera singing. Feedback-based skill learning for voice training has been exploited since the late 80s [2, 3]. A voice biofeedback can either target singing performance, i.e., the quality of the subject's vocal gesture; and its result, i.e., vocal quality [4]. In our approach, we propose two different feedbacks: (1) performance feedback related to face and larynx muscle activation indicative of the vocal gesture, and (2) one result feedback related to voice and formant tuning indicative of voice quality for Western opera singers.

2. Material and protocol

Audio signal is recorded using a B004L9KLT6 Yeti Pro USB microphone. Brain activity is monitored by a 20 channels EEG Neuroelectrics Enobio device, placed according to the international 10-20 system . Data are acquired, processed and feedback is displayed using Matlab R2016a, and the Psychophysics Toolbox extensions [5].

Controlling the psychological traits of the subjects, as well as their psychological state during an experiment, is a standard practice to put into context the outcomes of the experiment. In our study, we will use the following scales to evaluate the psychological traits which may have an impact on biofeedback outcomes: the 16 Personality Factors-5 (16 PF-5) [6], the STAI-Y anxiety scale [7], and a cognitive training expectation questionnaire [8]. We will also evaluate the relevant psychological states during sessions, employing a new scale that we constructed by using a selection of sub-items from the Brief Mood Introspection Scale (BMIS) [9], the locus of control scale related to technology (KUT) [10], the Learning Style Inventory (LSI) [11] and the NASA Task Load Index (NASA-TLX) [12].

3. Biofeedback-based skill-learning

3.1. Biofeedback procedure

We propose an interface for training opera singers, which embeds a muscular tension feedback and a formant tuning feedback (Figure 1). Subjects will perform warm-up exercises. Biofeedback training will be divided into 5 sessions. During the first two sessions, the feedback will be displayed as a continuous succession of horizontally right-left scrolling points, with the x-axis representing time and the y-axis representing performance. During the third session, the provided feedback will add a discrete post-trial feedback to this continuous feedback. This discrete feedback is a qualitative feedback indicating low to high performance coded by a pictogram. Then, during the two last sessions, feedback will only be post-trial. This training procedure relies on the hypothesis that feedback is progressively internalized [1] from one training session to another. For each session, a new set of warm-up exercises will be proposed in order to promote general singing skills instead of a specific training on a single exercise.

Figure 1: *Picture of the recording equipment.*

3.2. Formant-tuning feedback

Vocal effectiveness can be quantified by acoustic measures such as singing formant [13]. However, automatic detection of singing formant can be particularly difficult, especially in female high-pitch singing [14]. The Singing Power Ratio can instead indicate signing performances for both male and female singers [15]. However, as shown in [16], this measure is sensitive to sound nuances, which would be problematic for real-time performance estimation. In order to address this issue, we propose to use a normalized Singing Power Ratio (nSPR). We first normalize the intensity of each raw signal frame (division by the L2-norm of the frame). nSPR is afterwards estimated as the ratio between the difference in amplitude between the highest harmonic in the 2-4 kHz range and the highest harmonic in the 0-2 kHz range [15].

3.3. Muscular feedback

Muscular tensions should be avoided in Western operatic singing [17]. We will use electromyographic (EMG) sensors to monitor muscular tensions in singers. As a preliminary muscular performance index for future biofeedback, we used the output of a binary classifier designed to discriminate, from EMG signals, non-placed voice from well-placed voice. The optimal position of EMG sensors was determined in a pilot study where we recorded a professional singer: a total of 336 epochs of 1 sec with well-placed voice and 336 epochs of 1 sec with non-placed voice were collected. We compared the classification performances of EMG data collected from sensors placed over the right and left occipitalis, upper and lower left masseter, upper right and lower left sternohyoid, and clavicula. We then extracted from these EMG data Fourier power using Welch periodograms with Hamming windows of 500 ms, in signal epochs of 1 second, and subdivided into 11 frequency ranges (1-4, 4-8, 8-12, 12-20, 20-30, 30-45, 55-95, 105-145, 155-195, 205-245, and 255-295 Hz). Supervised feature selection was performed using the orthogonal forward regression method [18]. Three electrode positions provided optimal detection of voice placement: the upper and lower left masseter, and upper right sternohyoid, in the 12-20, 155-195 and 205-245Hz frequency range. The selected features were fed to a SVM classifier to predict the output vector; performance was estimated by leave-one-out cross-validation [19]. Classification of the voice placement quality according to these features led to an accuracy of 79% (sensitivity 76%, specificity 83%).

4. Conclusion and future applications

Our data collection is ongoing. We propose a feedback on two aspects: (1) muscular tensions, and (2) spectral cues of Western operatic singing. We conducted a preliminary study about muscle activation with a professional opera singer and could predict singing quality from three EMG sensors. Furthermore, we also use the Singing Power Ratio as a feedback and aim to measure the EEG neural correlates of feedback learning. EEG signals will be used to assess how distant brain areas interact in response to feedback and how it affects learning: event related potentials in response to discrete feedbacks, and EEG oscillations in response to continuous feedbacks [20].

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6. References

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