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Musification of Accelerometry Data Towards Raising Awareness of Physical Activity

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ABSTRACT

Previous research has shown that the temporal dynamics of human activity recorded by accelerometers share a similar structure with music. This opens the possibility to use musical sonification of accelerometry data to raise awareness of daily physical activity. In this study a method was developed for quantifying the daily structure of human activity using multigranular temporal segmentation, and applying it to produce musical sonifications. Two accelerometry recordings of physical activity were selected from a dataset, such that one shows more physical activity than the other. These data were segmented in different time-scales so that segmentation boundaries at a given time-scale have a corresponding boundary at a finer time-scale, occurring at the same point in time. This produced a hierarchical structure of daily events embedded in larger events, which is akin to musical structure. The segmented daily data of each subject was mapped to musical sounds, resulting in two short musical pieces. A survey measured the extent to which people would identify the piece corresponding to the most active subject, resulting in a majority of correct answers. We propose that this method has potential to be a valuable and innovative technique for behavioural change towards reducing sedentary behaviour and increasing physical activity.

1. INTRODUCTION

Miniature sensors, wearable devices and mobile technologies can track daily activity of people, both in extent (i.e., amount of movement) and type (e.g., walking, sitting). This capability has been utilised as a behavioural change technique [1] in interventions to promote a healthier lifestyle, increase physical activity and reduce sedentary behaviour [1] [3, 4]. These technologies may be effective aids in interventions to increase physical activity and reduce sedentary behaviour [5], but only in the short-term. Long-term adherence is still a major challenge [6–10]. Recent reviews suggest that more engaging methods are needed to effectively produce a change in behaviour [11].

Sonification is a potential strategy to increase long term engagement and adherence, especially since it has been shown that the temporal dynamics of human motion and activity share similarity with that of music [12, 13]. Several studies have explored the use of real-time sonification of movement to aid sports performance and rehabilitation [14]. For example, Ley-Flores et al. [15] found that sonification of exercise with metaphorical sounds affect body perception, causing people to feel strong and thus increase their amount of physical activity. Other studies investigated presenting activity patterns as musical sound to raise awareness about behaviour. For example, Krasnoskulov [16] developed a system in which data measured by an accelerometer and optical heart-rate sensor were mapped to musical parameters such as pitch, timbre, tempo, space and loudness. This form of musical sonification is rather direct and may not result in a clear representation of events. Consequently, some

[1] A short article by O'Keeffe, Scheid and West [2] explains the differences and similarities between physical activity and sedentary behaviour.

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studies have considered segmentation of data, so that the resulting sonification is structured in blocks that preserve the temporal relations of events. Last and Usyskin [17] developed a sonification paradigm that segments data into a user-defined number of segments, which was successful to convey the desired information. Vickers and Höldrich [18] progressed this to produce segments using zero-crossing of a one-dimensional data-stream. Then the segments were mapped to sound. These studies show that sonification and musical sonification are feasible ways to convey activity data. Temporal segmentation may be a relevant part of the process, as it allows for mappings between data and sound that have a clear correspondence. However, the temporal segmentation methods used by the mentioned studies have important limitations, as they are based on threshold, zero-crossings or clustering. These methods require careful calibration of input parameters and do not generalise well when patterns in data are multidimensional.

The present study has focused on the development of a system to produce musical sonification (also referred to as *musification*) of daily activity data recorded by wearable devices. The method employs a novel approach to multi-granular temporal segmentation, that results in a clear correspondence between daily events and sound. Additionally, the system does not require the final user to do any fine-tuning of segmentation parameters. We propose this system as an aid in behavioural change, by raising awareness of people's own daily physical activity in an engaging way.

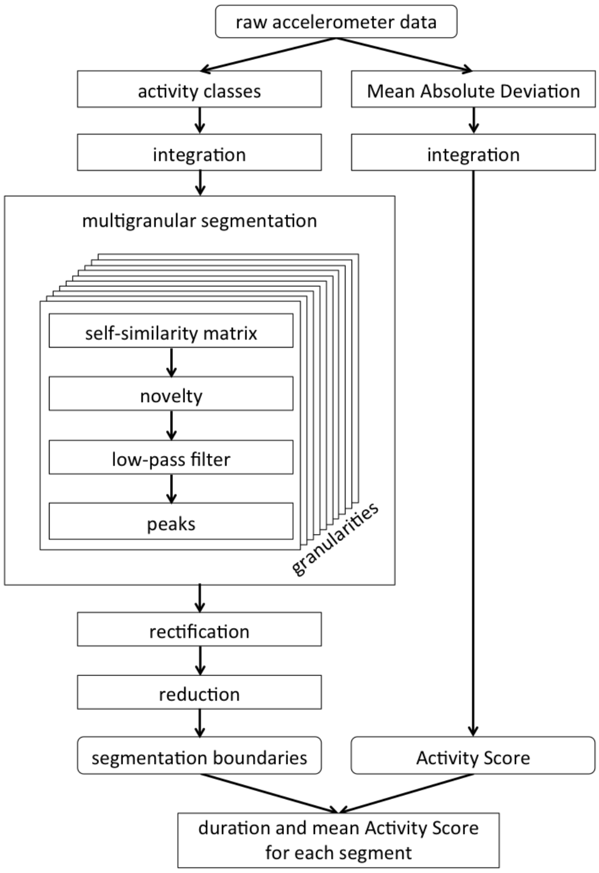

Figure 1. Multigranular segmentation of daily activity.

2. METHODS

2.1 Accelerometry Data

We used two multiple-day recordings of accelerometry from 75-year-old adults. These were chosen from the AGNES database [19, 20] so that one corresponds to a low-activity sedentary subject while the other corresponds to a high-activity non-sedentary subject. The data was obtained by two tri-axial accelerometers, one chest-worn and the other thigh-worn. These data were pre-processed to obtain features for successive non-overlapping epochs of 5 seconds. One feature is the Mean Absolute Deviation (MAD) of the square norm [21], from the thigh-worn accelerometer (Fig. 2a). The other features are the activities identified from the orientation of the accelerometers: lying, sitting, upright posture and walking [22] (Fig. 2b).

2.2 Segmentation

The segmentation procedure is shown in Fig. 1. After MAD is computed and activities are identified, numerosity is reduced by integrating in windows of 120 data points of 5 seconds each (10 minutes) with an overlap of half the length of the window. For MAD the integration is

$$A_i = \log_b \left(1 + \sum_{j=1}^{n} w_j\right), i = \{1 \ldots N\},$$

where vector A of length N is the Activity Score, N is the number of windows, the logarithmic base b is a free parameter to rescale A, and w is one window of length n. The logarithm preserves the data distribution, as the relation between time of inactivity and activity follows a power-law distribution [12]. For the examples reported in this article the logarithm has a base $b = 3$. Each activity is a binary vector, where an activity is represented by a one, otherwise a zero (Fig. 2b). The integration of each activity vector is the sum of the window, with the same length and overlap as for MAD. Additionally, integration acts as a low-pass filter removing unnecessary detail.

The next step is segmentation of the integrated data using the algorithm described by Foote [23]. That algorithm has been used for segmentation of musical audio and video. It can detect boundaries of segments at different *granularities* (i.e., time-scales). It has also been tested for segmentation of accelerometry data of dance [24] and daily activities [25].

The segmentation algorithm first computes a self-similarity matrix of the integrated activities (Fig. 3a). Then, a checkerboard kernel (i.e., a small matrix of four sections where the diagonal is negative units and the anti-diagonal is positive units) tapered by a normal distribution, is correlated along the diagonal of the self-similarity matrix. This was done several times, each with a checkerboard kernel of minimally different size. The size of the kernel corresponds to the granularity of the

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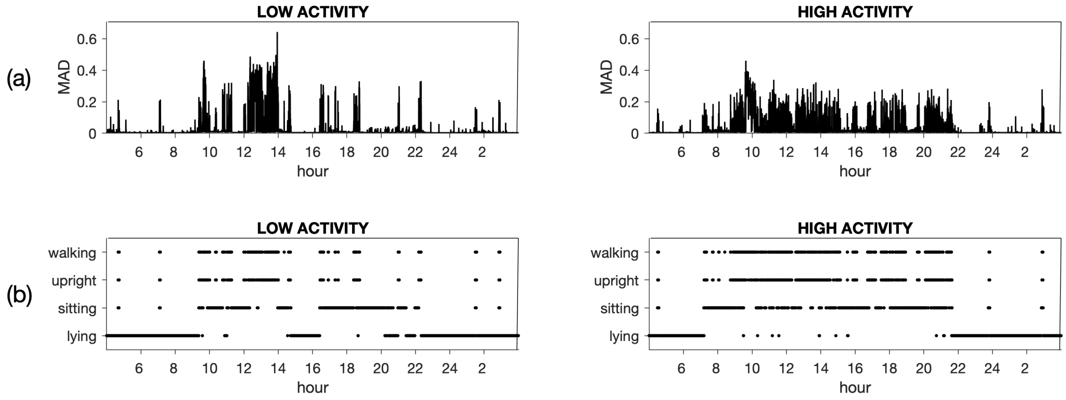

Figure 2. a) Mean Absolute Deviation every 5 seconds of accelerometer data; b) Classification of daily activities.

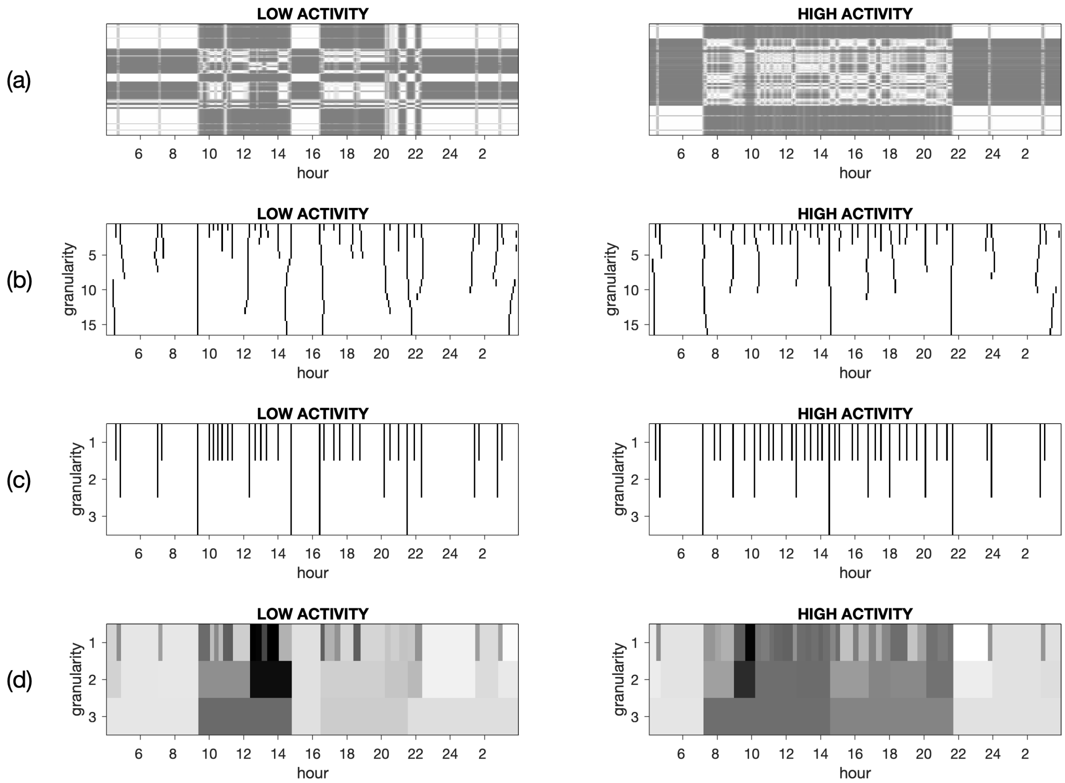

Figure 3. a) Self-similarity of activities; b) multigranular raw segmentation boundaries; c) rectified and reduced multigranular segmentation boundaries; d) segmented Activity Score, darker shades show greater average activity for a segment and vice versa.

segmentation. A smaller kernel detects finer granularity segments and vice versa. The size of the kernels was specified as the standard deviation σ_k of their normal distribution tapering. For the examples shown here, $\sigma_k = \{2, 4, \ldots, 32\}$ windows. This resulted in several novelty scores, one for each granularity, each of which was then smoothed with a normal-distribution (i.e., Gaussian) low-pass filter to remove irrelevant peaks. The peaks of each novelty score represent segmentation boundaries (Fig. 3b). The size of each filtering vector was set to each corresponding value in σ_k, while the standard deviation was set to 0.4 for all of them.

The segmentation boundaries at different granularities are not perfectly aligned in time (Fig. 3b) because, as the checkerboard kernel gets larger, it incorporates more information causing the novelty peak to move slightly in

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Table 1. Segmented Activity Score

fine		medium		coarse	
duration	mean Activity	duration	mean Activity	duration	mean Activity
5	0.45	8	0.45	38	0.48
3	1.11	-	-	-	-
30	0.48	30	0.48	-	-
8	1.03	21	0.92	88	1.48

First 4 lines of "high activity" segmented (corresponding to Fig. 3c and d). Duration is windows of integrated data. The headers of this table are not part of the actual list.

either direction. However, because the granularities were set with minimal difference ($\Delta\sigma_k = 2$ windows), it is safe to assume that they correspond to the same segment. Following this logic, every coarser granularity boundary has an origin in a finer granularity boundary, except for those at the borders. The temporal structure is hierarchical, where segments are embedded in larger segments. This reflects the structure of human daily activity. For example, a large portion of the day such as the morning, may contain activities like waking-up and getting ready, breakfast, commuting, and so forth. This hierarchical structure is also analogous to musical structure. For example, a song has sections like introduction, verse and chorus, each of which have sub-sections, such as melodic lines. However, in music the boundaries of each section exactly match in time, unlike the structure resulting from the procedure described above. If that multigranular structure were to be used as musical structure for sonification, it would result in a seemingly unnatural performance. For example, each granularity level may be assigned to a different musical instrument. If so, then instruments would begin and change sections of the song at different times.

Therefore, the segmentation boundaries were aligned to the finest-granularity boundary. Also the boundaries at the borders were removed. This resulted in sequences at different granularities being identical or slightly different. Thus, the finest and coarsest granularity sequences were kept, as well as the sequences that provide greatest variety in number of boundaries. For the examples given here, the reduction resulted in sequences at 3 levels of granularity: fine, medium and coarse (Fig. 3c). Finally, the median Activity Score was computed for each segment at each granularity level (Fig. 3d).

2.3 Musical Sonification

The result of the segmentation procedure is a list of paired columns, where the paired values are segment duration, in windows, and the mean Activity Score for the segment. If a segment's boundary doesn't have a corresponding boundary at a coarser granularity level, the values are omitted. The first line assumes a boundary at all levels of granularity. Table 1 shows an example.

The list was formatted as a CSV file and has a header line composed by the number of windows, the sum and grand mean of Activity Scores (from the matrix depicted by Fig. 3d), and the number of granularities. This file is the input to a separate sonification program consisting mainly of a sequencer and two synthesis modules (Fig. 4.). The sequencer loads the CSV file and immediately reads the header. The user specifies how long the performance will last and the program computes the duration of each window in real time units (e.g., milliseconds), using the first value in the header (number of windows). The second value of the header (sum of Activity Score) is used as the seed for all pseudo-random generators, to obtain a deterministic performance (i.e, the sonification of a CSV file will always be the same). This may help to perceive a strong connection between sonic material and actual daily activity information. The third value in the header (grand mean Activity Score) sets the tempo. The mean between the values of both subjects was mapped to 120 BPM (beats per minute) for crotchet notes (60 BPM for minim notes), as the typical healthy average heartbeat at rest is just over 60 BPM [26] and both preferred musical tempo and average walking steps have a period of about 120 BPM [27]. Hence, the sonification for the high-activity subject will have a slightly higher tempo than the sonification for the low-activity subject. The last element of the header (number of granularities) is used to compute the mean Activity for each combined segment. For example, for the first row in Table 1, all mean Activity values will be added and divided by 3. For the second row, the only value is for the finest granularity and will be divided by 3.

The user inputs a duration in seconds and clicks a button to start the performance. Then, the first line in the CSV file (i.e., the first row of Table 1) will be read and it will wait the duration given by the leftmost value multiplied by the duration of each window, then it will read the next line and so on. When each line is read, the values are sent to the synthesis modules as described below. This process continues until the final line is reached or until the user interrupts it by the click of a button.

Synthesis module 1 is composed by three synthesisers that produce bell-like sounds, whose pitches are pseudo-randomly produced according to a distribution that smoothly transitions from chromatic (i.e., all 12 tones allowed) to a user-selected scale. For this study a pentatonic scale was used. The transition is given by the mean Activity of all segments at the start of a finest-granularity segment. The higher this value is, the closer the distribution will be to the selected scale. For example, when the program begins playing the list in Table 1, it will compute the mean of the "mean Activity" values of the first row, which will determine the distribution of the pseudo-randomly produced notes. Given this distribution, each synthesiser produces a note at the start of each segment and the duration of the note is the duration of the segment. Each synthesiser has been set to play only at a distinct octave, with the synthesiser allocated to the coarsest granularity playing the lowest octave and vice versa.

The resulting sounds are somehow dissonant when activity is low and consonant within the user-defined scale, when the activity is moderately energetic. This defines

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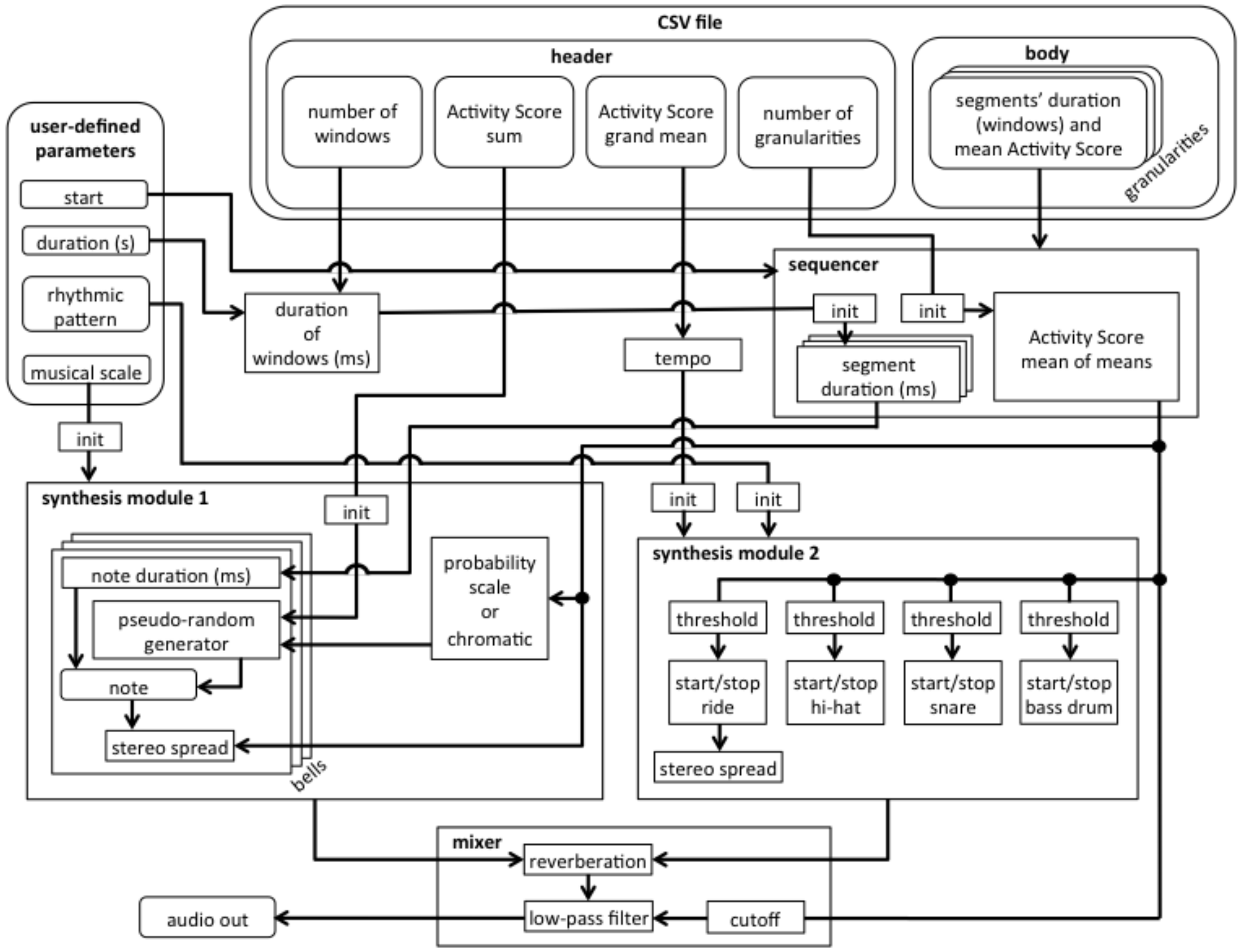

Figure 4. Sonification program.

high amount of activity as consonant and low amount of activity as dissonant. Also each synthesiser has a "stereo spread" capability that has been mapped so that the higher the mean Activity, the wider the stereo allocation of the notes, meaning the pseudo-random balance between their output to the two main output audio channels.

Synthesis module 2 is a drum-machine with 16 steps (quaver notes) and 5 voices produced by frequency modulation: ride cymbal, open hi-hat cymbal, closed hi-hat, snare drum and bass drum. The rhythmic pattern can be programmed by the user. The tempo is given by the grand mean Activity Score as explained previously and each instrument is activated when a level of mean Activity of the current segment exceeds a defined threshold. For this study the bass drum was set to be permanently active, while the ride cymbal was set to fade in when activity changes from very low to moderately low. Also the ride cymbal was set to permanently have a full stereo spread, resulting in a subtle and surrounding rhythmical noise. The open hi-hat was set to a medium threshold and the closed hi-hat was not used for this study. The snare drum was set to a moderately high threshold. The full drum set is active when activity is energetic.

In the examples (see Fig. 2 and Fig. 3), the full drum set and only notes within the defined scale play between about 12:30 and 15:00 for the low-activity subject and from about 9:00 to 10:00 for the high-activity subject. The output from the bell synthesisers and drum-machine is mixed and subtle reverberation is added to blend the sounds. Finally, a low-pass filter is applied to the final mix and its cutoff frequency is controlled directly by the mean activity of the current segment, so that the resulting sound is slightly brighter as there is more energetic activity and vice versa.

2.4 Perceptual Assessment

Two audio files were produced with the method described above, using excerpts from 6:00 to 23:00 of the data presented in the figures. These audio files were used as stimuli for a perceptual assessment. Data for this assessment were collected during 31 days by means of a short survey using QuestionPro, a service to make and publish questionnaires which can be answered with an internet browser, and Twitter. Participants were recruited via Twitter and Facebook using both free and paid adverts, the latter targeting Finland and major English-speaking countries, and via authors' direct contact within their acquaintance networks. In the survey, participants were asked to listen to each audio file, and indicate which of them represented the more active person. The order of presentation was randomised. The survey included the researchers' contact information, notified participants that no personal information would be collected, and that data collection complied with the General Data Protection Regulation of the European Union. The stimuli can be listened on Twitter: `https://twitter.com/listeningsurvey` and Facebook: `https://www.facebook.com/ListeningsurveyJYU`.

3. RESULTS AND DISCUSSION

The methods described in this report are firstly, a system that processes accelerometry data of daily activity, resulting in multigranular hierarchical segmentation akin to musical structure. The second method is a program devised as a proof of concept, to demonstrate a possible musical sonification of the daily activity data utilising the segmentation obtained. The resulting sonification has, by design, one main property, which is that there is a clear association between sonic events and daily activity. The perceptual assessment of two example sonifications produced with the system described measured the extent to which a person would correctly identify the sonification for high activity data, when presented along the sonification for low activity. A total of 1847 responses were collected by a survey on the internet, of which 1225 (66.3%) correctly identified the sonification corresponding to high activity. A one-proportion z-test was performed to evaluate the statistical significance of the results, yielding $z = 14.03$, with a p-value $< 1 \times 10^{-5}$. This may be sufficient to reject the null hypothesis, suggesting that the proportion of correct responses is significant.

The described musical sonification system may be useful in public health interventions towards increasing healthy physical activity or reducing sedentary behaviour, by making a person aware of their intraday activity in an engaging manner. In practice, the musical sonification system would be part of a portable system comprising hardware and software. Such a system would record daily activity, produce the musical sonification and possibly recommend actions to the user. The hardware may be composed of already existing technologies such as miniature accelerometers and mobile computing devices like a smartphone or smartwatch. Future research shall be carried out to implement the system and test it in ecologically valid conditions. Preliminary testing shall be carried out in order to explore the extent to which the musical sonification may work as an engagement strategy, and to identify the conditions in which it may be effective. These conditions may include personal characteristics of target users such as age, personality or income, as well as environmental conditions. Also it would be useful to compare the multigranular segmentation daily profiles of users with self-reports on their activities, to assess the extent of their correspondence.

While this report describes a method for multigranular segmentation and musical sonification of intraday activity of one subject, it is trivial to expand the method to work with different data. First, instead of using classified data for the segmentation, the Activity Score may be used alone. Also instead of using a single time period, like a day, an average of several days may be used, resulting in a representation of a typical day. Furthermore, instead of using data for a single subject, a group of subjects may be used. A population may be pre-clustered in groups with homogeneous characteristics, such as age, gender, and so on. The resulting multigranular temporal segmentation may be useful to examine the typical intraday behaviour of the group. Its musical sonification will represent the group and this may open new and interesting doors for community music making. For example, daily data of a person may be uploaded to a server, where it would be combined with data of other people in their social circle. This would enable them to produce music as a group, instead of individually. This way of collaborative music-making may be a relevant avenue for exploration in further research, as it has been observed that social support through collaboration was the primary motivator for adults to maintain activity tracker use [28].

4. CONCLUSION

This study has developed a system to produce musical sonification of daily activity data recorded by wearable devices. The sonification may be used as a tool for raising awareness and behaviour change by conveying daily activity information to users in a clear and engaging way. This capability may be used in interventions to increase physical activity (i.e., total amount of bodily motion) and reduce sedentary behaviour (i.e., proportion of time sitting or lying down) in hard to reach populations such as older adults, teenagers or people with visual or learning difficulties. A key property of the musical sonification is that it shows clearly not only the overall physical activity over a period of time, but of the temporal structure within, such as commuting to work, or taking a lunch break. This property would allow someone to identify, by listening to the sonification, the times of the day they were more or less active and spent more or less time sitting. That was achieved by devising a novel multigranular temporal segmentation procedure that preserves the time relations between events.

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