Musical Genre Classification by means of Fuzzy Rule-Based Systems: A preliminary approach

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***Abstract*—Musical Genre is part of the basic information required for classifying musical audio, and fundamental for music information retrieval systems. The problem of automatic musical genre detection has attracted large attention in the last decade, due to the emergence of digital music databases and Internet. Although a number of techniques has been applied to the problem, no general solution still exists, due to the imprecise features that properly define musical genre.**

This paper presents a preliminary attempt to apply Fuzzy Rule-Based System (FRBS) in cooperation with Evolutionary Algorithms to musical genre classification. The novelty of the approach -which allows us to use fuzzy information extracted from audio files- is aligned with the fuzzy nature of the problem at hand, where no clear-cut rules are available for the classification.

Preliminary results presented allows to foresee the potential of the technique.

I. Introduction

When dealers, radio station, or anybody interested in classifying music contents has to characterize them or establish a basic classification, musical genre is the first and main categorical description employed. The proliferation of Internet based music stores and Electronic Music Distribution (EMD) systems, associated to huge music catalogues stored on distributed databases, has increased the interest and importance of the classification process. Obtaining relevant results after queries requires a correct association between genre and musical pieces.

Although manually labeling songs was the traditional method, it will no longer be possible: as reported by [1], labeling hundred of thousand songs for Microsofts MSN Music Search Engine needed about 30 musicologists for one year.

Therefore, automatic annotation processes are required, although no strict definition and boundaries are established for efficiently performing the classification: cultural, historical and marketing factors traditionally influences the process. Yet, from the point of view of automatic information retrieval, several techniques and methodologies have already been tried, using information that can be analyzed from audio signals: instrumentation, rhythmic structure and pitch content of the music. These features can be used for similarity retrieval, classification and audio thumbnailing [2]. Nevertheless, the relationship between these main features and the musical genre is not straight, and the presence of ambiguities doesn't guarantee the correct automatic classification.

This paper presents a preliminary approach to musical genre classification by means of a new perspective: Given the imprecise nature of the features to be considered, a fuzzy approach is applied. Fuzzy Rule-Based System (FRBS) in cooperation with Genetic Algorithms (GA) allows us to perform musical genre classification.

The paper is organized in the following sections: Section II reviews related work; Section III describes the techniques applied in this new approach; Section IV shows the obtained results and their analysis; and, finally, Section V concludes the paper with a discussion of the results.

II. Musical Genre Classification

The process of genre classification usually involves two main steps: (i) feature extractions and (ii) classification. The first steps tries to extract from the audio signal information of interest, while the second one must include an algorithm capable of deciding music labels from the features extracted [3].

A number of different feature sets, usually based on some form of time-frequency representation, have been proposed to represent audio signals. Some of the pioneering works dealing with music signals tried to analyze isolated musical instruments [4], using pitch, amplitude, brightness, and bandwidth. Histograms of the relative frequencies of feature vectors have also been employed, as well as statistics based on Wavelet transform (DWT) coefficients [5]. Nevertheless, the previously described analysis doesn't consider the rhythmic structure of the music. Automatic beat detection has also been applied by other authors' classification [6]. However, only recently researchers have considered feature extraction and classification as a means to classifying musical genre: Tzenatakis et al presented one of the first attempts in 2002 [2].

Scaringella et al presented in 2005 a survey of the techniques that have been applied to the problem [7], recognizing that no general agreement exists about the main features to be considered for the distinction about musical genre. A number of low-level features that can be useful are summarized:

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(i) Timbre features -Temporal, energy, Spectral Shape and Perceptual features- as well as their first and second-order transformations are employed by researchers, but no clue about which should be considered the main ones are provided; (ii) Melody-Harmony, (iii) Rhythm (iv) semantically significant features. Nevertheless, the variety of techniques and proposals keeps authors from deciding which should be considered the most relevant features to be employed.

If we focus instead on the second part of the equation, the methods required for establishing a classification once the features have been extracted from the audio signals, several approaches have very recently been applied to automatic musical genre classification. An Expert System approach has been presented in [8]. Nevertheless the approach requires a manner to obtain reliable high-level descriptors from the audio signal. Moreover, expert systems are expensive to implement and to maintain. Attention has thus move to Machine Learning approaches.

As described in [7], a number of unsupervised and supervised classification methods relying in Gaussian methods for developing timbre models, or Hidden Markov Models (HMMs) to model the relationship between features over time has been proposed. Scaringella also reports in [7] the application of Support Vector Machines and Artificial Neural Networks in this context. While these approaches are relevant, researchers are sometimes not only interested in obtaining a classifier system, but also information from the classifier itself: ANNs usually behave like black boxes, and hardly ever provide information from inside.

Only very recently, researchers have considered the usefulness of Evolutionary Algorithms in the context of musical genre classification. In [9], for instance, authors use Genetic Algorithms to the problem of feature selection, working with different parts of music signal, in order to perform genre classification.

All of the above described works, have tried to fight the information impreciseness required to establish correct genre classification.

Our approach faces the problem from a quite different perspective: instead of trying to make the information for the classification as precise as possible -with a complex process of feature extraction, selection and filtering- so that the technique employed can make the classification as reliable as possible, we consider the opposite point of view. We think that techniques capable of coping with imprecise information are required here. Our approach make thus use of Fuzzy Logic -namely Fuzzy Rule-Based Systems (FRBSs) [10] in cooperation with Genetic Algorithms (GAs) when the tuning of some parameters are required. Fast Fourier Transform (FFT) is applied to the fragment of music to be analyzed, and the frequencies with higher energies -and their relationship- is the only input to the classification system. We rely on the different harmony principles behind the musical genres considered in this preliminary work for the system to correctly work. To the best of our knowledge, this is the first approach to exploit the intrinsically imprecise nature of the problem for performing a classification by means of FRBSs and GAs.

III. Methodology

FRBSs has been successfully applied for solving classification problems [10]–[12]. The main advantage of FRBSs is their capability of using impreciseness -Fuzzy information- to generate good classifiers systems. Moreover, recent works have shown that their capabilities can improve when they are combined with Genetic Algorithms for tuning the main Fuzzy Rules parameters [10]–[12].

In this paper we present a proposal to solve the problem of musical genre detection -and classification- by means of FRBSs. Two genres will be considered: *jazz* and *classic* music.

Our starting point will be a number of songs, that we sample: one second of music is randomly extracted and the frequency spectrum is computed by means of the FFT. Several samples can also be extracted from each song. Then, frequencies with higher energies are extracted and the relationship among them computed. We hope this information provides relevant information concerning the harmony that the song features, which could be useful to distinguish between musical genre. This will be the input information for FRBS that we want to develop. Even when the information provided is quite scarce and imprecise when compared with previous approaches, we hope the results will show the interest of the new method and their capability for coping the lack of precise information from the input.

A. Initial FRBS

A FRBS is composed by a Data Base definition (DB), i.e., the definitions of the Membership Functions (MFs), and the inference engine parameters, the Rule Base (RB) [10]. In this subsection the initial FRBS ($FRBS_{init}$) developed in this work is described.

To obtain the whole DB, we need to defined the MFs and the RB. The first step is to determine a set of interesting system variables by analyzing the set of examples. As stated before, we begin with a set of samples -one second long-obtained from classic and jazz audio files. We then apply the FFT to each of the fragments and the frequencies with higher energies are extracted -from first to fourth-. We compute the relationship between those frequencies, giving rise to three numerical values that will act as input variables: the main input variables of the FRBS. The idea was to provide the system with information that might be useful when establishing harmony differences among styles. If the frequencies with higher energy values are described as *F1, F2, F3, F4*, where F1 is the highest value and F4 is the lowest one, the variables used by the FRBS are described as follows:

1) X1: Relationship between F1 and F2 ($F1/F2$).
2) X2: Relationship between F1 and F3 ($F1/F3$).
3) X3: Relationship between F1 and F4 ($F1/F4$).
4) Y: Output value (where 1 is a *classic* music and 0 is a *jazz* music)

The next step is to obtain the MFs and the RB of the system. For this we use the Wang & Mendel method [13]. This method works as follows:

1) Generate a set of linguistic rules candidates to solve the problem. It is necessary to look for the rule that best surrounds each sample data set. Thus, RC^1 rule structure is obtained by assigning to each variable the best linguistic label associated with a fuzzy set that best matches with the corresponding component of the example e_1, i.e.

$$RC^I = If\, X_1\, is\, A_1^I\, and...and\, X_n\, is\, A_n^I\, then\, Y\, is\, B^I$$

where

$$A_i^I = arg\, max_{A' \in A_i}(\mu_{A'}(x_i^I))$$
$$B^I = arg\, max_{B' \in B}(\mu_{B'}(y^I))$$

2) Assign a degree of importance to each rule. This is obtained by calculating the envelope of the rule on the example as follows:

$$VE_\Pi(RC^I, e_I) = \mu_{A_1^I}(x_1^I) \cdot ... \cdot \mu_{A_n^I}(x_n^I) \cdot \mu_{B^I}(y^I)$$

3) Get a final RB from the set of linguistic rules candidates. To this end, the linguistic rules are grouped according to their background and in each group selects the rule with the greatest value of casing.

Using this method we obtain a FRBS with 4 variables (3 inputs and 1 output), with 9 linguistic labels for each variable. The MFs are shown in Figure 1 and the RB is show in Table I.

where the linguistic labels are the following ones:

1) ES: Extra small.
2) VS: Very small.
3) S: Small.
4) MS: Medium small.
5) M: Medium.
6) MH: Medium high.
7) H: High.
8) VH: Very high.
9) EH: Extra high.

This labels have been selected following previous research using FRBS. Although they maybe not directly related to harmony principles, we want to simply check the usefulness of the approach.

B. Genetic Tuning of the Proposed Fuzzy Rule-Based System

Even though the approach described in the previous section has provided good results in classification problems, we want to study whether $FRBS_{init}$ could be further refined for the problem at hand by performing a genetic tuning of the MFs; i.e., by means of a GA [14], [15], the MFs of the FRBS can be adjusted. This kind of hybridization between fuzzy logic [16], [17] and GAs is well-known as Genetic Fuzzy Systems (GFSs) [10], [18], [19].

This section briefly introduces the genetic tuning technique and the GA used to optimize the MF parameters of the initial FRBS presented in the previous section.

TABLE I
FUZZY RULES

Rule	X1	X2	X3	Y
1	ES	ES	MS	EH
2	ES	ES	ES	ES
3	VS	VS	VS	EH
4	ES	ES	VS	ES
5	VS	VS	ES	ES
6	VS	ES	ES	EH
7	EH	MH	MS	EH
8	ES	MS	S	EH
9	ES	VS	ES	EH
10	ES	VS	VS	EH
11	S	VS	VS	EH
12	ES	ES	S	EH
13	VH	MH	MS	ES
14	ES	ES	EH	ES
15	MS	S	VS	ES
16	ES	M	MS	ES
17	VS	S	VS	ES
18	ES	MS	VS	ES
19	ES	VH	M	ES
20	ES	EH	MH	ES
21	ES	VS	MS	ES
22	M	MS	S	ES
23	ES	ES	M	ES

1) Genetic Tuning of Membership Functions:

With the aim of making a FRBS performs better classifications, researchers have tried to improve the preliminary Data Base (DB) definition, i.e., the definitions of the MFs, or the inference engine parameters once the Rule Base (RB) has been derived [10], [18], [19]. In order to do so, a tuning process considering the whole knowledge base (KB) obtained (the preliminary DB and the derived RB) is used a posteriori to adjust the MFs or the inference engine parameters. A graphical representation of the tuning process is shown in figure 2.

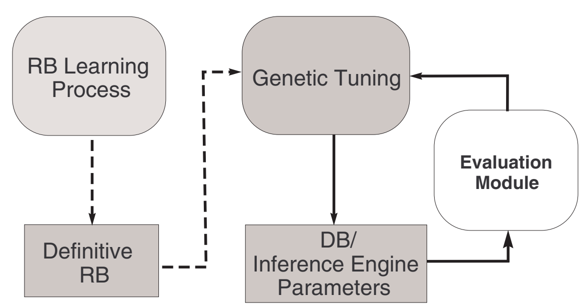

Fig. 2. Genetic tuning process.

Among the different possibilities to perform tuning, one of the most widely-used approaches to enhance the performance of FRBSs is the one focused on the DB definition, usually named *tuning of MFs*, or *DB tuning* [20]–[27]. In [23], we can find a first and classic proposal on the tuning of MFs.

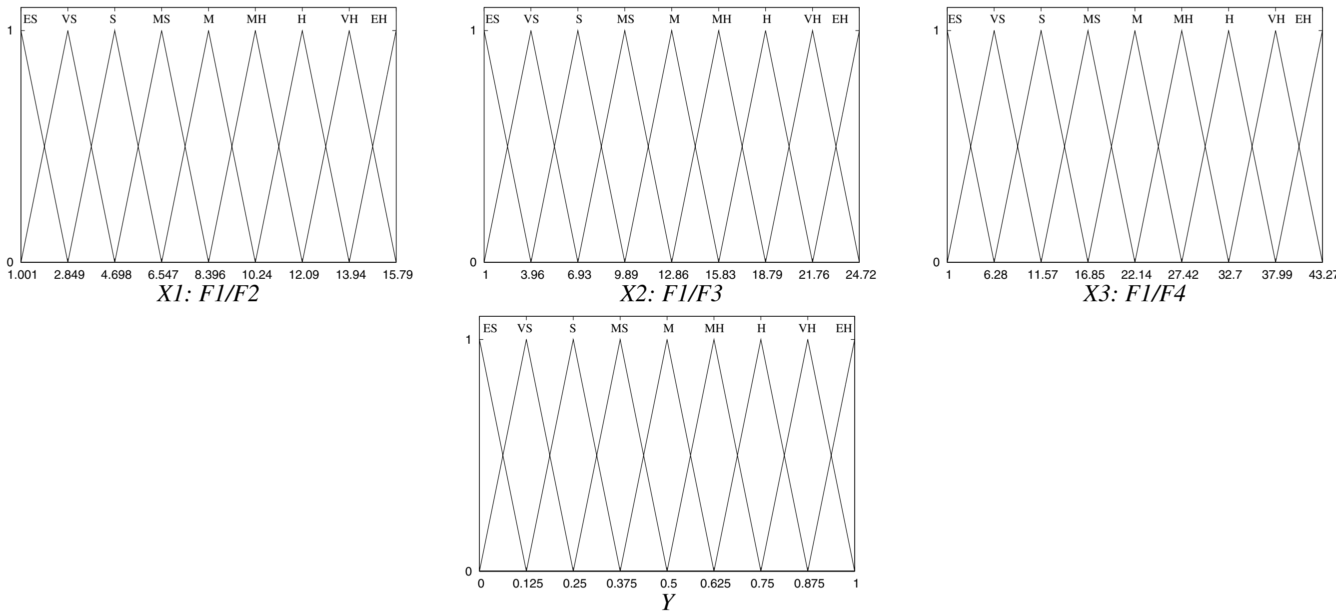

Fig. 1. MFs

In this case, the tuning methods refine the parameters that identify the MFs associated to the labels comprising the DB. Classically, due the wide use of the triangular-shaped MFs, the tuning methods [10], [23]–[25], [27] refine the three definition parameters that identify these kinds of MFs (see Figure 3).

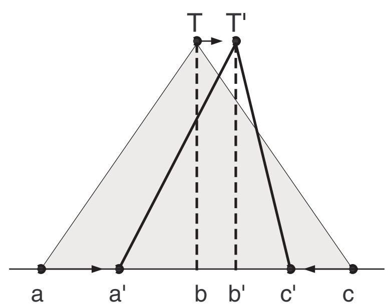

Fig. 3. Tuning by changing the basic MF parameters.

In this paper, we perform a DB tuning to refine the three definition parameters that identify the triangular-shaped MFs in order to improve the $FRBS_{init}$ performance. In the next subsection, the evolutionary algorithm used to perform the genetic tuning and to improve the $FRBS_{init}$, obtaining the FRBS known as $FRBS_{tuned}$, is described.

2) Evolutionary Algorithm: To perform the genetic tuning we consider a GA that presents a real coding scheme and uses the stochastic universal sampling as selection procedure together with an elitist scheme. The operators employed for performing the individual recombination and mutation are uniform mutation and the max-min-arithmetical crossover [24]. The remaining parameters are the following ones:

- Generations = 1200
- Population size = 61
- Crossover probability = 0.6
- Mutation probability = 0.1

In the following, the components needed to design this process are explained.

Chromosome Evaluation: For each input example, the $FRBS_{init}$ generates an output value into interval [0, 1]. If this value is higher than a threshold value (L) the example will be classified as a *classic* music; otherwise, it will be classified as a *jazz* music. Thus, every input example can be considered as:

- Classic Success (CS): If the example is labelled as a classic music and it is a classic music.
- Classic Failure (CF): If the example is labelled as a classic music and it is a jazz music.
- Jazz Success (JS): If the example is labelled as a jazz music and it is a jazz music.
- Jazz Failure (JF): If the example is labelled as a jazz music and it is a classic music.

The objective of this algorithm is to minimize the number of CFs and JFs obtained by the $FRBS_{init}$. To evaluate a determined chromosome C_j we use the following fitness function:

$$Fitness(C_j) = \frac{|CF|}{|D|} + \frac{|JF|}{|D|} \quad (1)$$

where $|CF|$ is the number of CFs obtained, $|JF|$ is the number of JFs obtained and $|D|$ is the dataset size.

The fuzzy inference system uses the center of gravity weighted by the matching strategy as a defuzzification operator and the minimum t-norm as implication and conjunctive operators.

Coding Scheme and Initial Gene Pool: A real coding scheme is considered. Each chromosome is a vector of real numbers with size $3 \cdot F + 1$ (F being the number of MFs in the given DB) in which the three parameters that identify each MFs and the threshold value are coded. Then, a chromosome C_j has the following form, being m^i the number of MFs of each of the n variables in the DB:

$$C_j = C_{j1}\ C_{j2}\ \cdots\ C_{jn}\ L_j\ ,$$
$$C_{ji} = (a^i_{j1}, b^i_{j1}, c^i_{j1}, \ldots, a^i_{jm^i}, b^i_{jm^i}, c^i_{jm^i}),\ i = 1, \cdots, n$$

The initial gene pool is created making use of the initial DB definition of the $FRBS_{init}$. This initial DB with 0.5 as threshold value is encoded directly into a chromosome, denoted as C_1. The remaining individuals are generated at random in the variation intervals associated to each MF and to the threshold value. For each $MF_f = (a_f, b_f, c_f)$ where $f = (1, ..., F)$, the variation intervals are calculated in the following way (See Figure 4):

$$\begin{array}{l} [I^l_{a_f}, I^r_{a_f}] = [a_f - (b_f - a_f)/2, a_f + (b_f - a_f)/2] \\ [I^l_{b_f}, I^r_{b_f}] = [b_f - (b_f - a_f)/2, b_f + (c_f - b_f)/2] \\ [I^l_{c_f}, I^r_{c_f}] = [c_f - (c_f - b_f)/2, c_f + (c_f - b_f)/2] \end{array} \quad (2)$$

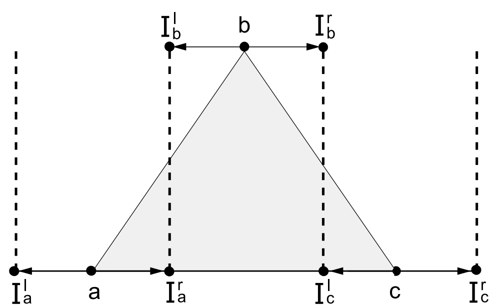

Fig. 4. The variation intervals.

The variation interval for the threshold value L is [0, 1]. Therefore, we create a population of chromosomes containing C_1 as its first individual and the remaining ones initiated randomly, with each gene being in its respective variation interval.

Max-min-arithmetical crossover: If $C_v = (a^1_{v1}, \ldots, e_{vk}, \ldots, L_v)$ and $C_w = (a^1_{w1}, \ldots, e_{wk}, \ldots, L_w)$ are to be crossed, the following four offspring are generated

$$\begin{array}{l} C_1 = dC_w + (1-d)C_v \\ C_2 = dC_v + (1-d)C_w \\ C_3 \text{ with } e_{3k} = \min\{e_{vk}, e_{wk}\} \\ C_4 \text{ with } e_{4k} = \max\{e_{vk}, e_{wk}\} \end{array} \quad (3)$$

This operator can use a parameter d which is either a constant, or a variable whose value depends on the age of the population. The resulting descendants are the two best of the four aforesaid offspring. We have employd a value of 0.35 for the parameter d in our experiments.

Uniform mutation: If $C_j = (a^1_{j1}, \ldots, e_{jk}, \ldots, L_j)$ is a chromosome and the element e_{jk} was selected for this mutation (the domain of e_{jk} is $[e^l_{jk}, e^r_{jk}]$), the result is a vector $C'_j = (a^1_{j1}, \ldots, e'_{jk}, \ldots, L_j)$ and

$$e'_{jk} = e_{jk} + (e^r_{jk} - e_{jk}) \cdot r, \quad (4)$$

where r is a random number into the interval $[-1.0, 1.0]$.

IV. Experiments and Results

The experiments have been conducted using 200 samples -100 jazz and 100 classic- obtained from the personal archive of researchers: music by Charly Parker -the famous saxo player jazz musician- and classic music by Wolfgang Amadeus Mozart.

Once the input variables were generated by means of FFT, the process of defining and tuning the FRBS was performed using a PC, Intel processor -dual core 1.7 GHz- and 2 Gb of RAM. The process took 4 minutes. Once the $FRBS_{inint}$ has been tuned by the genetic algorithm, the new $FRBS_{tuned}$ obtains the MFs tuned shown in Figure 5. The final classification results provided by both system are included in Table II.

TABLE II
Results

	$FRBS_{init}$	$FRBS_{tuned}$
Classic Success	28%	90 %
Classic Failure	72%	10%
Jazz Success	96%	76%
Jazz Failure	4%	24%
General Success	62%	83%
General Failure	38%	17%

Some conclusions can be drawn: Firstly, it seems that FRBS can more easily classify Classic than Jazz Music, at least with the information provided as input (higher energy frequencies relationship) and the samples employed for the testing procedure. Second, as expected, the GA-tunned system significantly improves the quality of results, that reaches 83% general success rate.

The results are impressive when compared with previous research if we take into account the information provided. Nevertheless, the presented results are a preliminary attempt: more samples, music genres and validation techniques will be applied to certify the usefulness of Genetic-Fuzzy Systems for Music Genre Classification.

V. Conclusion

This paper has presented a preliminary approach to Musical Genre Classification by means of Fuzzy Rule-Based Systems adjusted by means of Genetic Algorithms. To the best of our knowledge this is the first attempt to employ Fuzzy Rules for addressing this problem.

Two different musical genres has been considered, Jazz and Classic music, and 200 samples have been successfully classified. The experiments performed has shown very positive

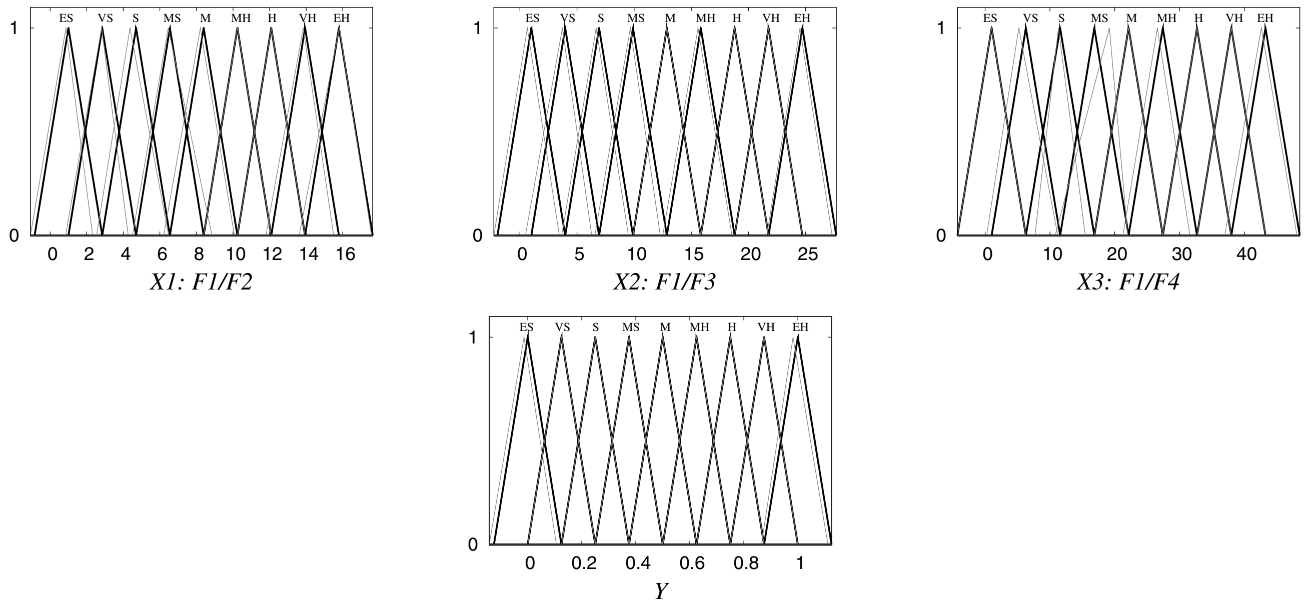

Fig. 5. Initial (grey) and Tuned MFs (black).

results despite the imprecise and very scarce input information: three variables computed as the relationship among the four higher energy frequencies from each of the samples and the corresponding classification value required for the training process.

Although the number of genres and samples have been kept reduced for this first attempt of using FRBSs, the impressive results obtained allow us to be optimistic for the future of the technique. We hope to continue the research including a larger number of genres as well as an increased number of audio files and samples, extracted from available databases. We hope to obtain a general FRBSs based classification system competitive with previously described one, or even better when provided with input information traditionally employed by previous approaches.

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REFERENCES

[1] R. Dannenberg, J. Foote, G. Tzanetakis, and C. Weare, "Panel: new directions in music information retrieval," in *In Proc. Int. Computer Music Conf.*, 2001.

[2] G. Tzanetakis and P. Cook, "Musical genre classification of audio signals," *IEEE Transactions on Speech and Audio Processing*, vol. 10, no. 5, pp. 293–302, 2002.

[3] T. Li and M. Ogihara, "Music Genre Classification with taxonomy," in *Acoustics, Speech, and Signal Processing, 2005. Proceedings. (ICASSP '05). IEEE International Conference on*, 2005, pp. 197–200.

[4] E. Wold, T. Blum, D. Keislar, and J. Wheaten, "Content-based classification, search, and retrieval of audio," *IEEE Multimedia*.

[5] G. Li and A. A. Khokhar, "Content-based indexing and retrieval of audio data using wavelets," in *In IEEE International Conference on Multimedia and Expo (II*, 2000, pp. 885–888.

[6] J. Laroche, "Estimating tempo, swing and beat locations in audio recordings," in *In Applications of Signal Processing to Audio and Acoustics, 2001 IEEE Workshop on the*, 2001, pp. 135–138.

[7] N. Scaringella, G. Zoia, and D. Mlynek, "Automatic genre classification of music content: A survey," *IEEE Signal Processing Magazine*, vol. 23, no. 2, pp. 133–141, 2006.

[8] F. P. Daniel and D. Cazaly, "A taxonomy of musical genres," in *In Proc. Content-Based Multimedia Information Access (RIAO*, 2000.

[9] C. N. S. Jr., A. L. Koerich, and C. A. A. Kaestner, "Feature selection in automatic music genre classification," *Multimedia, International Symposium on*, vol. 0, pp. 39–44, 2008.

[10] O. Cordón, F. Herrera, F. Hoffmann, and L. Magdalena, *GENETIC FUZZY SYSTEMS. Evolutionary Tuning and Learning of Fuzzy Knowledge Bases*. New York, USA: World Scientific, 2001.

[11] R. Alcalá, J. Alcalá-Fdez, M. Gacto, and F. Herrera, "Improving fuzzy logic controllers obtained by experts: A case study in hvac systems," *Applied Intelligence*, vol. 31, no. 1, pp. 15–30, 2009.

[12] R. Alcalá, J. Benítez, J. Casillas, O. Cordón, and R. Pérez, "Fuzzy control of hvac systems optimized by genetic algorithms," *Applied Intelligence*, vol. 18, no. 2, pp. 155–177, 2003.

[13] L. X. Wang and J. M. Mendel, "Generating fuzzy rules by learning from examples," *IEEE Trans. Syst., Man, Cybern.*, vol. 22, no. 6, pp. 1414–1427, 1992.

[14] D. Goldberg, *Genetic algorithms in search, optimization, and machine learning*. Upper Saddle River, NJ, USA: Addison-Wesley Professional, 1989.

[15] J. Holland, *Adaptation in Natural and Artificial Systems*. Ann Arbor, MI, USA: University of Michigan Press, 1975.

[16] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, pp. 338–353, 1965.

[17] ——, "Outline of a new approach to the analysis of complex systems and decision processes," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-3, pp. 28–44, 1973.

[18] F. Herrera, "Genetic fuzzy systems: taxonomy, current research trends and prospects," *Evolutionary Intelligence*, vol. 1, no. 1, pp. 27–46, 2008.

[19] O. Cordón, F. A. C. Gomide, F. Herrera, F. Hoffmann, and L. Magdalena, "Ten years of genetic fuzzy systems: current framework and new trends," *Fuzzy Sets and Systems*, vol. 141, no. 1, pp. 5–31, 2004.

[20] R. Alcalá, J. Alcalá-Fdez, and F. Herrera, "A proposal for the genetic lateral tuning of linguistic fuzzy systems and its interaction with rule

selection," *IEEE Transactions on Fuzzy Systems*, vol. 15, no. 4, pp. 616–635, 2007.
[21] R. Alcalá, J. Alcalá-Fdez, M. J. Gacto, and F. Herrera, "Rule base reduction and genetic tuning of fuzzy systems based on the linguistic 3-tuples representation," *Soft Computing*, vol. 11, no. 5, pp. 401–419, 2007.
[22] J. Espinosa and J. Vandewalle, "Constructing fuzzy models with linguistic integrity from numerical data-afreli algorithm," *IEEE Transactions on Fuzzy Systems*, vol. 8, no. 5, pp. 591–600, 2000.
[23] C. Karr, "Genetic algorithms for fuzzy controllers," *AI Expert*, vol. 6, no. 2, pp. 26–33, 1991.
[24] F. Herrera, M. Lozano, and J. L. Verdegay, "Tuning fuzzy logic controllers by genetic algorithms," *International Journal of Approximate Reasoning*, vol. 12, no. 3-4, pp. 299–315, 1995.
[25] J. Casillas, O. Cordón, M. J. del Jesús, and F. Herrera, "Genetic tuning of fuzzy rule deep structures preserving interpretability and its interaction with fuzzy rule set reduction," *IEEE Transactions on Fuzzy Systems*, vol. 13, no. 1, pp. 13–29, 2005.
[26] H. B. Gürocak, "A genetic-algorithm-based method for tuning fuzzy logic controllers," *Fuzzy Sets and Systems*, vol. 108, no. 1, pp. 39–47, 1999.
[27] O. Cordón, F. Herrera, and M. Lozano, "A three-stage method for designing genetic fuzzy systems by learning from examples," in *Proceedings of the 4th International Conference on Parallel Problem Solving from Nature (PPSN IV)*, ser. Lecture Notes in Computer Science. Springer, 1996, vol. 1141, pp. 720–729.