Towards an Automated Composer of Popular Spanish Songs: Integrating a Music Generator and a Song Lyrics Generator

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***Abstract*—We describe the integration of two creative systems in what can be seen as an automated composer for Spanish popular music. We first present a system that generates melodies with a Markov Model learned from a corpus of Spanish popular music. Then, given the importance of the lyrics in this context, the latter was integrated with an existing lyrics generation system, adapted to suit this purpose. Several experiments were carried out to evaluate the quality of the results. Overall, melodies transmit a feeling of Spanish popular music, while the text of the lyrics is acceptable for a first approach.**

***Index Terms*—Computational Creativity, Music Generation, Lyrics Generation**

I. Introduction

We can say that, today, Computational Creativity [1] is an established subfield of Artificial Intelligence. One that has attracted researchers with multiple origins and motivations, and where a variety of intelligent systems has been developed for the generation of a wide range of artifacts with a creative value, such as music [2], [3] or poetry [4], [5].

However, few creative systems have tackled both the previous at the same time, towards the production of music with lyrics. The main contributions of this work is the development of an automated composer, in this case focused on popular Spanish songs. It is based on the integration of two systems: ETHNO-MUSIC, a new system for generating popular melodies; and Tra-la-Lyrics [6], longer-established, which generates lyrics for a given rhythm. This is in line with recent collaborations between different creative systems (e.g., [7], [8]) and shows that, with the current landscape of creative systems, it is not always necessary to develop new systems from scratch.

On the specifics of the new system, most initiatives on music generation have focused on music with a rather tonal character and, to date, there has been no study addressing the generation of Spanish popular music. This genre differs from classical music in many aspects, including the sonority (meaning the tonality of the music), the sound disposition or the rhythmic formulas used. The automatic generation of this kind of music also depends on multiple factors that are intrinsically connected, such as the representation of the tonality, the melodies and the rhythm. Moreover, unlike classical music, Spanish popular music is always linked to a functionality. In this sense, lyrics are essential for identifying the purpose for which the music was conceived, i.e. if it is a work song or a love song.

Drawing on this phenomenon, new melodies are generated, based on original Spanish popular songs in multiple sources of popular music. Musical excerpts were then analyzed and their relevant features were encoded and stored to be used as the training corpus for music. Among the different learning models that have been applied to generate music from a corpus, Markov Models (MM) were selected due to their successful application in related works [2], [3], [9].

Generation of lyrics starts once the melody is ready. Simple heuristics are applied for splitting the melody into parts, and then lines of text are generated for each part, while trying to maximize two main constraints: (i) one syllable per note; (ii) stressed syllables matching strong beats of the melody. The current version of Tra-la-Lyrics is built on top of PoeTryMe [5], a platform for poetry generation in different languages. In this case, generation is based on the Spanish instantiation, though with an augmented semantic network and new line templates, acquired automatically from songs in Spanish. In order to set the generation domain and establish a connection between lyrics and the subjects typically addressed in Spanish popular songs, seed words were carefully selected.

In the end, the resulting process is analogous to having two different people composing a song: one that composes the melody and another the lyrics. In this case, the melody is composed first, unlike other creative systems, which generate music for given lyrics (e.g. [10], [11]). Given that the composition of a song by humans may follow a different order – starting with the lyrics vs starting with the melody –, we believe that it makes sense to tackle this challenge both ways.

Out of the compositions resulting from our integration, some were selected for human validation. Overall, the most positive aspects were that melodies were pleasant and had a sound and rhythm that gave a feeling of the Spanish popular songs, and that the text of the lyrics was within the target domains. Less positive aspects, but still average, were the rhythm and meaning of the lyrics. In the remainder of this paper, the integration effort is described with more detail and illustrative examples of generated songs are presented and discussed, together with the validation results.

II. Integration

The generation of popular Spanish songs results from the integration of two creative systems: ETHNO-MUSIC, in charge of generating melodies, and Tra-la-Lyrics [6], in charge of lyrics generation. Figure 1 gives an overview of the resulting generation flow.

ETHNO-MUSIC is provided with a memory to store beforehand different melodies. It takes the melodies stored and trains a model for generating a new composition. For the purposes of this paper, Markov Models (MM) were used as the learning algorithm. Once the melody is available, Tra-la-Lyrics is used for generating lyrics that suit the melody.

A. Music Generation

In the current work, music is generated based on the features of Spanish popular music, which include the rhythm or the sonority.

1) Music Retrieval: To generate melodies following the popular song standards, MMs are applied. They need a set of musical sources for the learning process, which should reflect the most common sonorities of the Spanish popular music. Therefore, the melodies are extracted from specialized songbooks, recordings and digital scores.

According to ethnomusicologists [12], three main factors should be considered in Spanish popular music: melodic behavior, rhythm and style. Regarding the melody, the modal music in Spain can follow seven diatonic modes (Jonic, Dorian, Phrigian, Lidian, Mixolidian, Eolian and Locrian). The melodic behavior consists of continuous chromatizations and instabilities. In addition, melodies do not follow any predetermined scheme in terms of tonic and dominant functionalities, as they are based on modal paradigms. Popular music also contains a very uniform beat due to the syllabic text used in these songs, because the prose in this type of repertoire has a regular rhythmic nature, thus totally avoiding a prosodic rhythm. Finally, one of the key aspects of popular music is their style, based on functionality, namely the context in which the music has been conceived. In this sense, we can classify music in different genres, each one representing their own musical features, such as sonority, lyrics and rhythm. Consequently, popular music could be classified accordingly as work songs, love songs, lullabies, wedding songs, sacred songs, dance music, and others.

Despite the general features shared by most popular songs, there was a series of musical parameters (i.e. rhythms or sonorities) spread throughout the Iberian peninsula that, over time, became different in each region or even disappeared in some. According to some authors [13], in Spanish popular music, the work, love songs and lullabies share features related to the key signature, rhythmic patterns and general sonority or tonality, which made them very interesting to use as a corpus in the development of the learning model. Therefore, in order to train the MM, melodies related to these genres that shared some common features were collected.

2) Encoding Melodies: To represent the information needed for the training of the MM, sources were digitalized. To identify popular music, we did not only analyze the particular duration or pitch, but also the duration of the musical phrases, the degrees in which the melody reposes (notes with a long duration), and the particular cadences. Drawing on these properties and also inspired by a concept of viewpoints [14], Table I shows the features encoded for training the MM.

TABLE I
Musical features encoded in the songs and used in the training of the MM.

Feature	Description
Pitch	MIDI number that corresponds to the musical note
Duration	Number that represents the rhythmic formula or one note. Each number can represent a whole, a half, a quarter, etc.
Degree	Number from 1 to 7 that represents the degree of each note according to the scale — 1 means the first degree, 7 means the last note in the scale
First in bar	Boolean number, where 1 represents the first note in a bar, otherwise it is 0
Time Signature	Represented by two numbers, one for the numerator and another for the denominator
Musical phrase	Represents the position of a note in a musical phrase, and can take three possible values: 1 if the note is the first in the phrase, -1 if it is the last one, and 0 otherwise

Currently, many songs are already encoded as MIDI (Musical Instrument Digital Interface) [15]. This is due to the availability of this format throughout the Web, the low difficulty in creating such files based on digital scores, and their structure, which allows a relatively easy access to musical features. Although XML or other encodings like MusicXML or MEI are also available and also encode musical features, we selected MIDI because

Fig. 1. Overview of music generation flow.

it is the format which most appears in the web, and which can be listened in almost every device. MIDI files include instructions that allow the reconstruction of the song by a sequencer and a synthesizer that works with MIDI specifications.

MIDIs provide information on musical events like pitch, duration and time signature, extracted for the purposes of this work. Yet, other, such as phrase construction, main sonority, melodic degree (position that a note takes in the scale) and bars, have to be manually added. This information has been encoded by following the codification proposed by [16], which use numbers to describe some musical parameters. These data are finally stored in a CSV file.

3) Generating the Melody: Once the files are available, the necessary information about the music is extracted. The data previously analyzed and incorporated in the files are used as to train the learning model. First, a model is learned for representing the data, which may be used for generating music. Among the possible approaches, MMs are a widely used tool to model the temporal properties of various phenomena, from the structure of a text to economic fluctuations, as well as content generation applications, such as text or music generation. MMs are a specific case of Bayesaian Networks, in which the probability of an event occurring (in this case, a note or silence with a certain duration) depends only on the N-previous events. In this particular case, *N* has been established empirically to 4.

The music composition system modeled tries to create only one melody with a specific rhythm. Therefore, a MM has been learned to generate the melody and the rhythm at the same time. Once trained, each next transition (i.e, each note) is iteratively calculated by applying the probabilities of the MM according to the previous stages. Finally, each note generated by the learning model is encoded in MIDI, to be used in a standard synthesizer.

B. Lyrics Generation

Tra-la-Lyrics [6] generates text based on rhythm, and is currently built on top of PoeTryMe [5], a versatile poetry generation platform. Tra-la-Lyrics can thus be seen as instantiation of the latter. It that shares most of PoeTryMe constituents, including the line generation module, which produces semantically coherent lines, with the help of a semantic network, and a grammar with line templates. Therefore, Tra-la-Lyricis follows a generate-and-test strategy to generate lyrics with the music already created.

Yet, in addition, Tra-la-Lyrics has a parts analyzer, for splitting the melody in parts; a rhythm analyzer, for extracting the rhythm of the melody; and a generation strategy that considers the position of the stressed syllables. Briefly, lyrics are produced after splitting the melody in smaller parts and getting a representation of the rhythm as a sequence of strong and weak beats. The generation strategy selects the best lines for each part, out of those generated by the line generation module.

1) Parts Analyzer: In PoeTryMe, a generation strategy selects and organizes lines, produced by the line generator, according to a given form. The end of a line is a suitable place for rhymes. For poems, the form is given by the number of stanzas, lines and target lengths. Given a melody, the limits of lines have to be identified automatically. We thus set simple heuristics for splitting melodies into parts, based on the lengths of the longest pause (*LP*) and longest note (*LN*): the melody is split after pauses that are $LP/3$-long or longer and notes that are $LN/2$-long or longer, if resulting parts have at least *minP* notes. Parts with more than *maxP* notes go through the same splitting process until they have less than *maxP* notes. The heuristics are similar to the LBDM algorithm for music segmentation [17], but only applied to rhythm, rather than pitch segmentation.

2) Rhythm Analyzer: The rhythm analyzer is the same as in the original version of Tra-la-Lyrics [18]. It is based on the dot system [19], which sets the metrical accents of each beat inside a bar, and thus the strengths of each note, according to their position. The first beat of each bar is always the strongest. Strengths are then distributed according to the beats (stronger) and downbeats (weaker), depending on the time signature. Tra-la-Lyrics only considers those that are substantially stronger, when compared to the remaining, as actual strong beats. For instance, in a 4/4, those will be the first and the third crotchets, and in a 3/4, only the first crotchet is used as the only strong beat.

3) Generation Strategy: Similarly to other instantiations of PoeTryMe, lines are selected with a generate-and-test approach. Briefly, for each line in the poem structure, textual fragments are retrieved from the line generation module. This strategy is responsible for selecting the fittest fragments for each line, from a maximum of *n* retrieved fragments per line. The fitness function is based on features that are relevant to the rhythm. It has penalties for: the difference between the number of syllables in a textual line and the number of notes in the musical part (α); unstressed syllables in strong beats (β); stressed syllables in weak beats (γ); and words interrupted by a pause (δ). In order to increase the chance of rhymes, there is a bonus for each pair of nearby lines with the same termination (ϵ), unless they end with the same word, which results in another penalty (ζ).

4) Line Generation: PoeTryMe has line generation modules for producing text fragments in Portuguese, English and Spanish, with a semantic network and a grammar with templates, tightly connected with the relation types in the network. Towards generation within a semantic domain, the network is first constrained by a set of seed words. Line generation involves selecting a relation instance (e.g. computer usedFor work; guitar usedFor music; hat usedFor shade), and using its arguments for filling the placeholders of a suitable rule (e.g. usedFor $\rightarrow$ *be my [arg1], i'll be your [arg2]*).

Given the kind of text to generate, it made sense to use the Spanish instantiation, though with some additions that enable the generation of more varied lines. In the Spanish adaptation, semantic relations covered mainly synonyms and hypernyms, while lines of the generation grammar had been extracted from an anthology of about 400 Spanish poems. For this work, the semantic network was enriched with relations between two Spanish words in the most recent version of ConceptNet [20]. Moreover, for the creation of the grammar, a set of about 9,000 Spanish song lyrics, retrieved from the MusixMatch database[1] was also exploited. To complete the adaptation, lyrics had to be generated with seed words related to concepts typically invoked in Spanish popular lyrics.

III. Results

The integration of ETHNO-MUSIC and Tra-la-lyrics results in a new system for the generation of songs, covering melody and lyrics. Here, we describe the settings used towards the generation of several Spanish popular songs and discusses some generated examples.

A. Music Generation Settings

For the generation of the music, 102 popular songs were selected, namely 68 work songs and 34 love songs, all using similar rhythm patterns, with a time signature of 3/4. Each song consisted of 3 or 4 musical phrases with similar length, with the same sonority, the Phrigian mode with possible modifications in its evolution to E minor.

Melodies were encoded as described earlier and saved in a CSV file. Their features were the corpus for training the MM. The number of states that it can remember for the future generation of the melody was empirically set to 4. During the generation process, each iteration of the MM consists of adding a new note to the melody. The MM is iterated until four musical phrases have been created.

For the experiments, a total of 40 melodies were generated with ETHNO-MUSIC, out of which five we were happy with were selected for lyrics generation by Tra-la-lyrics.

[1] https://www.musixmatch.com

B. Lyrics Generation Settings

In order to split the melody in parts, we empirically set *minP* = 4 and *maxP* = 18. For each of the five melodies, lyrics were generated with groups of seed words that set two generation domains, common in Spanish popular songs:

- Work in the fields: *trabajo, siega, tierra, sembrar, semillas, trigo, cereales, campo, sol, paja, cosecha, cosechar* (in English, work, harvest, land, sow, seeds, wheat, cereals, field, sun, straw, harvest, harvest)
- Love: *amor, novia, moza, mozo, bella, belleza, feliz, alcoba, morena, guapa, sonrisa, ojos, bonito, bonita* (in English, love, girlfriend, girl, lad, beautiful, beauty, happy, bedroom, brunette, pretty, smile, eyes, pretty)

For each melody-domain pair, 10 lyrics were generated. Though, out of each 10, only the one with the best rhythm-based score, computed automatically, was selected for human validation, which makes a total of 10 songs.

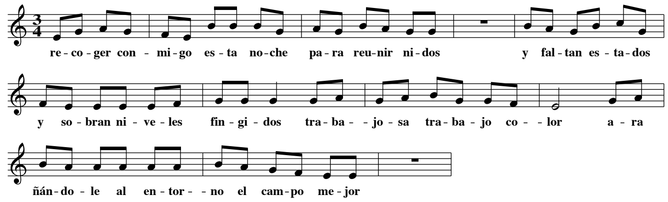
For each line, we empirically set the number of generations $n = 1,750$. In order to match the target rhythm, the parameters of the fitness function were: $\alpha = 1$, $\beta = 0.5$, $\gamma = 0.1$, $\delta = 0.3$, $\epsilon = 2$, $\zeta = 1$.

C. Examples

Figures 2 and 3 show examples of two generated songs, selected from the validation sample. For each example, we present the score, the Spanish lyrics assigned to the corresponding notes, and a rough English translation of their text. All the melodies generated share representative features of popular music, such as the constant repetition of pitches and the limited tessitura. Additionally, to some extent, lyrics match the rhythm and use a varied range of words related to the selected topics.

In the melody of figure 2, the limited tessitura is clear as the notes go from E to B. The rhythmic formulas are very repetitive and centered on the syllabic text that accompanies the melody, instead of showing complex rhythm figures. The melody rests on the E note and the third degree, which is typical of modal music, unlike tonal, where rests are preferred in the fifth or tonic degrees. Lyrics for this song were generated with the work-related seeds, which is clear by the presence of words like *trabajo* (work) or *campo* (field), from the seed set, and also other related words, such as *recoger* (to collect, related to harvest). On the rhythm, a minority of unstressed syllables is on strong beats, namely the first syllable of *fin-gi-dos* and the last of *en-tor-no*, but this is somehow compensated by the presence of two rhymes, *nidos/fingidos* and *color/mejor*.

In the melody of figure 3, besides the repetitive rhythm, there are musical rests, another desired feature. The use of short musical phrases is very typical in Spanish popular songs because they are thought for short lyrical phrases that people can remember. Lyrics for this song were generated with the love-related seeds, which results in the presence of words like *amor* and *mozo*, both



Take with me this night to join nests
We run out of terraces and exceed pretended levels
Hard color working scratching the better field

Fig. 2. Song in Phrigian mode, with Spanish lyrics on the domain 'trabajo' (work), including rough English translation.

in the seed set, and indirectly related words such as *maravillosa* (wonderful, related to pretty) or *barbilla* (chin, a part of the face, as the eyes). On the rhythm, we identify two unstressed syllables in strong beats, namely the first syllable of *bar-bi-lla* and the first of *al-guien*. This is again compensated by the presence of two rhymes, *vulgaridad/enfermedad*, *amor/interior*.

You look your appearance in the shape of vulgarity
because of a wonderful and irresistible disease
Your chin and face, my sweet love
somebody stole the key of my heart

Fig. 3. Song in Phrigian mode, with Spanish lyrics on the domain 'amor' (love), including rough English translation.

IV. Validation

Once designed and implemented, we got insights on the validity of the new automated composer. Due to the inherent subjectivity of human listeners, this kind of evaluation remains a challenge for music composed automatically [21]. The same happens for creative text. Following other examples of subjective evaluation by a group of human listeners (e.g. [22]–[24]), who perform listening tests , we follow a similar approach for evaluating the musical results and the lyrics of the system.

More precisely, ten generated songs (five melodies with two lyrics for each) played with a MIDI synthesizer and shown in a score with the notes and the lyrics, were presented to 7 users, experts in popular music. For each song, we asked their opinion on the musical aspects, the text of the lyrics and on their connection, with the following questions, to be rated with a 5-point Likert-scale, between 1 (poorly) and 5 (perfectly well):

1) Melody: How pleasant is the melody?
2) Sound: How well does the melody, in some way, give a feeling of the popular style of the songs?
3) Rhythm of the Melody: How well does the rhythm suit the popular music style?
4) Rhythm of the Lyrics: How well does the text suit the rhythm of the original melody?
5) Subject: How is the text related to any of the following topics: work, love?
6) Meaning: How much sense does the text of the lyrics make? Is it possible to, somehow, interpret it?
7) Overall quality: In general, what is the quality of the melody plus lyrics?

Some of the questions involve an appreciation of music and text as a whole (Rhythm of the lyrics, Overall) and others are more focused on only one of the previous. Yet, although each of the systems had been somehow validated on their own, having both music and lyrics may influence the way that the results are perceived by humans. Plus, this instantiation of PoeTryMe/Tra-la-Lyrics has significant differences from previous (e.g., music is automatically split in parts, lyrics are generated in Spanish, text of Spanish lyrics was exploited, as well as ConceptNet for additional knowledge).

We expect the system to reflect the perceptual quality of the melodies according to the popular songs style. Likewise, we wanted to verify the quality of the lyrics according to the positive ratings given by the listeners. Table II presents the mode (M_o) and median (M_d) ratings for each assessed item.

TABLE II
Overall validation results for the 10 assessed songs.

Item	Rating 1	2	3	4	5	M_o	M_d
Melody	0	3	21	36	10	4	4
Sound	1	4	22	39	4	4	4
Rhythm (Melody)	2	9	23	34	2	4	4
Rhythm (Lyrics)	3	13	27	25	1	3	3
Subject	2	12	23	25	8	4	3
Text Meaning	7	17	28	15	3	3	3
Overall Quality	3	5	36	24	2	3	3

For every assessed item, the majority of the ratings falls in 3 or 4. Yet, the proportion of 4s is higher for the melody-related aspects than for the text-related, where the proportion of 3s is higher. This suggests that the melody is pleasant, and the sound follows quite well the standards of Spanish popular music, as does the rhythm. The worst scoring item is text meaning, which shows that generating text on a topic is only halfway for generating a meaningful test. On the other hand, the quality of the lyrics is lower, but still average. The overall quality of music and lyrics is also average.

V. Conclusion

We described the effort and results of integrating a music and a lyrics generator towards the development of an intelligent system that creates popular Spanish songs with lyrics, automatically. The music generator is based on a MM, trained on features extracted from a corpus of Spanish popular music. The lyrics generator produces textual fragments that match a given rhythm, with syntactic coherence handled by a grammar and semantics controlled by the combination of the previous grammar with a semantic network.

We see this as a successful effort, because the resulting system generates melodies that follow the Spanish songs standards, with Spanish lyrics on topics typically covered by the popular songs. This is confirmed by a human evaluation which also revealed that the less positive aspects, though still average, are the rhythm of the lyrics and, especially, their meaning.

Besides the success of integrating two different systems developed independently, given that this was our first approach to our goal, we can say that we are happy with our results. Yet, during this work, we identified limitations, some with the help of the human validation, to be addressed in the future, for a new version of the composer.

Regarding the lyrics, despite the utilization of a mature system for generation, alternative strategies could be tested for matching the rhythm. Although the instantiations of PoeTryMe often use a generate-and-test approach, an evolutionary strategy, available in the same platform, could make more sense for lyrics, where the fitness function has more parameters. Generating meaningful lyrics is always a challenging task and we are aware of the limitations of PoeTryMe on this topic. We will investigate this issue further. Yet, natural improvements would be using a larger corpus for extracting the grammars or, for the specific case of this work, use a corpus of lyrics of Spanish popular songs, which we still could not find. Given the importance of lyrics in popular music for ethnomusicologist studies, a deeper analysis of popular songs and their lyrics should be addressed towards the generation of better lyrics of this kind.

An improvement on the integration process would be to have the music generation system providing the division of musical parts directly to the lyrics generation system, together with the melody. This would possibly avoid the heuristics currently applied for this purpose. In order to improve the automatic generation of music, more features of melodies could be used, including a more general view of the composition. It would also be interesting to test singing voice synthesis software for singing the generated songs, which could possibly make the validation clearer.

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