Towards the Automatic Recommendation of Musical Parameters based on Algorithm for Extraction of Linguistic Rules

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Abstract. In the present article the authors describe an analysis of data associated to the emotional responses to fractal generated music. This analysis is done via discovery of rules, and it constitutes the basis to elevate computer-assisted creativity: Our ultimate goal is to create musical pieces by retrieving the right set of parameters associated to a target emotion. This paper contains the description of (i) variables associated to fractal music and emotions; (ii) the data gathering method to obtain the tuples relating input parameters and emotional responses; (iii) the rules that where discovered by using an algorithm LR-FIR. Even though similar experiments whose intention is to elucidate emotional responses from music have been reported, this study stands because a connection is appointed between fractal-generated music and emotional responses, all with the purpose of advancing in computer-assisted creativity.

Keywords. Recommender systems, knowledge discovery, rules extraction, fractal music.

1 Introduction

Music is a type of complex sound that promotes regulation of emotions, communicative expression, identity construction, and interpersonal coordination [12]. Music not only influences emotions but also our cognitive system: the central nervous system is deeply involved in the integration and interpretation of sounds as well as the peripheral auditory processing [11]. However, it is not the physical sound parameters underlying music but the corresponding auditory qualities perceived by the auditory system that cause the effect on emotions. Hence the quantitative relations between the auditory stimuli and the perceived emotions are of particular importance for the realization of music [36].

Emotions are defined as episodes of synchronized body responses, indicating the valuation of an event and leading to a series of reactions of limited duration [34]. Despite being difficult to characterize, they have been framed in several forms. The *Circumplex Model of Affect (CMoA)* developed by Rusell [26, 27] classifies them according to two dimensions: Valence and Arousal. Valence refers to the degree of attractiveness or aversion that an individual feels towards, in this case, an emotion. Arousal measures to what extent an emotion leads to action or to physiological readiness for activity, thus defining a state in which bodily resources are mobilized, including the peripheral nervous system, the endocrine system, and the immune system [11].

Attempts to create music by computer systems abound. Some developments include the creation of musical pieces from the Mandelbrot set [35], non-linear models such as cellular automata [21, 22], evolutionary methods [41, 2, 28], or swarm computing [4, 5, 25]. DNA-like data has been transformed into music [1]. Melodic sequences have been generated by using the Chua's circuit [3].

The linguistic approach to create music is given in [30, 29]. Classification according to genre by using semi-supervised and supervised techniques is described in [24]. Our own work on computer assisted creativity is reported in [18] and [17].

Provided that emotional reactions were enacted by digitally created music, then it could be attainable to find the link between the input data (used to create musical pieces) and emotions. Hence, we proceed to find the relations between the input parameters on which fractal music is created, and the emotions actually felt. This is done through Knowledge Discovery in Databases (KDD). As defined in [23], KDD is the nontrivial process of identifying valid, novel, useful, and understandable patterns in data.

Hence, the first step we took in order to unite emotions and computer algorithms consisted in developing an evaluation template based on the CMoA. This improvement permits to pair emotional responses with musical pieces in such a way that both, input data leading to musical pieces and output data pointing to emotions, are organized within a database. Knowledge, consequently, can be discovered by processing its contents.

We present in this paper the results of applying a particular kind of KDD known as LR-FIR, which has originally presented in [6]. The advantage of using such approach is the discovery of *Linguistic Rules*, that not only codify the underlying knowledge hidden into large datasets, but it also serves as a characterization of the system under study. In this case, the resultant set of rules explains the relationship between the parameters used to create fractal music and the emotions as perceived by human listeners. This is an important step towards developing intelligent recommender systems.

This paper is organized as follows. Section 2 presents similar experiments that elucidate emotional responses to music. The explanation of the relevant Input Parameters is given in Section 3. The activities to acquire emotional responses to fractal music are presented in Section 3.1. Next, Section 4 contains a brief description of the LR-FIR algorithm. The experimental results and their interpretation are given in Section 5. Finally, conclusions and future work are presented.

2 Related Work

2.1 Emotions as a Parameter for Recommending Music

Mood has been used as a basic feature in music recommender and retrieval systems [7]. A listening experiment was carried out establishing ratings for moods, valence and arousal. 288 songs over 12 musical genres from popular music where evaluated. However, in [34] it is stated that emotions are not the same as mood.

A method for creating automatic music mood annotation is presented in [14], where a database of 1,000 songs was employed. Also, tests of different classification methods, configurations and optimizations have been conducted, showing that Support Vector Machines perform best. However, the researchers restrict the study to four broad emotional categories: happiness, sadness, anger, and relaxation. They argue that those categories reflect basic emotions covering the four quadrants of the 2D representation from Russell. Nonetheless, it is said that six are the basic human emotions conventionally accepted [34] .

A personalized affective music player (AMP) that selects music for mood enhancement is described in [10]. They employ bio-signals to measure listeners' personal emotional reactions as input for affective user models. Regression and kernel density estimation are applied to model the physiological changes the music elicits. Using these models, personalized music selections based on an affective goal state were made.

MEMSA (Mining Emerging Melody Structure Algorithm), is proposed to discover a new kind of pattern, called Emerging Melody Structure (EMS) [15]. It is argued that customization of on-line music experiences will improve with the application of this technique.

An evaluation of seven multi-label classification algorithms was performed in order to rank and classify 593 songs according to emotional evaluations [37]. The study was conducted to enhance music information retrieval systems that will use a target emotion as the most important parameter to retrieve music from large collections. In another study, impression was used for music information retrieval [13].

An intelligent system aimed at creating new musical pieces is reported in [33], where feature extraction helps discover musical patterns of popular songs, and then profit from those patterns to create novel compositions. Human evaluation acts as feedback to adjust genetic algorithms that create pieces of music [38].

ISSN 1405-5546
DOI: 10.13053/CyS-18-3-2048

The outstanding difference among those reports and our research is that we are not looking to recommend what musical piece to reproduce, or buy, by a given individual. We intend to use the knowledge so an intelligent agent can indeed make recommendations according to a target emotion, providing input parameters on which a new musical piece will be created. Nonetheless, these recommender systems have inspired us to upgrade the capabilities of our Multi-Agent System by including a recommender agent which will provide the most likely input parameters on which a musical piece might provoke a given emotion.

2.2 Classification of Music Clips According to Emotions

The emotion detection problem is viewed as multi label classification problem where music is classified into multiple classes simultaneously [16]. The classification technique is Support Vector Machines that were trained to extract acoustic features from music clips, ranging from ambient music, classical, fusion and jazz. One subject participated in the experiment. Emotion recognition is also viewed as a multi-label classification problem [32]. It is proposed a framework where mood is represented as either a single multi-dimensional vector or a time-series of vectors over a semantic space of emotions. Their review considers emotion recognition on the combination of lyrics and content-based audio analysis. We, on the other hand, employ clips containing only music and do not perform audio analysis because we know in advance the seed parameters under each musical piece is created.

An attempt to establish a link between emotions and music genre is presented in [8]. Three data sets of classical music, two data sets of film music, two data sets of popular music and two data sets of mixed genre, all of which define the emotions exerted by them, were analyzed. Thirty nine musical features were obtained and cross referenced. However, low correlations were found among the music genre and emotions.

The classification of musical pieces according to emotions, taking into account both, musical content and lyrics, was reported in [9]. They employ fuzzy clustering in order to map such input information into a two dimensional model of emotions. They also built an affective lexicon, then detected the emotion of a sentence, and then found clusters. The musical stimuli consisted in 981 Chinese songs.

Automatic mood detection of audio files is presented in [20]. They report a computational framework that estimates automatically the mood inferred in music clips. However, the authors correctly make the distinction between emotion and mood, as noted by most of psychology books. Another difference with our research is that they extract features from digital files, on which they classify the analyzed clip according to how they trained a classifier.

Classification of music with the intention to facilitate its retrieval from large collections is presented in [40]. They employ audio feature extraction to analyze the contents of musical clips, and process those features by a multimodal fusion process. The emotional model used is Thayer's arousal-valence plane.

Even though those reports are extremely valuable, we are not using our dataset to classify music. Our approach is to discover cluster formation of Input Parameters that will further be used to recommend and create newer musical fragments based on non-linear dynamic systems. Neither we process the audio signal, since our intelligent system works on the parameters associated to fractal equations.

The effects of mode, texture, and tempo on emotions were studied in [39]. A 2 (mode: major vs. minor) $\times$ 2 (texture: nonharmonized vs. harmonized) $\times$ 3 (tempo: 72, 108, 144 beats per min) experimental design was employed, in which 177 college students rated four, brief musical phrases on continuous happy-sad scales. It is mentioned that major keys, non- harmonized melodies, and faster tempos were associated with happier responses, whereas their respective opposites were associated with sadder responses.

The dataset that we employ to discover rules displays a rich variation in: (i) tempos, from *Adagio* (sixty beats per minute), to *Prestissimo* (220 beats per minute); (ii) scales (major, minor, natural, harmonic and blues); (iii) harmonies (chords) and

ISSN 1405-5546
DOI: 10.13053/CyS-18-3-2048

melodies (without chords). Hence, we analyzed a wider range of input parameters. Emotions, on the other hand, presented in the Valence–Arousal plane, which presents four different quadrants. A brief description of the relevant variables is given next.

3 Variables for the Creation of Fractal Musical Fragments

In spite of having the capability to create musical fragments based on several recursive, non-linear systems, we restricted this study to the Lorenz equations [19]. Therefore, musical fragments used as auditory stimuli mirror diverse combinations of input parameters, including: (i) variables of the Lorenz equations, and (ii) musical parameters.

Regarding the Lorenz equations, variables x, y, and z are the initial values of the attractor. In this case such variables represent initial notes. Consequently, they must be confined within the valid ranges of MIDI notes, that is to say, integers between zero and 127. Variables $sigma$, r and b are determinant for the actual shape of the attractor. They can take any real value, but our MAS is programmed so these values lie between minus two hundred and two hundred.

Table 1 displays the range of values that were used to compute the Lorenz attractor.

Table 1. Range of Lorenz parameters

Lorenz parameters					
x	y	z	sigma	r	b
[0,127]			[-200, 200]		

The algorithm we employ to extract rules (Section 4) obliges to divide each of the variables into discrete groups. We describe how the relevant variables for the case at hand were grouped. The variables in Table 1 were divided in four classes.

Because the variables of the Lorenz attractor must be paired with musical parameters i.e. Tempos, Notes Durations, Musical Scales, Chords and Instruments, we review them briefly and describe what classes were fixed for each of them. The proposed classification for variable Tempo is given in Table 2. Ten classes are used so the LR-FIR algorithm performs accordingly.

Notes Durations are tied to Tempos, so they are expressed in values such as whole duration (1), half duration (1/2), a quarter (1/4), and so on. For the present study, Notes Durations lie between $1/16$ and 1. The Notes Duration variable was grouped in four classes.

The entire range of musical parameters is summarized in Table 3.

The Instrument variable is grouped as follows: (i) Class 1 (Grand Piano, Bright Acoustic and Harpsichord); (ii) Class 2 (Acoustic Guitar, Steel String Guitar); (iii) Class 3 (Electric Clean Guitar, Electric Jazz Guitar, Guitar Harmonics, Distorted Guitar, Overdriven Guitar, Electric Muted Guitar); (iv) Class 4 (Violin, Viola, Cello, Tremolo, Pizzicato, Orchestral Strings, String Ensembles); and Class 5 (Acoustic Bass, Electric Bass Finger, Electric Bass Pick, Fretless Bass, Slap Basses, Contrabass).

Similarly, the Chord variable was grouped as follows: Class 1 (Mayor chords); Class 2 (Minor chords); Class 3 (Augmented chords); Class 4 (Diminished Chords); Class 5 (Other chords); Class 6 (No chords). Musical Scales are grouped as follows: Class 1 (Pentatonic Scales); Class 2 (Harmonic Scales); Class 3 (Natural Scales); Class 4 (Blues Scales); Class 5 (Melodic Scales); Class 6 (without scale). Before dwelling into the experiments, we describe the work done in order to obtain the dataset from which rules are discovered.

3.1 Data Gathering

Data gathering was performed through a protocol where 42 subjects, all healthy, ranging from fifteen to forty-five years old, volunteered to evaluate the emotional responses felt after listening short musical pieces created by the MAS. Each individual was asked to select at will, from the entire set of pieces, which ones to evaluate. The subject was let free to decide when to stop. After listening to each musical piece, the individual selected what emotion was provoked. Soon after, the subject had to quantify Valence and Arousal.

Evaluation was performed by employing our MAS. Figure 1 is the GUI associated to Evaluator Agent, which serves as an interface between

ISSN 1405-5546
DOI: 10.13053/CyS-18-3-2048

Table 2. Tempo Classes. Values expresses in beats per minute

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
[60,65)	[65,70)	[70,80)	[80,95)	[95,10)	[110,120)	[120,145)	[145,180)	[180,220)	[220,300]

Table 3. Musical parameters

Musical Parameters				
Tempo	Notes Duration	Musical Scale	Chord	Instrument
[60,260]	$[1/16$, 1]	G Major Pentatonic	Add9	Pianos(3)
		G Minor Pentatonic	Augmented	Guitars(8)
		E Major Pentatonic	Diminished	String Instruments (9)
		E Minor Pentatonic	Major	Bass (6)
		C Major Pentatonic	Minor	
		C Minor Pentatonic	Major 7	
		C Major Natural	Minor 7	
		C Minor Natural	Major 9	
		C Minor Harmonic	Minor 9	
		G Minor Harmonic	7+9+5	
		G Blues	7-5+9	
		C Blues	7-5-9	
		C Melodic Minor	7+5-9	
		B Melodic Minor		

the creative module, users and a database were tuples are stored. The referred GUI is a Spanish version of Russell's Circumplex Model of Affect. To help understand it, we will describe the emotions in english words. The first quadrant contains Astonishment, Excitation, Euphoria and Happiness. The second quadrant is composed of Fear, Anger, Distress and Upset. Sadness, Depression, Droopiness and Tiredness constitute the third quadrant. Finally, the fourth quadrant contains Satisfaction, Serenity, Relaxation and At ease. The two dimensions are Valence (expressed as Agrado–Desagrado) and Arousal (expressed as Activación). Since all of the evaluators are spanish speakers, we decided to develop such GUI in spanish, yet those labels are a faithful reflection of the original.

Some of the resultant tuples relating input data and emotions are shown in Table 4. The entire dataset is available upon request. The knowledge discovery process was performed on the entire set of evaluations that we obtained.

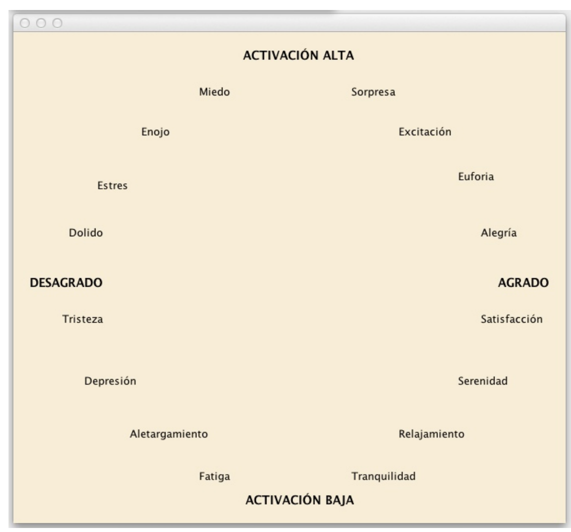

Fig. 1. GUI of the Evaluator Agent

4 Algorithm for Extraction of Rules

The algorithm we are employing to discover knowledge via the extraction of linguistic rules has been

ISSN 1405-5546
DOI: 10.13053/CyS-18-3-2048

Table 4. Sample of the psychoacoustics dataset

Instrument	Scale	Chord	TempoX	TempoY	TempoZ	DuraX	DuraY	DuraZ	x	y	z	sigma	r	b	Emotion	Arousal	Valence
Piano	PGMayor	none	145	145	150	0.1	0.12	0.2	12	15	16	4	23	2	Happiness	6.3	9.3
Piano	CNMenor	major	140	165	150	0.125	0.1	0.25	23	56	16	4	23	2	Sadness	4.6	3.7
Distortion Guitar	PGMayor	none	125	135	145	0.125	0.115	0.13	23	34	67	4	8	7	Stress	7.8	1.37
Guitar Harmonics	PEMenor	none	187	180	199	0.175	0.195	0.145	63	40	77	30	57	11	Excitation	7.9	7.8
PizzicatoStrings	PCMenor	none	187	180	199	0.205	0.275	0.345	65	41	79	40	23	115	At ease	2.58	7.45
Overdriven Gtr	GAMenorr	major	255	255	255	1	1	1	80	119	90	43	14	37	Stress	7.2	0.44
String ensemble	PGMenor	major	255	255	255	0.125	0.13	0.12	67	65	68	100	100	100	Euphoria	7.2	7.6
Electric Muted Gtr	PEMenor	diminished	255	255	255	0.132	0.137	0.131	12	120	92	200	200	200	Astonishment	8.5	6.12
StringEnsemble	PGMayor	none	124	124	124	0.55	0.5	0.45	15	15	15	-10	-10	-10	Droopiness	2.65	5.08
Piano	PEMenor	minor	90	90	90	0.065	0.065	0.065	12	100	45	-3	3	-3	Satisfied	4.7	8.92
Overdriven Gtr	PGMenor	add9	80	80	80	0.125	0.125	0.125	120	12	24	-65	-65	-65	Tiredness	1.9	1.75
Piano	BMelMinor	none	60	60	60	.125	.125	.125	23	45	78	-100	-100	-100	At ease	2.07	8.35
Bright Acoustic	CMelMinor	Minor	60	60	60	.125	.125	.125	67	10	9	-100	-100	-100	At ease	1.88	6.45
Bright Acoustic	CMelMinor	Minor	60	60	60	.125	.125	.125	67	10	9	-100	-100	-100	Tiredness	2.11	3.24
Piano	GBlues	Major	220	220	220	0.125	0.125	0.125	61	9	3	-150	-150	-150	Euphoria	7.31	9.15
Cello	CBlues	Minor	140	140	140	0.125	0.125	0.125	2	2	2	150	150	150	Anger	7.94	4.47

described originally in [6]. It is known as LR-FIR, whose main purpose is to serve as a tool for decision making. Figure 2 shows the main phases of the algorithm. Notice that LR-FIR first creates a so-called *Pattern Rule Base* by using Fuzzy Inductive Reasoning (FIR), which characterizes the Input–Output relationships. A *mask*, which denotes a dynamic relationship among variables, is also required. The Linguistic Rules (LR) are obtained on the basis of such Pattern Rule Base. The two major processes are:

1. **Basic Compaction**. The main goal of this step is to transform the Pattern Rule Base, R, into a reduced set of rules, *R'*. R is usually very large (almost as large as the number of training data available). An iterative procedure evaluates rules in R, and each of their premises. R is compacted on the basis of the knowledge obtained by FIR. A specific subset of rules R_c can be mapped to a compacted rule r_c when all premises P but one (P_a), as well as the consequence C share the same values. Premises, in this context, represent the input features, whereas consequence is the output feature in a rule. If the subset contains all legal values LV_a of P_a, all these rules can be replaced by a single rule r_c that has a value of -1 in the premise P_a. When more than one -1 value P_{ni}, is present in a compacted rule r_c, it is compulsory to evaluate the existence of conflicts by expanding all Pni to all their legal values LV_a, and comparing the resultant rules X_r with the original rules R. If conflicts C_f exist, then the compacted rule r_c is rejected, otherwise it is accepted. In the latter case, the previous subset R_c is replaced by the compacted rule r_c. Conflicts occur when one or more extended rules X_r have the same values in all its premises but different values in the consequence. Thus, *R'* includes all the r_c compacted in previous iterations and those that cannot be compacted R_{nc}.

2. **Improved Compaction**. Whereas the previous step only structures the available knowledge and represents it in a more compact form, the improved compaction step extends the knowledge base R to cases that have not been previously used to build the model R_b. Thus, step 1 leads to a compacted data base that only contains knowledge; the enhanced algorithm contains undisputed knowledge and uncontested belief. Two options are studied: In the first one, using the compacted rule base *R'* obtained in step 1, all input features P (premises) are visited once more in all the rules r that have nonnegative vales (not compacted), and their values are replaced by -1. An expansion to all possible full sets of rules X_r and their comparison with the original rules R are carried out. If no conflicts are found, then the compacted rule r_c is accepted, otherwise it is rejected. The second option is an extension of the basic compaction, where a consistent minimal ratio MR of legal values LV_a should be present in the candidate subset R_c in order to compact it in the form of a single rule r_c. This option seems more suitable since a consistent ratio is used to compact R_c in a

ISSN 1405-5546
DOI: 10.13053/CyS-18-3-2048

single rule r_c. Hence, the beliefs are minimal and they do not compromise the model previously identified by FIR. In option 1 beliefs are assumed to be consistent with the original rules; nevertheless, this could compromise the agreement with model identified, especially when the training data is poor and does not describe all possible behaviors.

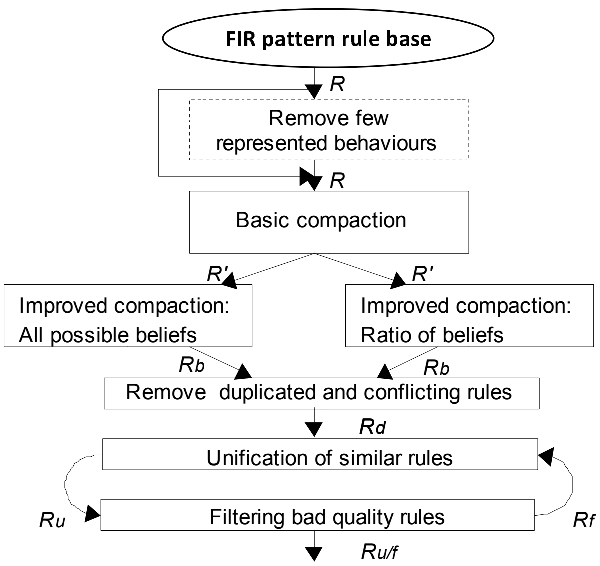

Fig. 2. Main steps of the rule extraction algorithm

Then, the obtained set of rules passes though a number of refinement steps: removal of duplicate rules and conflicting rules; unification of similar rules; evaluation of the obtained rules and removal of rules with low specificity and sensitivity.

5 Extraction of Linguistic Rules According to Emotions

We present, in Table 5, the resultant set of linguistic rules. Their interpretation comes afterwards.

In Table 5, *Spec.* means Specificity, *Sens.* means Sensitivity, and *Acc.* means Accuracy, which are he accepted metrics to assess the quality of classifiers.

5.1 Interpretation of the Linguistic Rules

Table 5 contains the linguistic rules that were discovered by applying the algorithm LR-FIR to our psychoacoustics dataset.

It can be seen that for the emotions in the first quadrant (Q1) of the Valence–Arousal plane (Astonished, Excited, Euphoric and Happy), four rules were discovered. All of them suggest the usage of high values of Tempos, that is to say, Tempos between 120 and 145 beats per minute (C7) and Tempos between 180 and 220 beats per minute (C9). In all of the cases the Chord to use must be taken from the class C1 (Major chords).

Two rules recommend the usage of Notes Durations between 0.125 and 0.25 (C2). The four rules lead to employ an Instrument that belongs in C1 (Piano, Bright Acoustic or Harpsichord), and one of the rules also recommends to employ any of the electric guitars (belonging to C3).

For the Emotions in the second quadrant of the Valence–Arousal plane (Angry, Fear, Distressed, Gloomy), the LR-FIR only extracts one rule, whose interpretation is straightforward. Chords should be minor; Instruments should be one of the Pianos, and Tempos must take values between 60 and 65 beats per minute.

As for the emotions in the third quadrant of the Valence–Arousal plane (Sad, Depressed, Tired, Droopy) five rules were discovered. Musical fragments could be created on Major chords or no chords at all. The Instrument should be picked from the Strings class (C4). Notes Durations may take a value between 0.125 and 1, which are the values contained in classes one, two and three for this variable. Even though the variable Tempo might be taken from C1 (60–65 bpm), C3 (70–80 bpm), C4 (80–95 bpm) or C7 (120–145 bpm), situation that might seem too vague, those values should be paired to Notes Durations. Thus, combining such Tempo values with the Note Duration values, musical fragments will possess the appropriate rhythm to provoke emotions in Q3.

Finally, emotions in the fourth quadrant of the Valence–Arousal plane (Satisfied, Serene, Relaxed, At ease) will likely be provoked by the Input Parameters that the three discovered rules suggest. Musical fragment should be created with

ISSN 1405-5546
DOI: 10.13053/CyS-18-3-2048

Table 5. Resultant linguistic rules

Linguistic rules according to Valence–Arousal			
Linguistic Rules	Spec	Sens	Acc
IF Instrument IN (C3 OR C4) AND duraZ IN C2 AND r IN C4 and tempoY IN C9 THEN Emotion IN Q1	0.98	0.1	0.69
IF Chord IN C1 AND duraZ IN C2 AND r IN C1 AND tempoY IN C9 THEN Emotion IN Q1	1.0	0.063	0.69
IF Chord IN C1 AND Instrument IN C4 AND r IN C2 AND tempoY IN C9 THEN Emotion IN Q1	0.96	0.047	0.66
IF Chord IN C1 AND Instrument IN C4 AND r IN C2 AND tempoY IN C7 THEN Emotion IN Q1	0.97	0.043	0.67
IF Chord IN C2 AND Instrument IN C1 AND r iN C3 and tempoY IN C1 THEN Emotion IN Q2	0.98	0.076	0.82
IF Chord IN C6 AND duraZ IN C2 AND r iN C1 AND tempoY IN 1 THEN Emotion IN Q3	0.99	0.061	0.82
IF Chord IN C6 AND Instrument IN C4 AND duraZ IN C4 AND tempoY IN C7 THEN Emotion IN Q3	0.98	0.061	0.8
IF Chord IN C6 AND Instrument IN C4 AND duraZ IN C3 AND r IN C4 and tempoY IN C3 THEN Emotion IN Q3	0.99	0.047	0.81
IF Chord IN C1 AND Instrument IN C4 AND r IN C2 AND tempoY IN C1 THEN Emotion IN Q3	0.97	0.047	0.79
IF Chord IN C1 AND Instrument IN C4 AND r IN C2 AND tempoY IN C4 THEN Emotion IN Q3	0.97	0.045	0.79
IF Chord IN C1 AND Instrument IN C4 AND r IN C2 AND tempoY IN C1 THEN Emotion IN Q4	0.98	0.056	0.79
IF Chord IN C1 AND Instrument IN C4 AND r IN C2 AND tempoY IN C9 THEN Emotion IN Q4	0.96	0.052	0.78
IF Chord IN C2 AND Instrument IN C4 AND duraZ IN C1 AND tempoY IN C1 THEN Emotion IN Q4	1	0.045	0.8

Major chords (C1), any of the Strings instruments (C4), and rhythms obtained with Notes Durations between (0.0625–0.125) paired with Tempos in the ranges of (60–65 bpm) or (180–300 bpm).

We emphasize here that the recommended Input Parameters according to a target emotional response is not done on a rule by rule basis, but by taking into consideration the entire subset of rules according to the quadrant under analysis. Hence, rules that might be contradictory are not, actually, because they are part of the solution and not a solution per se.

It is also worth noticing that parameter r of the Lorenz equations is thought to be determinant for the obtention of the proper auditory stimuli, according to the results of the LR- FIR algorithm employed.

Another point worth mentioning here is that we executed several experiments to discover rules. In each of them the underlying parameters of LR-FIR were changed. However, the set of extracted rules did not vary substantially. This could occur because the dataset actually contains a stable pattern. As future work, we intend to compare the knowledge obtained by using LR-FIR with another techniques of knowledge discovery i.e. clustering.

We created some fragments of fractal music with the Input Parameters suggested by the above set of rules, and asked ten of our students (20–24 years old, male and females) to assess them. In 80 percent of the cases their emotional response matched the emotion intended. Yet, more experimental validation is necessary.

6 Conclusions and Future Work

Even though recommendation of music has been reported in [31], our propossal differs because we link emotions and parameters via linguistic rules. This article depicts how to discover knowledge for automating the creation of musical pieces based on nonlinear models. With the newly discovered knowledge, it is possible to advance towards developing a recommender system which exploits

ISSN 1405-5546
DOI: 10.13053/CyS-18-3-2048

such knowledge. Thus, we can state that the enhancement of computer-assisted creation of musical pieces is achievable by upgrading such systems with KDD, promoting that Input Parameters associated with a desired emotion can be obtained.

Several questions have to be addressed, though. If we were to employ more knowledge discovery techniques, will the recommendations differ significantly? More experimentation is needed at this regard. Another question has to do with finding the right data for a particular subject. It might occur that the recommended input data could not match the actual response given by an individual. In this case, it is necessary to develop meta-computing techniques which allow to traverse among several possible solutions. That meta computing must include (i) weighting several fractal systems, (ii) decisions on the most suitable clustering technique and (iii) rewarding those solutions that match a subject's emotions. Hence, we will explore brain-inspired computation to promote plasticity and flexibility in our creative software. A final question refers to what extent the present findings can be transferred to another chaotic system, specially musical parameters such as Tempo and Notes Durations. Could musical fragments created with the Marcus-Lyapunov system utilize the Tempo values presented in the present article to provoke the same emotions?

Necessary and rather-sufficient knowledge has been discovered and stated as linguistic rules. We will channel our efforts to achieve the unmanned creation of musical pieces: users will only set what emotion is to be enacted, KDD will then provide input parameters, and music will be rendered automatically.

Acknowledgements

The authors are thankful to Karla López de la Cruz for coordinating the data gathering process.

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DOI: 10.13053/CyS-18-3-2048

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ISSN 1405-5546
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Article received on 02/07/2014; accepted on 23/09/2014.