Sonifying Twitter's Emotions Through Music

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Abstract. Sonification is a scientific field that seeks to explore the potential of sound as an instrument to convey and interpret data. Its techniques have been developing significantly with the growth of technology and supporting hardware and software, which have spread in our daily environment. This allowed the establishment of new communication tools to share information, opinion and feelings as part of our daily routine.

The aim of this project was to unite the social media phenomena with sonification, using Twitter data to extract user's emotions and translate them into musical compositions. The focus was to explore the potential of music in translating data as personal and subjective as human emotions, developing a musically complex and captivating mapping based on the rules of Western Music. The music is accompanied by a simple visualization, which results in emotions being heard and seen with the corresponding tweets, in a multimodal experience that represents Twitter's emotional reality. The mapping was tested through an online survey, and despite a few misunderstandings, the results were generally positive, expressing the efficiency and impact of the developed system.

Keywords: Musical sonification · Emotion detection · Twitter Algorithmic composition · Sound design

1 Introduction

Sonification, defined by Kramer et al. [12] as "the use of nonspeech audio to convey information", has been establishing its place as a new field of communication, exploring new techniques to represent complex data through sound [8]. Since the birth of the International Community of Auditory Display (ICAD) in 1992, where the study of auditory displays was proposed as a scientific field, sonification techniques have been developed significantly, with applications in areas

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such as Medicine or Seismology, and concepts from multiple areas, from Human Perception to Design and Engineering that form its interdisciplinary nature [8].

The development of the sonification field is directly connected to the significant growth that technology experienced in the last decade, with personal computers containing the hardware and software needed to manipulate sound [8], and auditory displays becoming a presence in everyday life. This technological growth and accessibility to the main population also allowed the establishment of new communication media as a daily routine: the social media. Facebook and Twitter are examples of these social tools that became the new mass media, not only for the common citizen, but also for companies, news industry and important figures. The study of social media data has gained new potential in several areas, such as marketing for extracting consumer's opinions, or social studies for understanding the user's moods and views about events. The field of sentiment analysis emerges from this potential, with the focus of studying computational analysis to extract opinion and sentiment from text, interacting with affective computing to explore the computer's ability in recognizing emotions [19].

This paper presents a project that handles with these three fields: sonification as the core, with data retrieved from social media, specifically Twitter, and analysed through sentiment analysis. The main goal is to explore new ways to read, through sound, data as personal and complex as human emotions. This study is primarily motivated by the potential of music in conveying emotions, and lies to this potential, exploring ways to transmit information through a melodic and harmonic composition. It involves two major challenges: the emotion extraction, implementing a system that properly analyses the tweets and classifies their emotions; and the musical mapping, choosing a set of parameters that can distinguish and embody the emotions. The main focus of this paper is on the musical mapping. However, we also briefly describe how the process of extracting emotional information from the tweets is implemented.

This paper starts with an overview of Sonification works and projects that used social media data, which influenced and inspired this work. Section 3 discusses the model of the emotions chosen, and the process for emotion classification. Section 4 presents the musical mapping and its structure. Section 5 details the implemented system and visualization. Section 6 presents the evaluation process and the analysis of the results. Section 7 lists possible improvements.

2 Related Work

There are many studies of sonifications developed in a vast number of areas, proven successful in practical and scientific terms [12].

The first two examples show the potential of sonification in scientific data. The work of Vicinanza, specifically his *Voyager 1 & 2 Spacecraft Duet* is a sonification of data gathered by the Voyager 1 & 2 NASA probes during 37 years of spatial exploration. It consists of two melodies in different frequencies, with the measurements made at the same times, but billions of kilometers apart [25]. The second example is *The Climate Symphony* by Quinn [21], where he used data from the chemical composition of an ice block in Greenland to translate into music the climatic changes endured by the great continental ice sheets.

In the poetry field, Coelho, Martins and Cardoso [3] created a *A Musical Sonification of the Portuguese Epopee*, specifically of The Lusiads, by Luís de Camões. It is an interactive sonification where the user can explore the poem by choosing different levels of "zooming", listening to it as a whole, as a canto/ subnarrative or a specific episode and therefore customising the experience.

Bulley and Jones developed *Living Symphonies*, a sound installation based on the fauna and flora of four ecosystems in the United Kingdom. The authors built a model that reflected the behavior, movement and daily patterns of every being in the wild, translating a network of interactions that formed the ecosystem [2].

Rhapsody In Grey, developed by Brian Foo in 2016, is a real-time visual sonification that uses data from an EEG of a patient with epilepsy to generate a musical composition. The goal of this project is to give an empathic and intuitive view over the brain activity during a seizure [4].

Using Twitter as the main data source, *TwitterRadio* is an audio-only interactive installation that seeks "to convey public opinions on the world trending topics through suitable musical forms" [18]. Developed by Morreale, Miniukovich and De Angeli, it takes the concept of a traditional radio, where the users can tune to a station and listen to a musical translation of the polarity retrieved from tweets with a certain hashtag.

#tweetscapes is the most similar project to this study, consisting in the sonification of German tweets in real-time. Developed by Hermann, Nehls, Eitel, Barri and Gammel, the goal was to create "a new sense of media awareness" [9]. Tweets were mapped according to the hashtags, replies and location, adding a visual geographic distribution that accompanied the sonification.

#Emotional Imaging Composer is an experience conducted in the Input Devices and Music Interaction Lab (IDMIL) at the McGill University, that aims to create a real-time audio expression of emotions, extracted from a vocal performance [28]. This interactive sonification is based on Russell's Arousal/Valence circumplex [23], positioning musical parameters over the two axis.

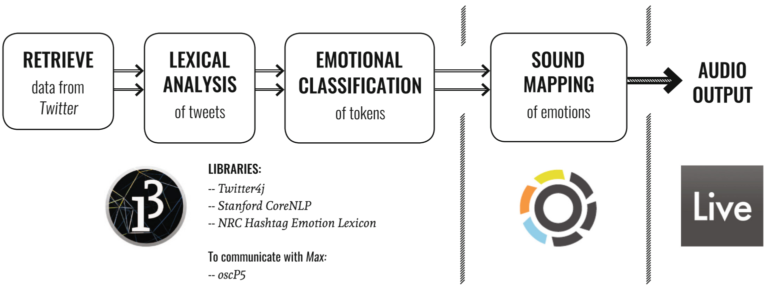

Fig. 1. Process flow diagram

The last example is a website created by Harris and Kamvar, named *We Feel Fine* [7]. It is a visualization that collects human emotions from a vast number of blogs, searching for entries that contain the expression "I feel" or "I am feeling" and providing a social and demographic study.

3 Processing Data

The process implemented in our system comprises four steps (Fig. 1) and uses three software tools to produce the sonification: Processing, to get and classify tweets, Max, to generate the musical composition, and Ableton Live, to play the composition using VST's plugins. The current section describes how the three first steps were implemented. The sound mapping step will be presented in detail in Sect. 4. The sonification system will be explained with more detail in Sect. 5, which includes the developed visualization. Section 6 describes the evaluation process, and the discussion of the obtained outcomes. The last section lists possible future developments and improvements based on the results.

3.1 Data Gathering

The emotional content of a tweet lies in two elements that will form the dataset: the hashtags, metadata tags that establish the subject and mood of a tweet, and the main text, that elaborates the subject and expresses the user's opinion.

To retrieve the tweets, we are using the *Twitter4j* Java library. The data is filtered by language, receiving only tweets in English. To ensure data with some relevance, the tweets are also filtered by the number of followers of each author: only tweets whose author has more than 1000 followers are considered.

3.2 Emotion Lexicon

We implemented a system based on a lexicon of words composed of associations of emotions to each word using a lexicon developed by Mohammad, the *NRC Hashtag-Emotion Lexicon* [17], with the aim of maintaining a simpler and more open approach. It is based on a model of emotions created by Plutchik [20] (Fig. 2) that comprises eight primary emotions: joy, trust, fear, surprise, sadness, disgust, anger and anticipation.

3.3 Lexical and Emotional Analysis

The next task was to implement a set of natural language processing (NLP) tools to parse the tweets, establishing the structure of sentences, word dependencies and "Part-Of-Speech Tagging", classifying each word with its root form, called lemma, and its grammatical category. Working in a Java environment, we have chosen the *Stanford CoreNLP* tool [15], developed by the Stanford NLP group.

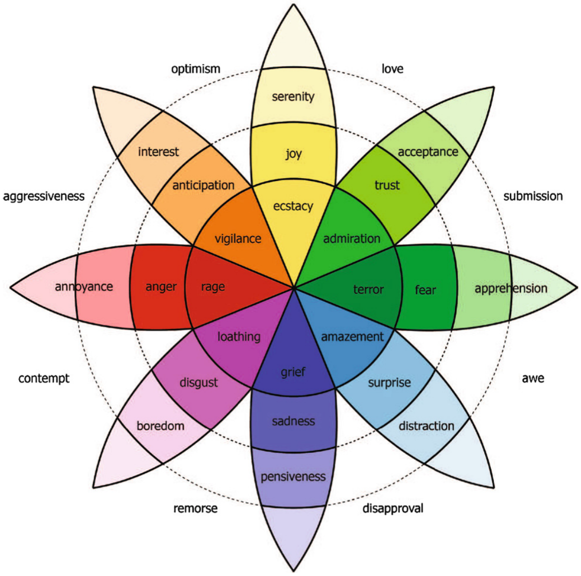

Fig. 2. Robert Plutchik's model of emotions

1. *Part-of-Speech (POS) Tagging*
JJ --> Adjective
NNS --> Noun, plural
VB --> Verb, base form

2. Negator;
don't like --> dislike

3. If a negation is detected, search the antonym of the word using *Wordnet*

4. Normalization
haaappyy --> happy
slo --> slow

Fig. 3. Steps of the lexical analysis

The analysis of the receiving tweets comprises three steps (Fig. 3):

1. Tweet's parsing and tagging: to define the main structure of the sentences and the words classes. Words classified as nouns, verbs, adverbs or adjectives are stored, due to these classes describing usually the emotion and intensity of a sentence.
2. Identify negations: find the antonyms of negated words using *Wordnet* [16].
3. Submit the remaining words to a combination of two normalisation lexicons [6, 14], converting the terms and abbreviations of the texting language to its correct writing form (example of the word "happy" in Fig. 3).

The emotional classification is then applied to the resulting list of words. First, we search the existence of each word in the *NRC Hashtag-Emotion Lexicon*. If it is not found, a search for the lemma of the word is made. Without results, *Wordnet* is used to find a synonym of the word, repeating the first and second steps if a result is found. For the hashtags, the process is more simplified: as the

NRC Hashtag-Emotion Lexicon contains a considerable amount of hashtags and their emotional associations, we search the hashtags directly in the lexicon.

TEXT: @SgtBigC Thank you for your service! I look forward to your tweets !

TOKENS / LEMMAS / TAGS: [@sgtbigc/@sgtbigc/NN, thank/thank/VBP, you/you/PRP, for/for/IN, your/you/PRP$, service/service/NN, !/!/., i/i/FW, look/look/VBP, forward/forward/RB, to/to/TO, your/you/PRP$, tweets/tweet/NNS]
NEGATED, FILTERED & NORMALISED: [@sgtbigc/@sgtbigc/NN, thank/thank/VBP, service/service/NN, look/look/VBP, forward/forward/RB, tweets/tweet/NNS]

SYNONYMS OF @sgtbigc:
thank: surprise (0.1104075), joy (0.8362264),
service: anticipation (0.048728146), anger (0.3141353), joy (1.4751366), disgust (0.104729064),
look: trust (2.5172772), surprise (0.08125829), disgust (0.2233381),
forward: anticipation (0.8324527), fear (0.38292524), joy (0.14821284),
tweets: anticipation (0.16105315), anger (0.27538794),

HASHTAGS: []

- - - Emotional Classification - - -
Anger - 0.58952326
Anticipation - 1.0422341
Disgust - 0.32806715
Fear - 0.38292524
Joy - 2.459576
Sadness - 0.0
Surprise - 0.1916658
Trust - 2.5172772

Fig. 4. Example of a tweet's emotional classification

3.4 Intermediate Results

All the steps were saved in a text file for evaluation, including the parsing (with each word, correspondent lemma and tag), the lexical analysis' resulting list, the emotions extracted from each word and the sum of every word's emotion, providing the tweet's classification. In the example shown in Fig. 4, *Trust* and *Joy* have the highest and similar values. The majority of the words obtain a classification, allowing a more complete and differentiating categorisation of each tweet. This process takes an average time of 1.6 tweets per second, ensuring a consistent set of variables to sonify and establishing emotional tendencies.

4 Mapping Twitter's Emotions to Music

In 1936, Hevner [10] conducted a series of studies of the expressive elements in music, associating a list of adjectives to musical parameters, such as major/minor mode, dissonant/consonant harmonies and firm/flowing rhythms. The results determined a tendency in the associations, achieving an universal affective nature in musical forms. The main challenge of this project is to explore this expressive dimension to map emotions. Gabrielsson and Lindström [5] gathered over 100 studies made in the last century on this subject, which served as an initial foundation for this sonification. The majority focused on evaluating simple parameters, like tone quality, melody direction, loudness or tempo. Studies of more complex parameters, such as harmonic progressions or chords natures are very limited, exploring only differences in consonant/dissonant harmonies. The authors concluded that although each parameter can influence the emotional expression, it is rarely determined by one factor, but a combination of several.

In our project, we decided to organize the mapping into three main musical aspects: melody, rhythm and harmony, associating probabilities with each parameter for each emotion. At the start of the program, the root note is defined, which provides the tonic for the harmonic progressions and the melody scale.

For the melody, each note is raffled from the current scale, the current chord, or as a chromatism, following probabilities that change according to each emotion (Fig. 5). Chromatic notes are dissonant notes that occur half-step above or below one of the chord's pitches. They travel outside a given scale and are generally used as transition notes to create tension before returning to consonance, releasing the tension. In our system, they are played on weak beats, lasting only half a beat, to keep a subtle dissonant and a tonal feeling. *Fear*, for example, has a higher chance of occuring a chromatic note (50%) than *Joy*, with only 5%.

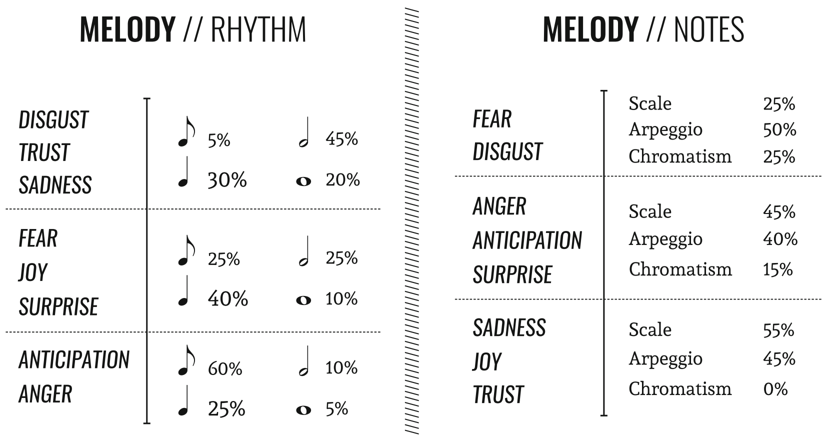

Fig. 5. Melody probabilities on notes and rhythm figures

Hevner also concluded that a slow tempo was associated with more solemn, sad or gentle sounds, whereas happy, exciting and vigorous sounds where likely translated by a fast tempo [5]. Translating this structure to rhythm figures, the duration of the melody notes were associated through probabilities for each emotion, using four rhythm figures: whole, half, quarter and eighth notes (Fig. 5). *Anticipation*, *Anger* and *Surprise* have higher changes of producing quarter notes, ensuring a more rapid and tense melody. In opposition, for *Trust* and *Disgust* there is a higher tendency to play longer notes.

The melodic interval between two consecutive notes is also raffled according to the emotion being conveyed (Fig. 6). *Joy* and *Sadness* have a higher chance of producing a stepwise motion, using seconds and thirds to provide a more stable and comfortable flow. On the other hand, *Surprise* has a higher probability of sixths and sevenths in order to create sudden jumps that bring an unexpected feeling. An emotion like *Trust* has then a higher probability of producing a consonant sound, in opposition to *Disgust*, that produces a heavily dissonant sound.

MELODY // INTERVALS

	ANTICIPATION / FEAR	ANGER	JOY / TRUST / SADNESS	SURPRISE	DISGUST
Tonic	0%	5%	5%	5%	20%
2nd	25%	30%	35%	10%	10%
3rd	25%	15%	30%	15%	10%
4th	10%	5%	5%	10%	10%
5th	25%	10%	10%	15%	10%
6h	5%	15%	5%	20%	15%
7th	5%	15%	5%	15%	15%
8th	5%	5%	5%	10%	10%

Fig. 6. Melody probabilities on intervals

The melody is built over a certain set of scales (Fig. 7), that were defined according to their association with the harmonic progressions and the constituent chords. They are commonly known to reflect certain emotional contexts. Some examples include the major scale (Ionian mode) the "one with which most people will be familiar" [13], very embedded in Western Music and considered happy and joyous; the minor scale (Aeolian mode), considered negative and sad; the Lydian mode, with a dreamy, mysterious nature; the minor harmonic, with a tone and half interval between the 6th and the 7th that breaks the melodic flow [1]; or the whole tone scale, without a tonal center that originates an unstable, floating quality [26].

MELODY // POSSIBLE SCALES

Ionian	1 2 3 4 5 6 7
Dorian	1 2 b3 4 5 6 b7
Phrygian	1 b2 b3 4 5 b6 b7
Lydian	1 2 3 #4 5 6 7
Mixolydian	1 2 3 4 5 6 b7
Aeolian	1 2 b3 4 5 b6 b7
Locrian	1 b2 b3 4 b5 b6 b7

Major Pentatonic	1 2 3 5 6
Minor Pentatonic	1 3 4 5 7
Major Harmonic	1 2 3 4 #5 6 7
Minor Harmonic	1 2 b3 4 5 b6 7
Phrygian Dominant	1 b2 3 4 5 b6 b7
Mixolydian Augmented	1 2 3 4 5 b6 b7
Diminished	1 2 b3 4 b5 b6 6 7
Whole Tone	1 2 3 b5 b6 b7

Fig. 7. List of melody scales

HARMONY // CHORDS

TRIADS

X	*Major*	1 3 5
X^{-}	*Minor*	1 b3 5
X^{DIM}	*Diminished*	1 b3 b5
X^{AUG}	*Augmented*	1 3 #5
X^{SUS4}	*Suspended4*	1 4 5
X^{SUS2}	*Suspended2*	1 2 5

TETRACHORDS

X^{Δ}	*Major 7*	1 3 5 7
X^{7}	*Dominant (7)*	1 3 5 b7
X^{-7}	*Minor 7*	1 b3 5 b7
$X^{\varnothing}$	*Half-Diminished*	1 b3 b5 b7
X^{o}	*Diminished*	1 b3 b5 bb7(6)
$X^{\Delta\#5}$	*Augmented Major 7*	1 3 #5 7
X^{ALT}	*Augmented 7 (Altered)*	1 3 #5 b7
$X^{\Delta\#11}$	*Major 7#11 (Lydian chord)*	1 3 #4 7
$X^{7\#11}$	*Lydian Dominant*	1 3 #4 b7
X^{7SUS4}	*7 Suspended4 add 9*	1 4 b7 9
$X^{6/9}$	*Major Six-Nine*	1 3 6 9
$X^{-\Delta}$	*Minor Major 7*	1 b3 5 7
X^{-6}	*Minor 6*	1 b3 5 6
$X^{-\Delta\#11}$	*Minor Major 7#11*	1 b3 #4 7

Fig. 8. List of chords

Music is built over tension and release moments that define the harmonic sequence, which have an impact on the conveyed emotions. Our approach for distinguishing each emotion harmonically was based on Hevner's studies, Gabrielsson and Lindström's analysis, comparing major to minor modes and consonant to dissonant harmonies. Hevner concluded that "it is apparent that the use of the major or minor mode is of the most clear-cut significance in the expression of four different mood effects" [10], with the major mode strongly associated with happiness, gaiety and playfulness, and the minor with sadness, agitation and disgust". A simple/consonant harmony is defined as happy, graceful, serene and dreamy, connected to joy and tenderness, and a complex/dissonant harmony as vigorous and sad, connected to agitation, fear and unpleasantness. These two notions serve as the basis for exploring the progressions and correspondent chords. Due the complexity associated with harmony, we decided to define a set of 20 chords with different natures (Fig. 8). These chords would serve as the structure for a series of progressions that translate each emotion (Fig. 10), ensuring the coherence of the sequence and the affective nature associated.

The chords may be played in three possible voicings (Fig. 9), chosen randomly: in the root position, with an added tonic in the bass (an octave lower), with the tonic and the fifth in the bass, or with the tonic and the seventh (third if triad) in the bass.

For each emotion, a progression is chosen from the list, all with equal probability. Each progression is associated with a number of scales from which the

HARMONY // CHORD VOICINGS

TRIADS

1	1 3 5
1 3	1 5
1 5	1 3

↓ **1 octave lower**

TETRACHORDS

1	1 3 5 7	(9,
1 5	3 7	b9,
1 7	3 5	#9...)

↓ **1 octave lower**

Fig. 9. List of voicings for the chords

HARMONY // EXAMPLES

ANTICIPATION

|| III^{-7} VI^{7} | II^{-7} V^{7} ||

JOY

|| I | VI^{-7} | IV^{Δ} | V^{7} I ||

|| I^{7SUS4} | $\mathrm{I}^{6/9}$ | I^{7SUS4} | I^{Δ} ||

SADNESS

|| I^{-7} | I^{-7} | $\mathrm{II}^{ø}$ | $\mathrm{III}^{\Delta\#11}$ ||

ANGER

|| V^{Δ} | V^{7} | V^{7ALT} | V^{Δ} ||

DISGUST

|| $\mathrm{I}^{-\Delta\#11}$ | $\mathrm{I}^{-\Delta\#11}$ ||

|| $\mathrm{I}^{\Delta\#5}$ | VII^{o} | $\mathrm{I}^{\Delta\#5}$ ||

Fig. 10. Examples of progressions

melody is created. The scales are either built over the modes of the major scale, or the pentatonic scale, or harmonic and melodic scales.

The harmonic structure explores known progressions (Fig. 10), such as the major *I (Major) - VI (Minor) - IV (Major) - V (Dominant)* or the minor *I (Minor) - I (Minor) - II (Half-Diminished) - III (Major)*, and combinations of different chord natures, building sequences that relate them with the tension associated with each degree. For example, the progression *I (Suspended4) - I (Six-Nine) - I (Suspended4) - I (Major)* combines different major chords with a suspended chord, always built on the first degree. The major chords maintain the stability, and the suspended chord adds tension and a more open sound, establishing the possible set of association with *Joy*.

The tone quality is adapted to each emotion, with associations of certain sounds and technical aspects to each musical context provided by the harmony.

For example, sounds with higher distortions were more connected to emotions like *Anger* and *Disgust*, with more reverb and sustain to *Fear* or *Joy*, or with a fast attack to *Anticipation*, *Surprise* or *Anger*. The overall tone quality resembles the ambient music genre, which evokes a more atmospheric and open sound.

5 Implemented System

The system that was developed implements the sonification in two stages: the first for reception, analysis and emotional classification of tweets, and the second for musical mapping and composition of the audio outcome. A visualization was also made, as a complement to the sound that shows the revised tweets.

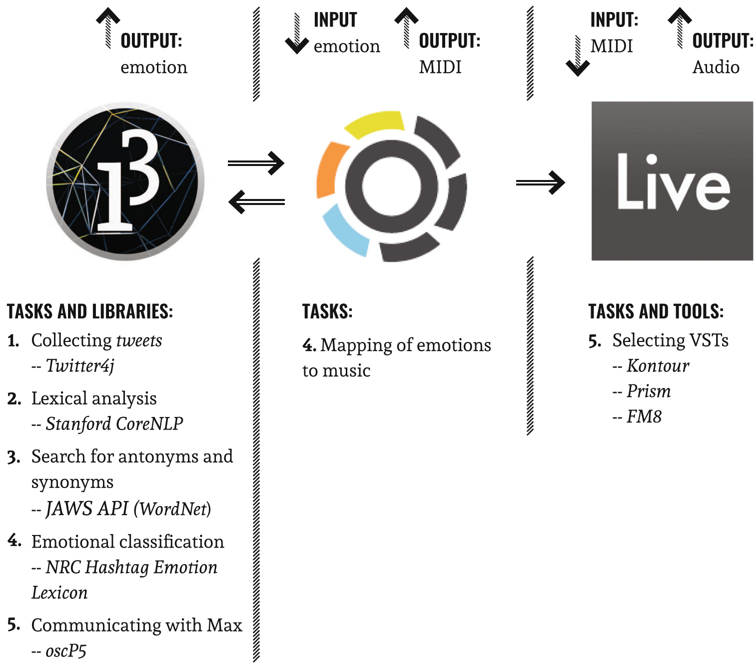

Fig. 11. System diagram

The system was developed over the dynamic communication of three modules (Fig. 11): a Processing sketch, a Max patcher, and an Ableton live set. The first two communicate using the Open Sound Control.

The Processing sketch begins by collecting and classifying tweets, task that runs in the background throughout the entire process. It also saves the values of the emotions extracted from each tweet and their sum. After the first 10 s of the program, the sketch sends to the Max patcher the most prominent emotion of the collected tweets. This begins the composition relative to that emotion, choosing the melody's starting note and a possible harmonic progression.

The progression chosen is repeated a random number of times, with the system choosing a progression again randomly at the end of the loop, ensuring a more dynamic, continuous and flowing composition. At the end of each progression's loop, the Max patcher sends a message to the Processing sketch requesting the next emotion with the highest value, which represents the emotional tendency of the tweets during that previous cycle.

For each progression loop and the correspondent emotion, one of the possible instruments is chosen for the melody and the harmony, which defines the channel and the VST that the Ableton Live Set will use to interpret the MIDI data. It can use three VSTs from the framework Reaktor 6, from Native Instruments: Kountour and Prism for the harmony, and FM8 for the melody.

Some of the resulting sounds produced so far are available at: https://soundcloud.com/mariana-seica/sets/music-emotions-sonification

5.1 Visualization

The main goal of the sonification is to be capable of transmitting emotions independently, relying only in the potential of sound to communicate information, and of music to convey the emotional qualities. However, a simple visualization was implemented to show the correlations between the composition and the analysed tweets.

The visualization (Fig. 12) is based on the flocking paradigm [22], implemented in Processing by Daniel Shiffman, which simulates the behavior of birds in groups and their movement. It is comprised of a set of agents that move according to three forces: separation, that keeps a certain distance between agents to avoid collision; cohesion, that steers the movement towards the center of the

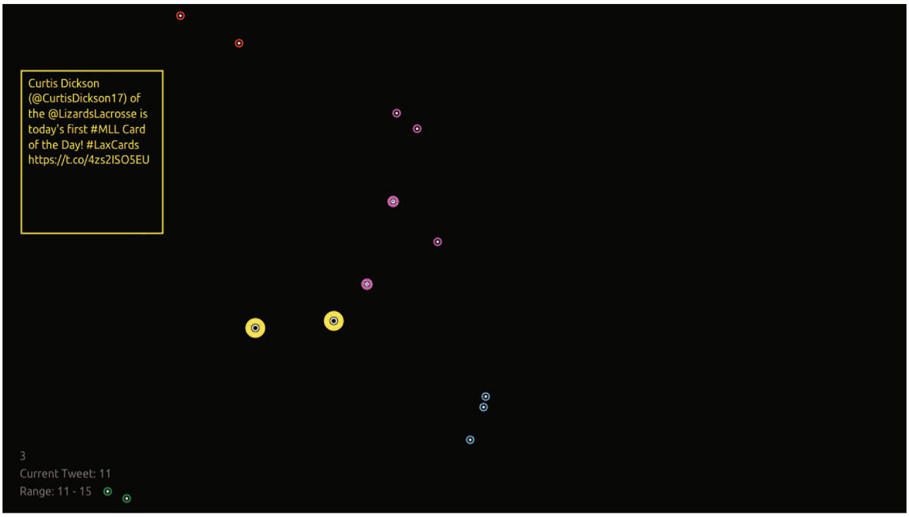

Fig. 12. Screenshot of the visualization

group; and alignment, that keeps the agents moving in the same direction as its neighbors.

Each tweet is an agent, represented by a circle belonging to a group. Eight groups were implemented, relative to Plutchik's eight emotions and represented by the correspondent colors. The tweets are collected and added to the group that represents its highest-scoring emotion.

For each progression cycle, the tweets classified with the current emotion, either its highest or not, are highlighted with an increase in their circle's size and stroke, with the rest disappearing. The text of each tweet is successively shown, with an animation that morphs the circle into a window. The change of progression triggers the death of the circles from the previous loop, that begin an erratic and frenetic movement until their size decreases and they disappear.

6 Evaluation

For the evaluation of the results, a survey was conducted online to understand how the emotions were being perceived.

The survey was comprised of 18 questions, which were divided in two sets of questions. In the first set, the participants were asked to listen to a composition, and evaluate its association with a given emotion, or chose the associated emotions from Plutchik's eight emotions list. In the second one, they were asked to listen to two compositions, and select the most plausible answer.

The chosen pairs of emotions to be tested were chosen from the Plutchik's Wheel of Emotions (Fig. 14), by selecting two opposite pairs and two neighbor-

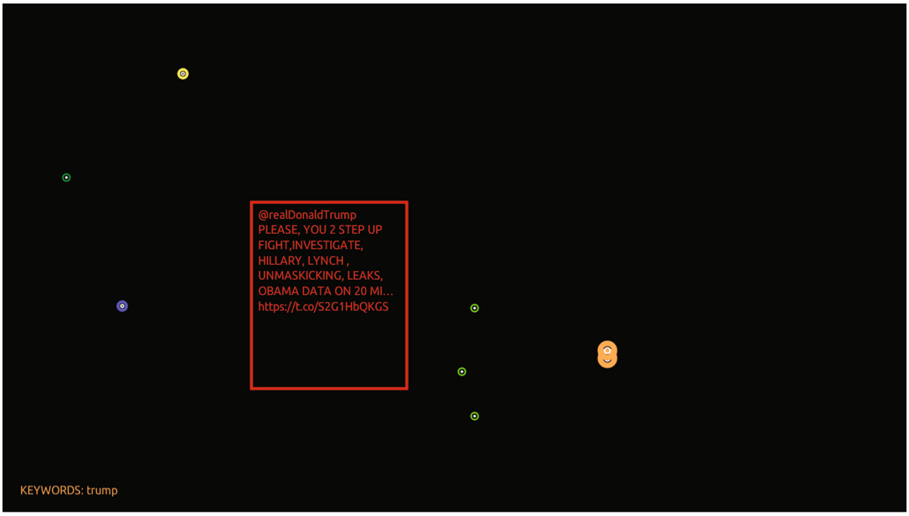

Fig. 13. Screenshot of the visualization, with the keyword "Trump" and an Anger tweet pointed out

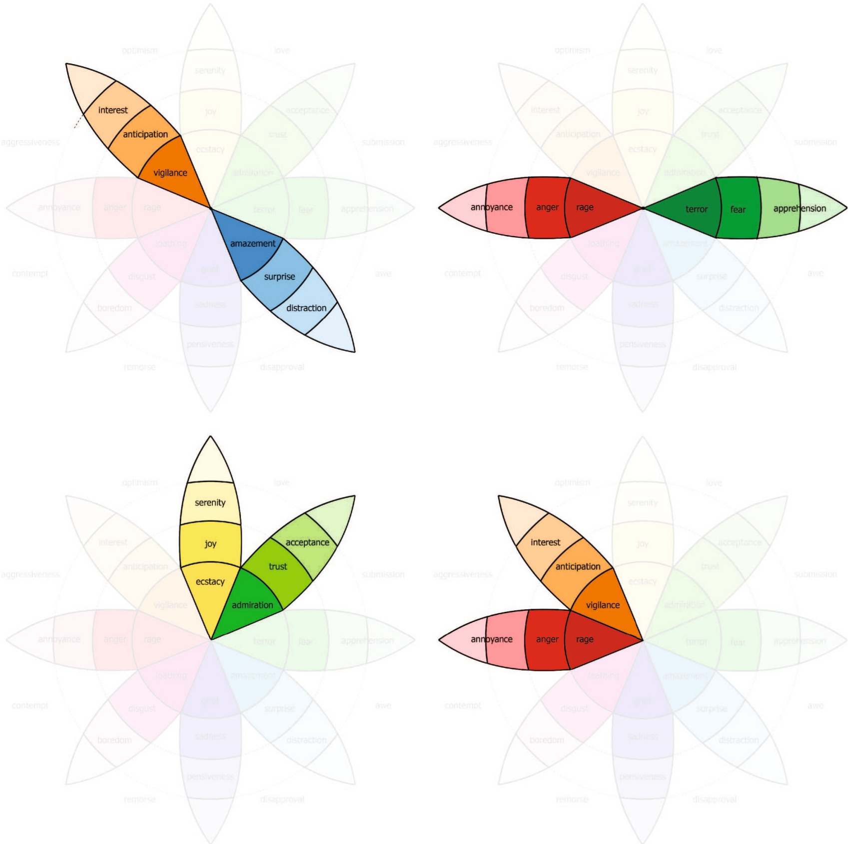

Fig. 14. Chosen pairs of emotions for the survey

ing pairs. They were also chosen due to the implemented mapping, which originated emotions with similar sounds and thus more likely to produce incorrect associations.

The participants were also asked to evaluate their musical knowledge, which could give us a general insight on how the musical background could influence the perception of the sounds. The evaluation was made from 1 to 5, in which 1 means someone who has never had any class or training of a musical instrument, and considers himself "tone deaf", and 5 means professionals in the music area, as teachers, artists or technicians. In the end of the survey, a comment section was added to allow the participants to share some insights and suggestions.

The survey was built using the *Jotform* platform, which allows the creation of a survey within a web environment with integration with Soundcloud, where the sounds were published.

6.1 Analysis of the Survey Results

The survey was shared among members of the Cognitive and Media Systems group (CMS) of the Centre for Informatics and Systems of the University of Coimbra (CISUC), people associated with music schools in Coimbra (teachers and students), and others from mixed backgrounds, collected on social networks. One hundred answers were obtained, which allowed to draw some conclusions.

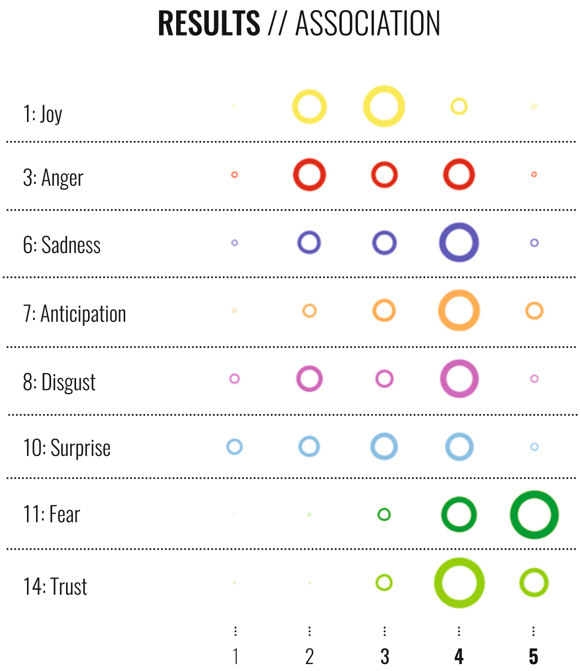

Fig. 15. Results of the association questions

For the eight questions regarding direct association with emotions (Fig. 15), some revealed an incorrect perception. *Joy*, for example, had the highest score in the most neutral value (3), with 41 participants, and the second highest in the previous score (2), with 34 participants, which revealed that more than 75% did not find a clear association. *Anger* is distributed by the three central values. *Sadness* and *Anticipation*, although they had a few scores in the values 2 and 3, the association was mainly positive, with 39 participants scoring *Sadness* and 41 scoring *Anticipation* with the second highest value (4). Therefore, 50% of the participants scored *Sadness*, and 60% *Anticipation*, with the two highest scores (4 and 5). *Disgust* also had a similar distribution, with 38 participants scoring the second highest score (4), with almost 50% of the participants distributed in the two highest scores. *Surprise* had less positive results, with 64 participants distributed in the three lowest scores, with 16 participants considering the lowest score of 1. *Fear* and *Trust* achieved the best results, with almost 85% participants scoring the first with the two highest values, and 80% scoring the second.

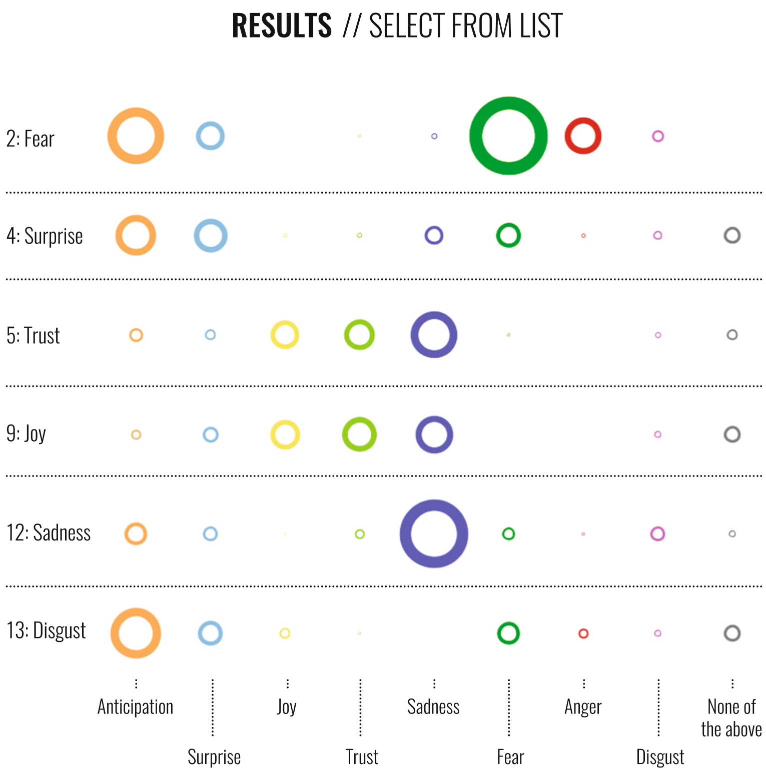

Fig. 16. Results of the selection questions

For the eight selection questions – choosing possible associations from a list with the 8 emotions (Fig. 16) – the results revealed more disagreement. *Joy* and *Trust* were perceived mainly for *Sadness*, emotion that got the highest score in both examples. They were also mistaken by each other, with almost 30 answers. *Surprise* also had a distributed set of associations, with 25 participants choosing *Fear*, almost 20 *Sadness* and the option *None from the list*, and 41 *Anticipation*, with only 34 choosing the correct emotion. *Disgust* produced the less positive results, with only 7 participants perceived it correctly. It was mainly mistaken by *Anticipation*, option chosen by half of the participants. *Sadness* revealed the highest agreement, chosen by almost 70 participants with a small distribution in the remaining options. On the contrary, *Fear*, although achieving a high value of association, with almost 80 participants, generated a higher distribution, with associations with *Anticipation* by 57 participants, *Surprise* by almost 30 and *Anger* by 37.

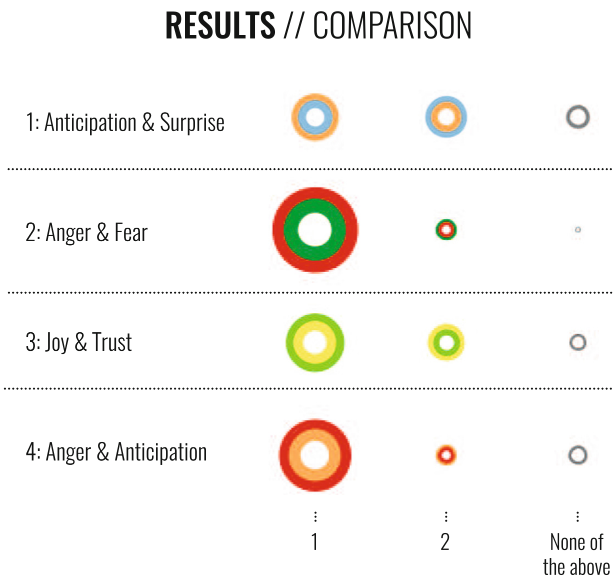

Fig. 17. Results of the second set of questions (comparison questions)

For the second set of questions (Fig. 17), some expected misconceptions were revealed in emotions with a similar sound. The first pair, *Anticipation* and *Surprise*, originated more mixed results, with the first and second answers with a similar amount of answers, and the *None of the above* option with almost 20% of the answers. The third pair, *Joy* and *Trust*, produced the worst results of the four sets, with only 33% participants choosing the right association. On the contrary, the comparison between *Anger* and *Fear*, and between *Anger* and *Anticipation* achieved a positive differentiation, with around 75% of the participants choosing the right answer in the first set, and 65% in the second.

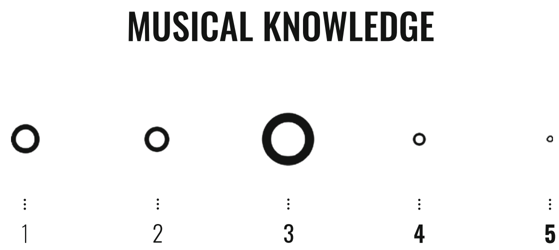

Fig. 18. Participants' level of musical knowledge

Regarding the musical knowledge of the participants (Fig. 18), the biggest portion considered themselves at an intermediate level, with 42 participants.

AVERAGE // MUSICAL KNOWLEDGE // ANSWERS

	Mean & Median	Mean & Standard Deviation	**Mean // Standard Deviation // Median**			
1: Joy			4.00	±	0.894	4
2: Fear			2.59	±	1.097	3
3: Anger			2.20	±	1.6	1
4: Surprise			2.79	±	1.051	3
5: Trust			2.61	±	1.037	3
6: Sadness			2.50	±	1.323	3
7: Anticipation			2.56	±	1.165	3
8: Disgust			3.13	±	1.053	3
9: Joy			2.43	±	1.202	2
10: Surprise			3.00	±	0.866	3
11: Fear			2.50	±	1.19	3
12: Sadness			2.61	±	1.157	3
13: Disgust			2.86	±	1.125	3
14: Trust			2.55	±	1.162	3
15: Anticipation & Surprise			2.64	±	1.042	3
16: Anger & Fear			2.45	±	1.129	3
17: Joy & Trust			2.48	±	1.131	3
18: Anger & Anticipation			2.34	±	1.064	2

Fig. 19. Table comparing statistical measures between the musical knowledge of the participants and the results

The lowest scores achieved the highest distribution, with 23 and 20 participants in the values 1 and 2, respectively. The highest scores only had 15% of the participants, with just 5 selecting the highest level.

The correlations between the musical knowledge and the correct perception of the emotions revealed a balanced result (Fig. 19). We chose to calculate the mean, median and standard deviation for the participants who, in each question, selected the right answer, so we could have a general view on how the musical knowledge could improve the perception. In the selection questions, we picked the participants who chose the correspondent emotion, even if they had also chosen multiple options. In the association questions, we used only the participants that chose the highest score (5). In the second set of questions, we used the participants that opted for the correct answer.

The three values were calculated so we could understand the distribution of the data and compare some discrepancy caused by extremely large or small values. In general, the mean of the level of participants that chose the right answer is at the intermediate level (3). The only value that stands from this scenario is in the first question, were the mean of the five participants that scored the highest value reached the second highest level of musical knowledge (4). The values tend to be symmetrically distributed around the mean, with the median reaching an equal value to the rounded mean in almost every answer. The only exception is the third question of the first set, with the median decreasing a value relative to the mean, and the standard deviation with the highest score of the 18 questions, which shows a higher distribution between the levels of musical knowledge.

The general conclusion points out that the level of musical knowledge is not directly connected with the correct perception of the emotions. Nevertheless, only 15% of the participants had the two highest values of musical knowledge, so it could be beneficial to test the results with a a larger music community, to withdraw more concrete conclusions.

6.2 Discussion and Reflection

The submitted answers, along with suggestions and appreciations left in the comments section, allow us to understand the necessary revisions and future experimentations to improve the perception of certain emotions.

The subjectivity of emotions is an underlying topic to consider, for the characterization of Plutchik's eight emotions, and the number of emotional realities that could be associated with each one. This scenario may have influenced the larger discrepancy of the results in the selection questions: by giving the participant the freedom of choice from a list, one gives her the opportunity to think and associate several realities, which contribute to a selection of more options.

Trust was one of the most commented emotions, as being hard to describe and ambiguous, easily mistaken by *Calm* and *Peace* and even associated with choir music by one participant. Another one associated *Trust* with *Love*, as a feeling of safety, or "someone in a good mood on a calm Spring Day". These metaphors with daily realities were curious to observe, as emotions are lived in these contexts.

Joy was one of the most questioned emotions, and the one that demands more exploration, as it was characterized by sounding too calm and passive to represent *Joy*. However, it should be noted that, in the association question relative to *Joy*, the mean of the musical knowledge reach the value 4, which may represent a better perception by the ones with a musical background. It may be one of the emotions that could benefit more from a strong rhythmic element, which could convey a more vivid and cheerful *Joy*.

Fear, although it produced some misconceptions with *Anticipation* and *Anger* in the selection questions, was one of the emotions that revealed the best results, connected to *Distrust*, *Suspense* and an upsetting sound, "as if something bad was about to happen".

Sadness also had positive results, characterized as *Melancholy*. It originated some misconceptions in the selection questions, probably due to the calmer nature of *Joy*, which even using chords with different natures, had a similar rhythm and tone quality that could influence these doubts.

Anger, although it produced mixed results in the direct association, it was correctly distinguished when compared to other emotions as *Anticipation* and *Fear*. Characterized as "evil, as if someone was planning something bad, does not show anger directly". Therefore, like *Joy*, it could also gain with a more structured and present rhythmic element.

Disgust, also it produced positive results in the association questions, it produced several misunderstandings in the selection question, chosen only by seven people and characterized as "not disgust, but when someone is starting to get mad". The mapping of this emotion was thought to be simultaneously upsetting and boring, with unusual chord natures that produce high levels of discomfort, which may have produced confusing compositions that were hard to understand.

Anticipation and *Surprise*, emotions in a neutral spectrum (which can be either positive or negative), also lead to mixed results. The first still obtained a positive association, with 60% participants, and was correctly distinguished between *Anger* when compared directly. However, it was still confused with *Disgust* and *Fear*, characterized as "when someone is planning something malicious". *Surprise* had worse results, with a weak association and misconceptions with varied emotions, especially *Anticipation*.

Although the results produced a few misconceptions, we can say they were generally positive, with several comments from participants stating this study as "interesting", "challenging", that made them "think about emotions and the influence of music", and that "even if the emotions were not the intended, the compositions really show emotions".

7 Future Developments

The complexity of several fields addressed in this project demands a series of improvements, which could enhance the main two steps of this sonification: the emotional classification of text and the musical mapping.

The emotional analysis, as it is being made by classifying each filtered word through the chosen lexicon, becomes a fallible method, prone to errors due to the limited number of lexicon words and lack of analysis of phrase structure. Besides, the personal language used in social media has usually underlying intentions, with sarcasm and irony changing the emotional tone and creating a higher complexity. One possible solution is to adapt the lexical and emotional analysis to *Python* language, which offers a larger set of possible tools for linguistic review. It would also be interest to adapt the analysis to multiple languages, which could allow a classification of the almost 30 languages that the Twitter API offers, and a global view of the emotional scenario. To expand the emotional spectrum, it would be a possibility to expand the Plutchik's model to the 24 emotions, that could provide a higher set of emotional realities. Another hypothesis is to change the emotional model, using Russell's circumplex model of affect and its two-axis numerical graph to explore more emotional states.

The musical mapping can be expanded in several ways. Winters and Gresham-Lancaster [27] suggest that the focus and complexity of the musical forms should be, instead of the orchestral level (tone quality), in terms of rhythm, tempo and intensity, combined with the sound envelope, mainly the speed of the attack, decay and articulation. The rhythm was revealed through the results as being one of the main parameters to explore with more detail, from tempo variations (BPM) to time signatures. The melodic rhythm can be improved through the addition of rests and the exploration of upbeats, to refine the system of chromatisms. Loudness will also be a priority parameter to explore, to distinguish more energetic emotions like *Joy*, *Anticipation* and *Fear*.

The visualization, as it was a relatively simple experimentation to complement the sonification, can be largely improved, exploring other visual styles and objects that could enhance the communication of tweets, and how the musical parameters could influence the object's movements.

8 Conclusion

With this project, we proposed a structured and musically complex mapping that could translate emotions through a musically captivating sonification. Its implementation produced a sonification of the eight main emotions of Plucthik's model [20], extracted from Twitter in real-time and accompanied by a visualization of the collected tweets and emotional classification.

Underlying problems of the Sonification field are kept unsolved, namely the cultural issues. The implemented mapping, as it was built over the rules of Western Music, does not produce the same results in different regions. Winters e Gresham-Lancaster [27] discuss this problematic, stating that harmonic and melodic artefacts can be highly effective for western listeners, but may not work with others. It is then clear the cultural limitation these sound objects represent.

The cultural matters heighten the emotion subjectivity, whose study is still "one of the most confused (and still open) chapters in the history of psychology" [20]. This scenario comes not only from the difficulty in defining emotions, but also from the musical expression, and its ability in not only conveying emotions, but also induce them [24]. These two types of emotions (perceived and induced) rise from the interaction between the user and the sound object in a given context [24], which is dependent by several individual factors as personality, mood, cultural and musical background.

The relationship between emotions and music is a field that demands a profound study and understanding, due to the complexity of the data and the chosen channel for transmission. This project was an effort to tackle this relationship in the Sonification area, exploring its multidisciplinary nature. The results, although they produced a few misconceptions, were generally positive, expressing the effectiveness and impact of the musical mapping. Several issues that arise focused on the context and musical preferences, which change between listeners and influence the understanding of musical parameters.

The proposed intentions were achieved, with the development of a structured and thought sonification process that transmits the emotional nature of the data in an effective and comprehensible way to the user. We sought to explore how could the use of sound contribute in understanding data, demonstrating the sound potential as a tool to communicate, building a sound object that could be relevant not only in the Sonification field, but for Design as well, usually focused on visual communication. The resulting sound object is another proof, from the increasing number of Sonification projects, of the chance to elevate sound from a supporting communication element to a lead element, expanding the auditory and musical universe.

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