THE SONIFICTION OF EMG DATA

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ABSTRACT

This paper describes the sonification of electromyographic (EMG) data and an experiment that was conducted to verify its efficacy as an auditory display of the data. A real-time auditory display for EMG has two main advantages over the graphical representation: it frees the eyes of the analyst, or the physiotherapist, and it can be heard by the patient too who can then try to match with his/her movement the target sound of a healthy person.

The sonification was found to be effective in displaying known characteristics of the data. The 'roughness' of the sound was found to be related to the age of the patients. The sound produced by the sonification was also judged to be appropriate as an audio metaphor of the data it displays; a factor that contributes to its potential to become a useful feedback tool for the patients.

1. INTRODUCTION

Physiotherapists use EMG sensors to monitor the electrical activity of the muscles of patients. Electrodes attached to the skin of the subject detect the electrical signals from the muscles below the skin, and send it to a computer where the signal is transformed into digital information. The computer typically runs an application that receives the data, performs some basic statistics on it and displays it in graphical form.

Such applications nowadays display the data in real-time as it is gathered and can also store it for later analysis. The physiotherapist will try to spot irregularities as the data is gathered, but the data can only be thoroughly analysed at a later time because of its complexity.

EMG signals are believed to be full of information about the muscle activity and it is hypothesised that this visual analysis does not exploit to the full the information contained in the data.

1.1. Traditional analysis of the raw signal

The raw signal contains all the possible information we can have from EMG.

"[The analyst] should monitor the raw signal, even though other signal processing may be used, so that artefacts can be detected and controlled as necessary" [1, p. 74]

"In the past, probably the most common way to interpret EMG was by visual inspection of the raw signal. The observer should be able to identify when the raw signal indicates that a muscle is active and when it is relaxed. The relative amount of activity may be classified either by words, such as nil, negligible, slight, moderate, marked or very marked, or by numerical values, such as 0-5, with 0 being no activity and 5 being maximal activity. Such visual observations are based on signal amplitude and frequency."[1, p. 74]

The raw signal should be monitored for all investigations, because the investigator can pick out major artefacts and eliminate that area or part of the signal. Monitoring the raw signal in real-time means looking at a graph that contains a lot of noise. The expert analyst is used to check for anomalies in the signal, but this monitoring requires a lot of experience and focus (since the analyst cannot look away from the screen).

Sound can be a good alternative for monitoring the raw signal, and one that allows vital eye contact and focus with the patient to be maintained.

2. SONIFICATION OF EMG DATA

One aim of this research is to study if it is possible to meaningfully map EMG data to sound parameters in order to create an informative sound display of the data. We aim to study known parameters in the data (such as the effect of a patient's age on their muscle condition) and test to see if these can be detected in a sound-only display. If found to be effective, this new display has the potential to become a new useful tool for more general analysis and the monitoring of EMG, in particular when coupled with other standard analysis methods. Previous work with EMG and sound is covered in [6] (using EMG as a musical input), [7] which considers EMG signals as sound-ready data:

"EMG signals are in the audible range. From the origin of the technique long time ago, a loudspeaker is connected to the output of the amplifier and in this way the patient can hear his or her own "muscle noise" in real time. The patient can hear the variation with the increase of effort or the rhythmical appearance of the discharge of Motor Unit Potentials (the basic functional units of the neuromuscular system). This activity is highly informative for the physician carrying the test." [7]

. As we have shown in [8], the analysis of complex data sets, which are normally displayed visually, can be enhanced by using an audio display and an interesting observation concerning this is made in [9] that:

"the interference patterns of a surface electromyographic (EMG) signal are too complex to permit visual analysis." [9]

2.1. The data

The data used in this research was gathered by physiotherapist Dr John Dixon, research fellow at Teesside University (Middlesbrough), for his PhD research [2].

Dr Dixon measured the EMG data of 3 muscles of the leg: the Vastus Medialis, the Vastus Lateralis and the Rectus Femoris.

The subjects belonged to 3 particular groups: i) young (< 45 years old) asymptomatic (i.e. not known to be exhibiting symptoms in this case of osteoarthritis) participants (23 subjects), ii) old (> 45 years old) asymptomatic participants (17 subjects) and iii) old (> 45 years old) patients (17 subjects) with symptoms of osteoarthritis (OA) of the knee.

The aim of Dr Dixon's thesis was to investigate whether the onset of EMG activity in vastus medialis oblique (VMO) was delayed relative to that of vastus lateralis (VL) in symptomatic OA knee patients compared to asymptomatic control subjects. In his investigation Dr Dixon could not find that such a delay existed.

In this sonification experiment, the contraction data were transformed into sounds and listening subjects asked to rate the sounds following certain criteria.

In the real-time sonification set up, the EMG sensors are connected to our collaborator's existing clinical Biopac [3] analogue-to-digital converter (which allows file storage and visual analysis), and also into a computer running our sound mapping software (written in PD). Figure 1 shows this set-up, with a patient about to perform a leg extension (with resistance from the machine).

Figure 1. *The clinical set-up for gathering data*

Twelve data sets were selected from the young asymptomatic group, nine from the old asymptomatic group and nine from the old OA symptomatic group. The subjects were chosen randomly from the existing groups.

2.2. The aim of the experiment

There are some characteristics of these datasets which are known to change with the age of the subjects, as reported by John Dixon [2]. In particular:

1 - The overall amplitude of the signal tends to reduce with age;

2 - The slope or rise of the signal tends to reduce with age.

These two characteristics represent the muscles having less power with increased age and taking a longer time to reach the maximum power.

The main aim of the experiment described here is to verify that these two characteristics are clearly displayed by the chosen sonification algorithm.

2.3. Design criteria for the sounds

Initial experimentation was carried out using example data sets from patients of our collaborators at the Teesside Centre for Rehabilitation Sciences. We used the Interactive Sonification Toolkit [4] to experiment with various methods of converting the EMG data into sound (sonification). This toolkit allows researchers to take in multiple data sets, and try out a range of data-scaling and sonification techniques.

Our design criteria for the sonification algorithm were:

- Should portray an accurate analogue of the signal
- Sounds should be made in real-time, in response to movement
- Should be pleasant to listen to (or at least not annoying)
- Needs to be audible when analysing the data at different speeds
- Should allow signals from several EMG sensors to be listened to together.

Our first experiments involved audification - the direct conversion of data samples into sound. This has an obvious analogy with the signal, and indeed some of the older EMG machines made audible their input signals in this way. However the EMG data sampling rate is rather slow compared to the data rate needed for sound, so when analysing a signal slowly there was not fast enough change in the signal to make it audible. Also, when multiple sensors were used the resultant signal becomes very noisy.

2.4. The sonification algorithm

For each subject, there exists data on 6 channels: 2 channels (one for each electrode) on each of the muscles being recorded. The original sampling rate of the data is 2048 samples per second.

The final choice of sonification involved amplitude modulation; each EMG sensor was mapped to the amplitude of a different sine oscillator. The frequencies of the different oscillators were set in a harmonic relationship with each other with the intention of making the sound pleasing. This method also provides a tone if there is any movement in the signal, whatever speed of playback. It also allows the modulation of several sensors simultaneously, fusing their varying inputs into one complex, but easily understood, resultant sound.

Table 2 shows the mapping between the electrode data channel and the oscillator frequencies. The input spectrum shown here does not mean to represent a real EMG data channel spectrum which typically is complex and noisy. The outputs of these 6 amplitude modulations are then mixed and sent to the output. The resulting sound is perceived as one; i.e. one timbre (as supposed to a mix of different timbres playing simultaneously). Each data channel contributes to the output sound by introducing sound signal in a frequency band around the oscillator frequency of that particular channel.

Rectus Femoris electrode 1 freq = 261.6Hz (mid C)
Rectus Femoris electrode 2 freq = 523.2Hz
Vastus Lateralis electrode 1 freq = 784.8Hz
Vastus Lateralis electrode 2 freq = 1046.5Hz
Vastus Medialis electrode 1 freq = 1308.1Hz
Vastud Medialis electrode 2 freq = 1569.7Hz

Table 2: Frequencies used in the sonification

3. EXPERIMENTAL PROCEDURE

A listening test was set up so that a number of subjects could listen to the 30 sonifications created and then score them, on a scale from 1 to 5, for characteristics related to those listed in section 2.2.

A program was developed in Pure Data [5] that was used to run the experiment and gather most of the experimental results automatically (see Figure 2).

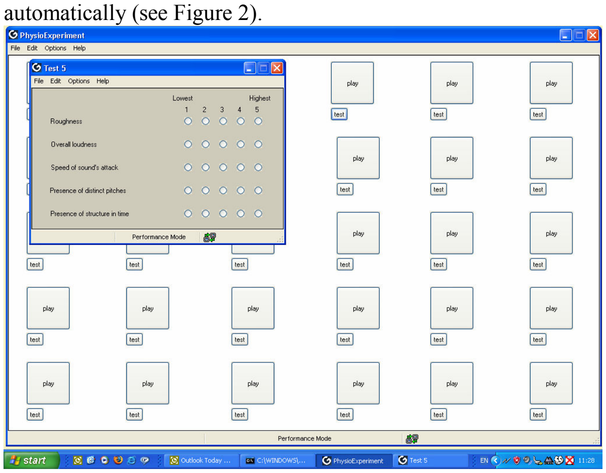


Figure 2. *The test interface developed in PD*

When this PD program was opened, the subjects were presented with a screen containing 30 buttons. Each button, if clicked, played the sonification of one data set. In order to be able to score each sound in relation to the others, it was important that the subjects had an idea of the overall range of variation of the sounds before starting to score. So, the subjects were asked, at the beginning of the test, to listen to all the sonifications at least once before starting the test.

For each sonification, another button was present in the screen labelled 'test'. After having listened to a sonification as many times as desired, the subject clicked on the corresponding 'test' button and was asked to score from 1 to 5 (low to high) various characteristics of the sound.

The characteristics were:

- **Overall loudness;**
- **Speed of sound's attack;**
- **Roughness;**
- **Presence of distinct pitches;**
- **Presence of structure in time.**

Overall loudness and **speed of sound's attack**, are the variables that should vary with age and therefore they were clear candidates to test the validity of the sonification. **Roughness** is a descriptor used to indicate the quality of the overall timbre of the sound. **Presence of distinct pitches** and **presence of structure in time**, were noticed to appear in some of the sonifications. No relation was hypothesised with either age or group. These characteristics were tested in order to verify if any significant unknown trend could be extrapolated from the results.

The scores of each subject were written automatically into a text file then saved in the computer.

Each subject was presented with the sonifications in a new random order so that biases due to order of presentation were cancelled.

The test was carried out in a silent room (in the recording studio performance area at York University). Good quality headphones (DT 990 Beyerdynamic) were used with a wide frequency response (5 – 35,000Hz). The volume of the sounds was maintained the same for all subjects.

3.1. Qualitative questioning

After the test, additional information about the sonifications was gathered via a questionnaire, which asked the subjects to score from 1 to 5 (low to high):

1) the pleasantness of the sonifications
2) how interesting they found the sounds

They were also asked to answer questions to find out if the sounds were tiring and inducing fatigue, something which might be detrimental if used in a clinical environment.

They were also asked questions to find out if the sound worked well as a sound metaphor of muscle movement.

- Did these sounds remind you of any natural sound? - These sounds are synthesised from data produced by the activity of leg's muscles. Do you find this sound appropriate to represent muscle's activity, i.e. movement? (please comment if you wish)

3.2. The test subjects

21 subjects performed the test. Their average age was 29. There were 3 females and 18 males. All the participants were British apart from one from Malaysia and one from France. 19 participants were researchers, students, lecturers in engineering (with a specialisation in sound), 2 people were researchers in physiotherapy, 4 people work with sound only sporadically.

4. RESULTS

For each one of the 30 sonifications and for each of the 5 characteristics, an average was made over all the test subjects (listeners). The averages were then ordered by age of the person whose muscles were portrayed by the sonification.

4.1. Loudness, attack and roughness

On average, the overall loudness decreases with increasing age as expected (see Figure 3), since loudness represents the signal amplitude and this was one of the known characteristics of this data set.

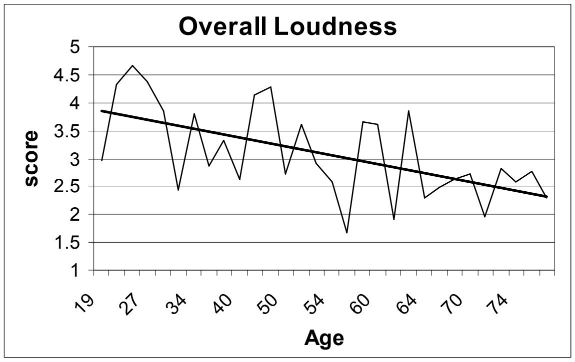


Figure 3. *Results for Overall Loudness against age*

There is a significant negative rank correlation between the age and the loudness average scores.

Non-parametric Spearman rank correlation factor = -0.57, significance test $p < 0.005$.

4.2. Attack Speed

The attack speed also decreases in average with the increase of age as expected (see Figure 4).

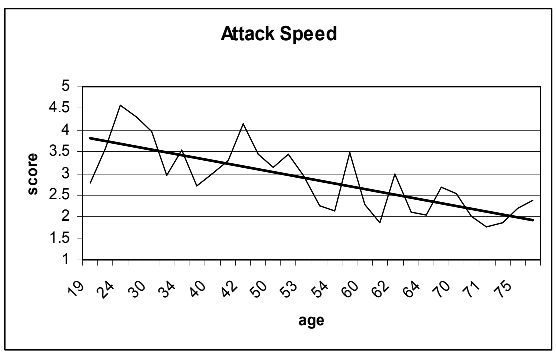


Figure 4. *Results for Attack Speed against age*

There is a significant negative rank correlation between the age and the loudness average scores. Non-parametric Spearman rank correlation factor = -0.58, significance test $p < 0.005$.

4.3. Roughness

On average, the perceived roughness of the sound decreases as the age increases (see Figure 5). There is a significant high negative rank correlation between the age and the loudness average scores. Non-parametric Spearman rank correlation factor = -0.75, significance test $p < 0.005$.

4.4. Correlation between the results for roughness and both loudness and attack speed

The roughness average scoring is very highly correlated with the loudness scoring, i.e. correlation = 0.91, significance $p < 0.005$.

The roughness average scoring is also highly correlated with the attack speed i.e. 0.73, significance $p<0.005$, but less than the loudness.

People perceive the sound resulting by this sonification to be rough when the loudness is high and the attack's speed is high.

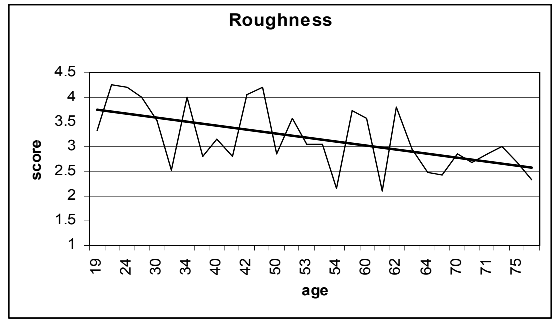


Figure 5. *Results for Roughness against age*

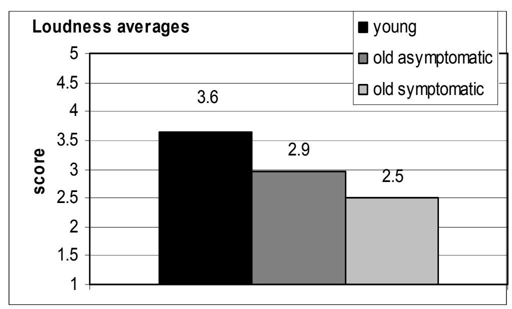
Since these two characteristics, overall loudness and attack speed, are known to be related to age (a fact confirmed by this experiment) then, on the basis of this correlation, we can expect a rough sound to belong to a young person and a less rough sound to belong to an older person (which is confirmed by the correlation between the roughness and the age).

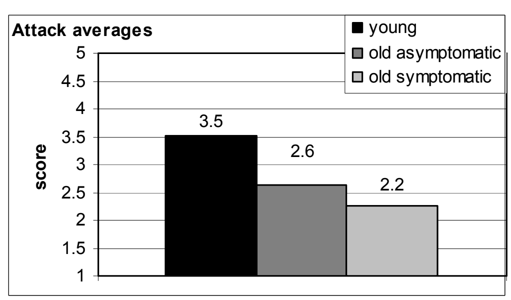
It seems, therefore, that the descriptor 'roughness' can represent both the loudness and the attack speed of the sound simultaneously and is an example of descriptor which could be used in the communication between a patient and a physiotherapists (both nor necessarily at ease with the language of sound parameters).

4.5. Looking at the results in relation to the groups

In this experiment there were 3 groups: young people asymptomatic, old people asymptomatic and old people symptomatic.

Looking at the average results by group for roughness, loudness and attack speed, it can be seen that the average score for all of these 3 characteristics decreases when looking at the groups' results in the following order: young people, old asymptomatic and finally old symptomatic.





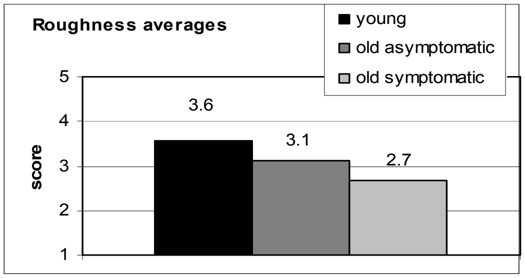


Figure 6. *Results for main characteristics in subject groups*

Significance test for 'Loudness': Friedman 10.5 $p < 0.006$ significant. Significance test for 'Attack': Friedman 9.56 $p<0.006$ significant. Significance test for 'Roughness': Friedman test 3 conditions 5.6 $p < 0.069$, this result is not significant because $p > 0.05$.

Looking at the significance tests, it can be seen that the differences between groups' results for loudness and attack speed are significant, while the roughness result is not significant. The significance test to check if the difference in results between the group of old asymptomatic people and the group of old symptomatic people (Wilcoxon test) is not significant.

Therefore with this experiment we cannot say that if sound is an indicator of the subject symptomatic or asymptomatic status.

4.6. Presence of distinct pitches and structure in time

No significant trends were found between the scores of these characteristics and age or groups.

4.7. Summary of main results

1. The overall loudness decreases with age as expected.

2. The speed of the sound attack decreases with age as expected.

3. The scoring of 'roughness' decreases with age.

4. The perception of roughness is highly correlated with the perception of loudness and speed of sound attack.

5. Roughness can be considered as a higher level descriptor of loudness and attack, i.e. a measure of age of subject.

6. By looking at the results of roughness, attack speed and loudness in relation to symptomatic and asymptomatic groups (which in this experiment are not significant because the number of subjects in the asymptomatic and symptomatic groups of the same age range is too small), since they are consistent for all three characteristics (i.e. there is a decrease in average rating from the asymptomatic to the symptomatic group), it is hypothesised that these three characteristics could distinguish between asymptomatic and symptomatic groups. To verify this another experiment should be run with a larger amount of sonifications/subjects in each group.

7. In particular roughness, attack and loudness scorings seems to be lower for old symptomatic patients than for old asymptomatic participants (considering the same age range). This should be verified with a higher number of sounds.

5. QUESTIONNAIRE RESULTS

5.1. Pleasantness and interest

The subjects were asked to score how they found the sounds in terms of pleasantness and interest. A score of 1 corresponded to very unpleasant and uninteresting, while a score of 5 represented very pleasant and interesting. The following two figures chart the results for each question asked.

The Average score for pleasantness was 2.9, and for the interest in the sound it was 3.7.

On average, the subjects found the sound *neither pleasant nor unpleasant* and they found it f*airly interesting*.

5.2. Fatigue

In order to have a rough measure of how fatigued the subjects were after doing this experiment (which lasted on average around 20 minutes) questions were asked regarding how tired they were at the end of the test.

5% were tired of listening to any sound

60% were tired of listening to this type of sound, but could have then listened to some different types of sound

35% could have listened to more of these sounds.

5.3. Metaphor

The sonification used in this experiment, does not attempt to create metaphorically an audio image that relates to how the data originated.

It is important, though, in order for the sonification to be a good display, that the sound's image is at least not in contradiction with the actual event that originated the data, because this could make the display very unclear. For example, in a visual display we would not represent apples with bananas because it would create mistakes of interpretation. To investigate this part of the problem, the subjects were asked to write what event they associated with the sounds they heard. It is interesting to see if the image, which was not predetermined during the choice of the sonification algorithm, could be consistent, or at least not in contradiction, with the representation of muscle activity.

The following question was asked:

Did these sounds remind you of any natural sound? If yes which one?

The subjects wrote various different answers, but surprisingly many answers were similar and could be grouped under the same label (see Table 3, below).

LABEL	ANSWER	NUMBER OF ANSWERS
animal sound	Whale sound (2) Birdsong	3
underwater sounds	Diving bubbles diver's breathing apparatus breathing underwater bubbles under water bubbles underwater (2)	7
sea waves	Waves (5)	7

	Pebbles washed by sea Waves on pebbles	
musical instrument	Flute Organ pipe Wind instrument	3
natural event	Thunder (2) Earthquake	3
materials	Sandpaper Dragging over wooden floor Gravel Creaking of ropes	4
mechanical sounds	Factory noises Tuning sounds Flight landing and take off Crackles	4

Table 3: Subjects' responses to metaphor questions

The majority of these images are related with an event that is characterised by a gesture. Either a human gesture, a movement or a natural gesture. In particular, the majority of answers can be related to air, wind and water:

- Underwater sounds 7
- Waves 7
- Musical instrument 3
- Wind/air 3
- Natural events 3

Therefore 30 answers out of 34 relate to gestures created by air, wind or water.

It can be concluded that the sound portrays gesture and movement even though considerations about appropriate metaphors were not taken into account when designing the sonification.

5.4. Summary of Results from questionnaire

1. The sound needs improving aesthetically so that, without losing its display power, it can be listened to without problems by analysts, physiotherapists and patients.
2. After 20 minutes of listening to this sound only 35% could have listened to it more. It seems to cause fatigue.
3. This type of sound portrays an audio image of movement so it is not in contradiction with what it tries to represent
4. 50% of the subjects found the sound appropriate or fairly appropriate. 25% found it inappropriate. A majority of people found it appropriate.

6. CONCLUSIONS

This paper has described a sonification technique to display EMG data gathered in real-time. The sonification uses amplitude modulation to create timbres that portray six channels of data.

This paper also describes the experiment conducted to evaluate the efficacy of this sonification. The sonification was found effective in displaying known characteristics of EMG data. The "roughness" of the sound's timbre was found to be correlated to the age of the patients. Despite the fact that the sonification was considered fatiguing to listen to, it was considered to be appropriate to represent EMG data, i.e. muscle movement, and the majority of subjects associated the sound with a natural gesture (e.g. breathing, sea wave, etc.) suggesting that the sound is a good audio metaphor of what it represents.

Muscle monitoring is a complex activity and currently involves therapists in many hours of visual data mining to interpret the data for use in the clinical environment. The sonification of EMG data allows the health care professional to observe the patient rather than the screen, using an auditory signal which may be better qualitatively understood than (and may provide additional information to) the more traditional visual displays. This is an innovative approach and has the potential to change clinical practice.

7. ACKNOWLEDGEMENTS

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