Life Soundtrack Recovery
for Alzheimer's disease patients

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Abstract

Music conveys emotion and is connected to personal memories. Personal memories are linked to social and emotional relations with peers, family and friends. Music memory has been shown in several studies as a spared condition by the neurodegenerative effects of Alzheimer's disease (AD). Other studies have suggested the enhancing effect of music in autobiographical memory recall in AD. Moreover, music listening is currently a widespread practice in therapeutic sessions for dementia treatment. However, the selection of music is generally manual and lacks of user-oriented approach, being difficult to match patient's musical taste as a result.

In this work, biographical data from the subjects is combined with musical preferences data in order to generate music playlists made of songs that can be considered part of their life soundtrack. For this purpose, we have built a music database of songs from a specific range of years, based on the age of our target group. The algorithm developed uses metadata generated through questionnaires and searches in last.fm for music that is similar to the preferred songs and artists of the subject. The goal is to generate a final playlist that is close to be the life soundtrack of the subject. This is evaluated by the subjects and its performance is discussed identifying the main challenges for future improvements.

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"The illness suffered by one's spouse or parent is also one's own tragedy,
and the possibility of still enjoying music together may matter greatly".
(Vernon Pickles & Raya A. Jones, 2006)

Chapter 1

Introduction

1.1 Motivation

Most of people would have experienced in life that music conveys emotion and is connected to personal memories. Moreover, personal memories are linked to social and emotional relations with peers, family or friends. These are part of the person's sense of belonging to a social group, contributing the identity formation or sense of self through the so-called autobiographical memories. In recent years several studies on the interrelation between music, emotion and memory have been conducted in different fields such as psychology or neuroscience. Among these, some have shown that music has a positive effect for Alzheimer's disease patients. Some studies suggest that music might be a spared condition by the neurodegenerative effects of Alzheimer disease. Some others have explored music as an autobiographical memories recall enhancer or even as an aid to learn new verbal information.

The use of music listening in therapeutic sessions for dementia treatment has been explored deeply and it is currently widespread. However, the selection of music is generally manual and lacks of user-oriented approach, being difficult to match patient's musical taste as a result. On the other hand, current music recommendation systems rely on different Music Information Retrieval techniques and approaches (e.g. audio context-based, audio content-based) and these can be adapted to users with special needs. Previous work has been carried out in this sense showing that Music Information Retrieval tools are useful in a music therapy framework in order to match patient's musical taste. In addition, it enhances the patient's motivation and engagement during the treatment, improving their daily life. In that sense, I think technology can provide unique means for patients, family and caregivers that may help to open new doors and interesting possibilities within the context of the disease.

1.2 Goals

The first of the general goals of this thesis is research and understand the concept of a life soundtrack. Our life soundtrack can be seen as a collection of songs and sounds that we like, are important for us, or those that are capable of bringing memories and moments of life back. Second, develop a supervised algorithm able to make musical inferences and give personalized musical suggestions for Alzheimer disease patients based on their biographic information and musical preferences. Third, study the adaptability of current MIR technologies such as recommendation systems based on metadata to the needs of Alzheimer disease patients.

Chapter 2

State of the Art

This chapter presents a review on the state of the art that is relevant for this thesis. The first section is devoted to explain what a dementia is and what are the characteristics and symptoms of Alzheimer's disease. Second section is dedicated to the important aspects underlying the relation of music, emotion and memory. Special focus is given on autobiographical memory, the implications of it to Alzheimer's disease patients and the use of music for therapy. In the third section, music information retrieval technologies relevant for this work are presented. Finally, fourth section is devoted to the work done on merging technologies with therapy.

2.1 Dementia and Alzheimer's Disease

Dementia is defined as the progressive loss of cognitive functions in a previously unimpaired person. It consists of a variety of symptoms suggesting chronic and widespread dysfunction, such as global impairment of intellect, difficulties with memory, comprehension, attention or thinking. Moreover, mental functions such as mood, personality, judgment and social behavior may also be affected. There are common elements shared by all dementias that cause significant impairment for social or occupational functioning resulting in a significant deterioration in these activities. With the aging of population, the number of people affected by dementia rises. The most common type of dementia, affecting from 50 to 60 percent of all patients with dementia, is Alzheimer's disease (Sadock & Sadock, 2008).

Alzheimer's disease in its early stages affects people causing memory lapses and problems finding the right words. With the progression of the disease the patients may confuse or forget names of people, places and recent events very frequently. Moreover, they experience changes of mood, feeling scared or frustrated by their increasing memory loss. This results in having difficulties with carrying out everyday activities. Despite there are common symptoms, the disease manifests itself and develops in a different way for each patient. There is currently no cure for Alzheimer's disease and the cause remains unknown, although it is likely that a combination of factors such as age, lifestyle, health, genetic inheritance and environmental factors are responsible (Jalbert, Daiello & Lapane, 2008).

2.2 Music, Emotion and Memory

Music conveys emotions which are connected with autobiographical memories which help people to retrieve and understand better their life story. On the other hand, it contributes to the person's sense of belonging to a social group and to the formation of identity. In this section the interrelation between music, emotion and autobiographical memory is presented from an evolutionary point of view. Then, these ideas lead to the concept of the musical self and its implications within Alzheimer disease. Afterwards, the consequences of Alzheimer disease and the impairments derived are explained. In the end, several studies using music for therapy in terms of cognitive stimulation are shown.

2.2.1 Music, Emotion and Autobiographical Memory: The Musical Self

From an evolutionary point of view, there are different theories on why music it has been present in human culture since ancient times. One approach is that music is an evolutionary adaptation for life developed in our hunter-gatherer past and which promoted social cohesion (Dunbar, 2003). Others say that is a product derived from cognitive skills such as language, enjoyable but biologically superficial and unnecessary for survival (Pinker, 1997). A different approach is considering music as "a transformative technology that builds on existing brain systems, but transforms our experience of the world" being able to connect us "through space and time to minds far distant from our own" (Patel, 2008). In this sense, learning to play a musical instrument, having an emotional response when listening to music, feeling connectedness to others or even shifting consciousness into a state of trance through music are some examples where this transformation takes place. In addition, listening to music can play an important role in identity formation and consequently in the sense of self, based on the thoughts and feelings expressed by music (Patel, 2008).

The concept of self is closely related with the person's sense of belonging to a social group. That is to say, the social and emotional relations with peers, family and friends are linked to personal memories which help us to reconstruct the story of ourselves. Consequently, autobiographical memory plays a central role in constructing or constituting the self or identity (Pickles & Jones, 2006).

Melodies, lyrics and memories associated with music are stored in long-term memory (Pickles & Jones, 2006). In particular, El Haj et al. (2012) have shown that music-evoked memories are retrieved faster, are more specific and accompanied by more emotional content and impact on mood than silent-evoked memories. To state this in a different manner, music triggers emotional responses that enhance the codification of long-term related memories in the brain.

In the literature an interesting phenomenon called "reminiscence bump" can be found. The concept was introduced by Rubin, Wetzler & Nebes (1986) and consists of a peak in personal memories that consistently come in late adolescence and early adulthood. In a further study focused on the reminiscence bump in music (Krumhansl & Zumpnick, 2012) it was shown that in addition to the typical increasing function in those years, the same peak appeared for music of the generation of the subjects' parents. For music-evoked autobiographical memories of their late adolescence and early adulthood, subjects considered those memories as developed in contexts in which they were listening the music alone and with others. On the other hand, for music popular when their parents were young, the intergenerational influence played a crucial role. These songs were associated with personal memories from when they were growing up, listening with parents, alone or with others. So that, there is an intergenerational continuity of musical preferences as well as an important period of time to consider for the associations between memories and music.

Music has the ability to transmit a sense of continuity of time that might have a presumably reassuring effect for people with dementia. In this sense, continuity of music, memory and autobiographical associations can be related with a "musical self" (Pickles & Jones, 2006) that describes people's story of themselves and of what music means to them. In other words, a continuing musical self in dementia is "a fragment of the disintegrating personality which maintains cognitive and emotional contact with music". This becomes extremely important in the case of Alzheimer disease, where the capacity for language and autobiographical memory are acutely impaired.

2.2.2 Alzheimer's Disease and Memory

Alzheimer's disease (AD) is the most common form of dementia and is characterized by a progressive decline in cognitive function and conduct disorder (Simmons-Stern, Budson & Ally, 2010). The capacity for language and autobiographical memory are functions which become severely impaired in AD. The deterioration of the autobiographical memory in AD implies changes in the strength, quality and direction of the identity (El Haj, Fasotti & Allain, 2012). In cases of advanced dementia, amnesia is presented without the possibility of recovery of recent semantic or episodic memories, not being aware of such losses (Pickles & Jones, 2006). Other declines are observed in emotional controls, motivation and social conduct.

Several studies have suggested that music might be a spared condition by the neurodegenerative effects of Alzheimer disease. In this direction, Cuddy & Duffin (2005) discuss that "music sparing may be the most available and accessible form of the sparing of a complex skill in dementia". Furthermore, music might linger as a significant or almost the only communication aid in advanced dementia.

2.2.3 Uses of Music for Therapy: Cognitive Stimulation

As several studies have suggested, music has a positive effect for Alzheimer's disease patients (Irish, Cunningham, Walsh, Coakley, Lawlor, Robertson & Coen, 2006; Simmons-Stern, Budson & Ally, 2010; Moussard, Bigand, Belleville & Peretz, 2012; El Haj, Fasotti & Allain, 2012). Irish et al. (2006) tested autobiographical memory in mild AD individuals, showing a considerable improvement when using Vivaldi's 'Spring' movement as background music for recall. Moreover, significant reduction on their anxiety state was found in music condition. Further examination on this phenomenon was conducted by El Haj et al. (2012), studying music-evoked autobiographical memories in AD. In their first condition they studied the response after being exposed to their own chosen music; the second condition was after being exposed to silence. Compared to silent-evoked memories, the ones recalled with music were more specific and they had higher emotional content.

Regarding music as a memory enhancer, Simmons-Stern et al. (2010) investigated the effect of music for encoding associated verbal information. As a result, patients with AD demonstrated better recognition accuracy for the sung lyrics than the spoken lyrics. Two conclusions were extracted from this study. The first is that the brain areas related with music processing may be preferentially spared in AD, permitting a more robust encoding that eases recognition. The second is that music raises arousal in AD patients, allowing better attention and improved memory.

On the other hand, music can be used as an aid to learn new verbal information in AD (Moussard, Bigand, Belleville & Peretz, 2012). This case study shown that individuals with mild dementia could still learn new verbal information associated to music. The progression of the performance shown that sung material may lead to better retention than a spoken one in the case of a long-term care. Moreover, the authors remarked the importance of the "recreational" characteristic of the musical stimulation which makes the experience more engaging.

Although the use of music for dementia therapy is widespread, the choice of music is usually discussed in rather general terms. So that, it is important to take into account musical preference differences, the degree of appreciation of music, and the possible hearing impairments among the AD patients (Pickles & Jones, 2006).

2.3 Music Information Retrieval Technologies

Music consumption has changed drastically in recent years, the web has become a relevant source for music discovery reaching the importance of radio, television, magazines or friends. Music recommender systems have arisen as a response to this problem. Many of them use different tools and techniques from the field of Music Information Retrieval (MIR) in order to match user's preferences and tastes. Different information-filtering strategies are used based on demographic data, collaborative filtering, audio content-based or context-based information, and hybrid approaches. This section contains an overview on different filtering strategies and several academic examples of proposals for music recommendation systems.

2.3.1 Filtering Strategies

Several filtering strategies within the context of MIR can be considered when recommending music automatically. The following are the most common used strategies:

a) Demographic data filtering

This strategy uses demographic data of the users such as gender, age or birthplace to estimate their tastes and preferences. It is the simplest strategy but severe limitations have been observed when implementing it (Celma, 2010).

b) Collaborative filtering

Usage and rating data are taken into account in this approach. The system give recommendations depending on the user's preferences and habits, considering many data from other users. It has been proven as extremely effective, but only when usage data are available (Domingues, Gouyon, Jorge, Leal, Vinagre, Lemos & Sordo, 2012). A problem associated with this type of filtering is that less-popular items from the long tail are rarely recommended. Another issue is popularity bias. That is to say, highly rated items are similar to many other items which are very often recommended.

c) Audio content-based filtering

The audio content-based approaches are focused on the very content of the audio signal. They are based on collecting and analyzing information about music audio content measuring similarity distances between timbral, temporal or tonal features (Bogdanov, Haro, Fuhrmann, Xambó, Gómez & Herrera, 2013). This approach is supposed to solve the "early-rater" and popularity bias problems. However, the automatic music content description algorithms are still relatively limited (Domingues, Gouyon, Jorge, Leal, Vinagre, Lemos & Sordo, 2012). Moreover, similarity does not account for any user data so it lacks recommendation personalization and user modeling.

d) Audio context-based filtering

The audio context-based approaches are based on collecting information from metadata, experts' annotations, social tagging or contextual data of the items by means of web mining. Information about artist names, albums, track titles, lyrics, genres, blog posts, reviews or artist biographies can be used as a method to retrieve related music (Celma, 2010).

In recent years, several combinations of these approaches have been studied and reported as hybrid methods. Further analysis on music recommendation examples are reviewed in the next section.

2.3.2 Music Recommendation

A music recommender is an "information-filtering technology which can be used to output an ordered list of music tracks that are likely to be of interest to the user" (Domingues, Gouyon, Jorge, Leal, Vinagre, Lemos & Sordo, 2012). This seeks to predict the rating or preference that a user would give to a music item (Bogdanov, Haro, Fuhrmann, Xambó, Gómez & Herrera, 2013). This type of systems have arisen from consuming music from web sites, online music collection services which can contain millions of music tracks, complicating music search, retrieval and discovery. Relevant and novel music is recommended to a user based on personal musical tastes.

Regarding filtering strategies previously explained, a first example combining demographic data and collaborative filtering can be found in Yapriady & Uitdenbogerd (2005). In that paper, gender, socio-economic background and age are taken into account as factors that can affect one's musical tastes. These are combined with collaborative filtering techniques in order to improve recommendation precision.

In relation to audio content-based information, Bogdanov et al. (2013) proposed a music recommendation and visualization system based on user preference musical examples. The data for similarity measures were taken directly from audio features using semantic music similarity measure, a semantic probabilistic model and the visualization of the user's musical preferences.

A hybrid method combining collaborative filtering and audio content-based information is used in Domingues et al. (2012) for an online recommendation system for music in the long tail. The system was evaluated online through an experiment performed in real-time on a commercial website specialized in music from the long tail. Comparing it against two recommender systems based on usage and content data, a higher user absolute acceptance rate, activity rate and user loyalty was achieved.

As it can be observed in the literature, many different approaches can be combined obtaining efficient results. However, when music recommendation is needed in a new scenario such as the case of this thesis, adaptation of the current systems is essential for accomplish the goals successfully. Given the applied scenario envisioned in this thesis, the focus switches in the next section to technologies and therapy, introducing and reviewing manual and domain specific music recommendation systems.

2.4 Technologies and Therapy

In recent years technology has been applied to dementia therapy through music and other media means. In this section, a review is given on an existing commercial software as an example of a manual media-aided memory retrieval system. Then, some further academic studies on the use of Music Information Retrieval techniques and tools oriented to music therapy are reviewed.

2.4.1 Manual Systems

An example of a manual system for music therapy is the Interactive Reminiscence Aid by MyLife Software (2012). It was “designed to support conversations, interaction and engagement between people with dementia and caregivers, friends and family”. The system has a database with photographs, videoclips, music and lyrics back to 1930s which are offered to patients for them to choose what they would like to look at or listen to. Temporal and regional classification of items is provided so that it can target the biographic data of the user. Further personalization of the system can be done by uploading items such as familiar photographies, music and videos, or through rating the database items by relevance.

The software is conceived in a way that patients, friends, family and caregivers can select and add the relevant content in order to start discussions, debates, anecdotes or personal memories from the past. For the caregivers and therapists, it can provide valuable information about the individual interests and taste of the patient. Another implication of this type of system is the possibility of reducing the intake of sedative-type drugs. Being a form of cognitive stimulation therapy, it can help to calm, stimulate and decrease agitation, helping to reduce the characteristic cognitive decline of the disease.

By means of a manual system, precise characterization of personal interest can be obtained when having a complete database that can match the patient. The constraints of this type of system are the given database limitations, which could be eventually completed by adding personal information or media. However, a complementary automatization of the retrieval process may add a value in this direction using MIR technologies.

2.4.2 Uses of MIR for Music Therapy

The use of MIR techniques and tools for music therapy brings a new paradigm: domain specific and user-tailored music recommendation systems. A first example of an attempt in this direction is given in Zhao et al. (2010) where a study on sleep quality measurement using EEG signal is presented. The work is intended to be completed by a content-based music recommendation system based on similarity measures. The authors proposed this system to improve the adaptability of music therapy which is often constrained by the time consuming task of selecting suitable music for each user.

Ye Wang et al. (2010) proposed a system that searches suitable music for therapeutic gait training for Parkinson’s patients. Tempo, cultural, and beat strength features are incorporated in order to help music therapists provide appropriate music. In this work, a database of music found on YouTube is utilized, evaluating the efficacy of the features considered. Although YouTube is an excellent potential resource for music therapists to find suitable music for patients, the search is difficult due to the lack of information retrieval organization in it. Finally a collection of 787 full songs obtained from YouTube was considered, reflecting a variety of music with which Parkinson’s disease patients, most of them elderly, are likely to be familiar. The results of the evaluation of the system showed a general satisfaction in both patients and therapists, especially in terms of the cultural and tempi features. Beat strength was seen as too subjective to be considered as a feature. In the end, the specific search criteria and estimated results given by the system are seen as a potential tool as well as a time-saver compared to the traditional music search approaches for therapy.

Chapter 3

Methodology

Given the framework described in the state of the art, the methodology followed in this thesis is explained in this chapter. One of the main goals of this work is to design and test an algorithm able to use current MIR technologies with the purpose of generating music playlists that represent the *life soundtrack* of an AD patient. A *life soundtrack* is considered in this work to be a collection of songs and sounds that we like, are important for us, or those that are capable of bringing memories and moments of life back. For this objective, a music database has been built based on the needs of our target users, taking into consideration their age and making it flexible and eclectic in terms of genres and music styles. The focus, in the case of popular music, has been set for local and international music listened to in Spain between 1940s and 1990s.

A survey and questionnaire have been designed in order to gather more information and build a base for our work. The *Life Soundtrack Survey* took place during one of the talks included in the event *Neuroconcerts*[1] organized by the Universitat de Barcelona. The survey was used in this study to support the hypothesis that most of the representative music within a life soundtrack of an individual is discovered or heard the first time in their youth. The second questionnaire was called *Music Preference Online Questionnaire* and was filled by the subjects that participated in our experiment. In that questionnaire the subjects provided information related to their age, place of birth, occupation and information about their musical

[1] http://www.ub.edu/neuroub/neuroconcerts.html

preferences. This was the main source of information from which the musical inferences were drawn in this work. A second use of both the survey and the questionnaire was to refine the music database with songs or musical pieces that were missing originally and were relevant for our target population.

The information given by the subjects who participated in the *Music Preference Online Questionnaire* was filtered and analyzed in order to understand the relevant parts that could be used later on. One of the main functions the algorithm was designed for was to make inferences about musical information that users did not provide originally. In other words, taking into account the basic biographical information and musical preferences of the different subjects, the algorithm aims to generate a playlist of relevant music for them. Further details about the algorithm are explained in the algorithm section (Section 3.3).

This chapter is organized in the following manner. The first section is an introduction on what it has been considered as a life soundtrack in this work, based on the reviewed literature material. The second section is devoted to the materials that have been used in the work. The third section is dedicated to explain the characteristics of the subjects involved in the experiments. In the fourth and fifth sections it is described in detail how the algorithm is designed and implemented, as well as the approach taken for the evaluation.

3.1 A *Life Soundtrack*

An important aspect within the framework of this study is the concept of a life soundtrack. Considering the literature reviewed in the previous chapter regarding the relationship between music and identity, we define a life soundtrack as a collection of songs and sounds that we like, are important for us, or those that are capable of bringing memories and moments of life back. In this sense, it is important to understand the relationships between the user's biographic data, musical abilities, musical preferences, memories and their collection of their lifetime songs. As a desirable result of the previous step, inferences will be made based on those relationships. For instance, knowing user's preferred songs, artists and genres, retrieving more music that is likely to be in their soundtrack will be our topmost goal.

3.2 Materials

This section explores the different materials used for the development of the methodology of this work. Different subsections are dedicated to explain in depth the content of the database, the *Life Soundtrack Survey* and its analysis and the building and data processing for the *Musical Preferences Online Questionnaire*.

3.2.1 Database

Alzheimer's disease is mainly affecting late adulthood and elderly population, considering this, the target age of interest for this work has been set in 50 years old and older. This has implications in the type of musical material we will work with. Excluding classical or folk music, which can be considered more as a 'timeless' type of music, the focus on popular music is from years 1940s to 1970s for music released and played in Spain, although the database includes songs from 1980s and 1990s as well.

A database of 1790 songs has been collected and used in this thesis. The database contains music released from the 1940s to the 1990s, including popular songs in Spain in these decades, folk and traditional regional music and music of different genres (e.g. copla, flamenco, pop, rock, jazz, classical music...). The different songs were taken from hit charts, international and spanish oldies compilations, and long tail specialized websites. When further information was needed, e.g. the year of release of a single, we used services such as Discogs[2] for international music, Lafonoteca[3] for spanish music and Viasona[4] for catalan releases.

One of the main challenges at the time of building the database was to gather the information and songs to construct a solid database. Most of the old spanish music compilations, especially the ones that were more useful or helpful for our purpose, were not usual or commercial compilations. They were compiled by internet users and music fans who decided to collect the songs and share them through their blogs or P2P accounts. So that, many of these compilations that were later on

[2] http://www.discogs.com/

[3] http://lafonoteca.net/

[4] http://www.viasona.cat/

incorporated into our database have been discovered through blogs or P2P services such as Soulseek[5]. Many other individual songs have been included during the process according to the answers collected in both the survey and questionnaire. The database is managed and accessed in iTunes as an independent music library. It is important to remark that it is a dynamic database that has been adapted to the needs and preferences of the users during the development of the work.

3.2.2 Life Soundtrack Survey

The *Life Soundtrack Survey* was taken on April 4, 2013 in the talk "Música, emoció i memòria" within the *Neuroconcerts* events organized by the Universitat de Barcelona. The survey (provided in the Annex A) was printed and given to the audience who assisted to the talk. During the talk they were invited to write in the survey personal data about their place and year of birth, whether they remembered the first music album that they bought and a list of 5 songs that they considered representative in their personal life soundtrack.

A total of 126 surveys were filled with this information. From this 126 subjects, 105 were born in different parts of Spain and 21 in other countries. In Table 3.1, the amount of subjects born in each decade is presented. The survey was completed with the years of release of the songs and albums indicated by the participants. The retrieval of this information was done through services such as MusicBrainz[6], Discogs, La Fonoteca and Viasona. Having this information we could test the hypothesis reviewed in the state of the art regarding the "reminiscence bump" (see Section 2.1.1). In order words, to test if the songs that were representative for the survey participants were discovered when they were young. This hypothesis can be tested with popular music, comparing the year of release of the song with the year of birth of the subject and calculating the age they were when it was released. We treated all five songs of each of the users equally, no level of importance or scale was used. We had a total of 426 "suitable" songs from the users for this study. In other words, songs which did not have a difference (year of release - year of birth) of less than -50 years. There were a total of 203 "not suitable" songs. From these, 76 songs had less than -50 years of difference (i.e. songs that were composed or published more than 50 years before their birth), so they were considered as "classical or folk

[5] http://www.soulseekqt.net

[6] http://musicbrainz.org/

music" and therefore not considered for this test. The rest were 127 songs which were considered "null" or not tagged because of lack of information about the song provided in the survey.

Analyzing the data, Figure 3.1 shows a curve representing the "reminiscence bump" reviewed in the literature for the case of our survey participants. Observing the graph, the highest number of relevant songs for our participants were released when they were between 10 to 20 years old. In this "bump" of years, there is a total of 171 songs from all the 426 "suitable" songs (40.1% of them). Then we can observe a clear decay after that age. However, we have set the age of "reminiscence bump" for our algorithm from 15 to 30 years old, taking into account the literature reviewed. The use of this information will be to "guide" our algorithm when selecting the songs released in certain years that were more relevant for our subjects.

Year of Birth	Subjects
1940 - 1949	16
1950 - 1959	17
1960 - 1969	16
1970 - 1979	16
1980 - 1989	27
1990 - 1999	34
Total	126

Table 3.1: Number of subjects per decade for the *Life Soundtrack Survey*

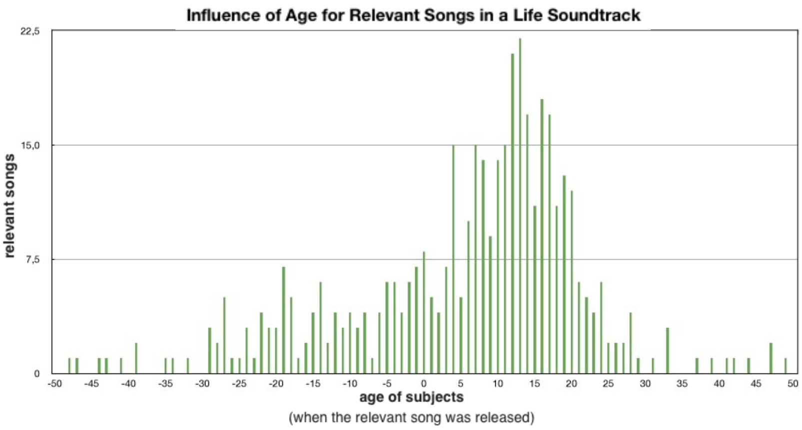

Figure 3.1: The "reminiscence bump" for the *Life Soundtrack Survey* participants

3.2.3 Musical Preferences Online Questionnaire

For evaluating the musical preferences of our subjects, an online questionnaire has been provided. The questionnaire has a total of 29 questions, including 3 questions about personal data (birth date, birth place, places where they lived), 3 questions about work data (occupation, work places, music at work), 4 questions about musical abilities (whether they play instruments, they like singing or dancing), 8 questions about musical preferences (preferred songs, artists, genres, language and mood) and 11 questions about musical memories (childhood and youth, media associated memories, wedding, good and bad memories). Figure 3.2 shows the look of the online questionnaire when presented to the subjects. The questionnaire is provided in the Annex B of this document for further information about the specific questions contained.

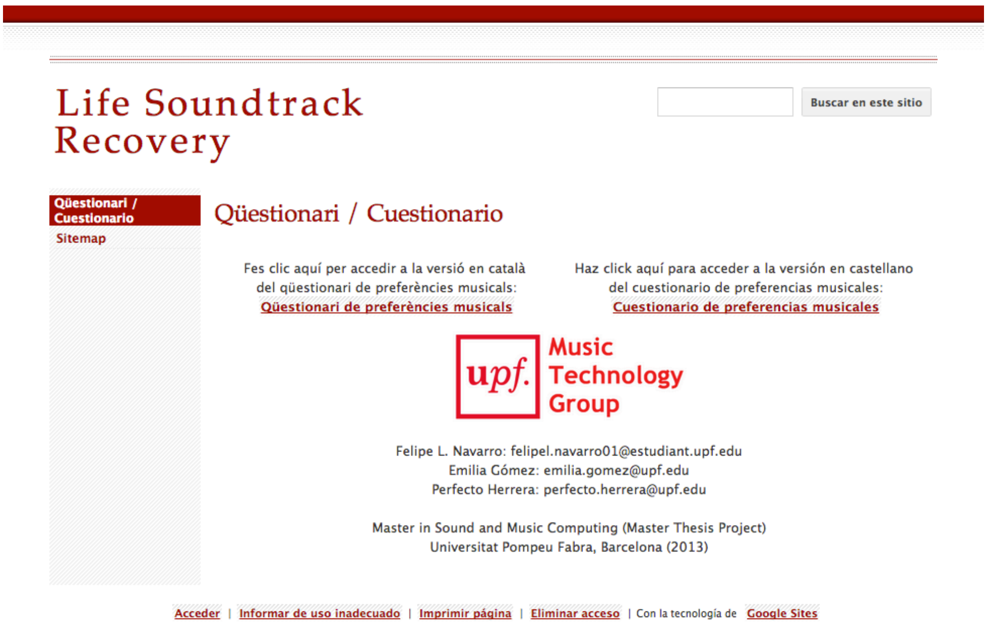

Figure 3.2: Website for the *Musical Preferences Online Questionnaire*

3.3 Algorithm

To test our hypothesis, a theoretical algorithm was designed and tested manually. The current process and stage of development implies mostly a manual processing of the information. The reason for developing this type of implementation is to design a good algorithm, taking into account the many different aspects within the context given, in order to facilitate the future work process of implementing it for automatizing the process. In other words, have an important weight of work in the process of thought and planning before actually implementing the automatic system. In this section the data used and the details of the algorithm are explained.

3.3.1 Data

The data provided by the questionnaires can be classified into direct musical data (i.e. preferred songs and artists) and non-direct musical data (i.e. biographical data, musical preferences). The different preferences and musical information are associated to the questions answered by the users in order to process the information lately.

In the context of this questionnaire, "direct musical data" is considered to be either specific songs provided by the user (name of the song and artist) or artist names. This information is of special interest for our algorithm for making musical inferences through similarity. The non-direct musical data contains biographic information and musical preferences information. As biographic information, we have the birth year, youth years (from 15 to 30 years old) and place of birth and residence. Regarding musical preferences, we consider preferred genres, instruments, language or mood. Then, we divide the non-direct musical data into two preference filters, as it is shown in Figure 3.3.

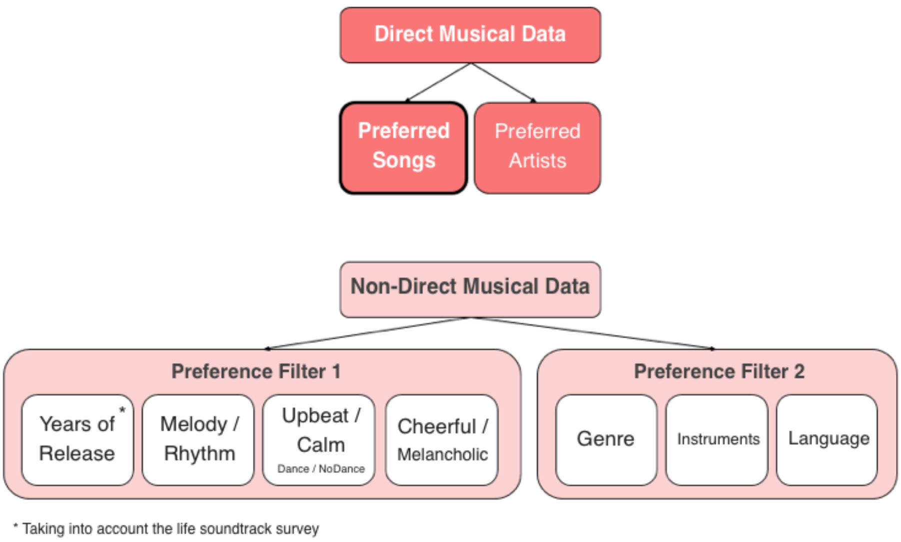

Figure 3.3: Direct and non-direct musical data

3.3.2 Algorithm Design

The algorithm sets as the reference the data about preferred songs and artists from the user. Then, similar artists and songs are retrieved through the well-known audio context-based tagging platform last.fm[7]. Several lists of candidate songs are built based on the direct musical data: list of preferred songs, list of preferred artists' songs, list of similar songs and similar artists' songs. In addition, one list is generated based on the non-direct musical data formed by songs related to the years of youth and the place of birth of the user. Then, preference filters are defined based on the non-direct musical data and they are applied afterwards to these lists to generate a final playlist of N songs. For the evaluation of the algorithm a final playlist of 20 songs has been chosen. The inferring of new artists has been favored, setting limited numbers of songs per artist in order to get more novel information about the tastes and preferences of the subjects. In Figure 3.4 we can observe the flow chart for the processing of the direct musical data and the first preference filter applied in the algorithm. Then, Figure 3.5 is showing how the playlist is generated mixing direct and non-direct musical data.

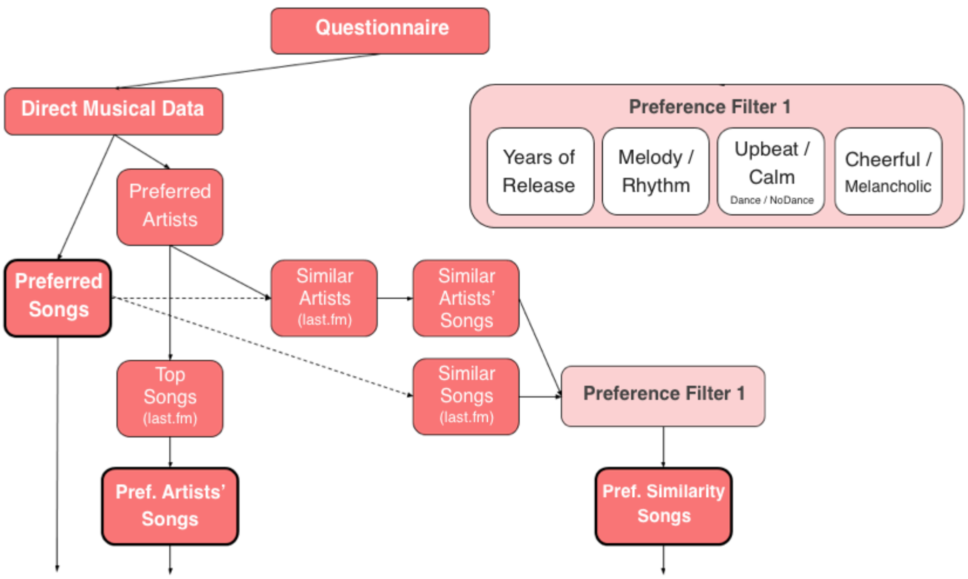

Figure 3.4: Lists of preferred songs, preferred artists' songs and preference similarity songs

[7] http://www.lastfm.com/

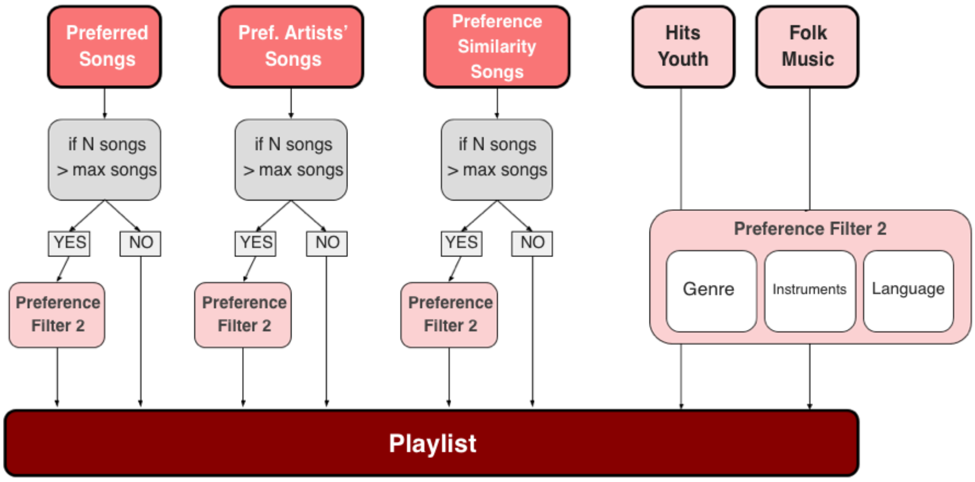

Figure 3.5: Final playlist formed by all lists

3.4 Evaluation

In this section, the evaluation process is described. First, a playlist of 20 songs for each of the subjects has been generated in order to match the user preferences and infer new musical data. Then, the playlists were sent by e-mail to each of the subjects asking them to evaluate the content of it.

3.4.1 Playlists

Based on the preferences indicated by the users, a playlist of 20 songs is generated for each of them Depending on the amount of direct musical data provided by the user, the number of songs per sub-list and number of inferences varied. Being the range of different cases as follows: from 0 to 10 direct songs ("preferred songs" and "preferred artists' songs"), from 8 to 18 inferred songs ("preference similarity songs") and 1 "youth hit" song and 1 "folk" song. Once the final selection of 20 songs was done, the order of songs was randomized in order to have an unbiased structure when presenting the playlist to the subject. Then, playlists were sent to each of the subjects by e-mail, explaining the process they had to follow in order to evaluate the playlist through an online form.

3.4.2 Subjects

Due to the complexity of testing the algorithm with AD patients, and since the problem is applicable to the whole population, we decided to select healthy subjects with special focus on the age of interest for which the disease is mainly affecting. However, in the chapter 5 it is explained how an adaptation of this algorithm could be done for AD population.

A total of 12 healthy subjects (non-AD users) from different parts of Spain have participated in the experiment, 6 men and 6 women. The age of interest for our experiment is mainly from 60 years old people and above. However, the system has been used by people of different ages as well (see Table 3.2).

Age	Year of Birth	Subjects
Above 70	1938 - 1943	4
60 - 69	1949 - 1953	2
50 - 59	1955 - 1961	4
Below 50	1972 - 1978	2
	Total	12

Table 3.2: Age of the subjects for the life soundtrack evaluation

3.4.3 Personal Life Soundtrack Evaluation

In order to do the evaluation and relevance feedback of the playlist, an e-mail was sent to each of the subjects inviting them to evaluate the playlist generated through an online survey (see Annex C). In this survey, an evaluation of each of the songs was provided to the user through these main four questions:

- Does the song sounds familiar to you?
- Do you like the song?
- Does the song brings memories to you?
- Would you listen the song again?

Further details on the evaluation are given in the next chapter devoted to results and discussion.

Chapter 4

Results and Discussion

In this chapter the results obtained from the personal life soundtrack evaluation are presented. The first section is devoted to the results extracted from the evaluation questionnaire by the subjects. In the second section a discussion about those results is provided.

4.1 Results

This section contains the results obtained from the subjects in their personal life soundtrack evaluation detailed in Section 3.4.3. First, the results are presented in terms of overall performance based on the evaluation of the playlists generated by the algorithm. The results are provided for each of the different types of lists included in each playlist: preferred songs, preferred artists' songs, preference similarity songs, youth hits and folk (traditional and folkloric music). Then, a more specific analysis is given for the different categories considered for the evaluation: *familiarity*, *liking*, *memories* and *listening intentions*.

The results are shown in Table 4.1 divided by list types and the different evaluation categories. List types respond to the different lists or sublists which are generated by the algorithm, being the final playlist a combination of those. There are five different types of lists. *Type A* represents the preferred songs list and is related to the direct musical data that the user has specified in the *Musical Preference Online Questionnaire*.

Type B is the list of preferred artists' songs, based on artists names that have been specified by the subject without a specific song title. In this case the algorithm is suggesting the most popular song for the artist to be incorporated into the playlist. *Type C* is the preference similarity songs list, which are the songs that are similar to the *type A* and *type B*. So that, *type C* represents the inferences suggested by the algorithm as music that is likely to be in their life soundtrack. *Type D* are youth hits; music that was popular in the range of years when the subject was young, considering youth years from 15 to 30 years old. *Type E* are folk music songs which are considered to be original from the place where the subject was born or has lived. In the case of *type D* and *type E*, one song of each type is included in every playlist. We report in these results the evaluation for all songs given to all of the subjects divided into list types. More specifically, 20 songs per playlist for a total of 12 subjects: 240 songs evaluated. Depending on each subject the weights (number of songs) for types *A*, *B* and *C* are different. As a result, there is a total of 59 songs of *type A*, 62 songs of *type B* and 95 songs of *type C*. Then, *type D* and *type E* have 12 songs each.

The different evaluation categories respond to our general idea of a life soundtrack. In other words, the most relevant aspects that should be taken into account when building and evaluating a personal life soundtrack. We think these aspects can be classified in four different categories: *familiarity* of the subject with the songs, *liking* for the songs by the subject, *memories* that these songs are capable to bring and *listening intentions*. For a song to be part of our life soundtrack, this song should be familiar to us. The first question included in the personal life soundtrack evaluation (Section 3.4.3) is regarding familiarity of the subject with the song. Subjects can optionally provide the name of the artist and title of the song if they remember it. Regarding familiarity in Table 4.1, we report the percentage of songs that have been considered familiar by the subjects. The percentage of song titles or artist names retrieved by the subjects is also provided. Whether the subject likes the song or not is another important aspect for the song to be considered part of the life soundtrack. Usually, songs that we love are those that we consider important in our life. The second question included in the personal life soundtrack evaluation is related with this point. In Table 4.1 we report these results inside the column called liking indicating the percentage of songs that were rated by the subjects as "I like it a lot" or "I like it". The percentage of both answers were summed together, considering these answers as an evidence that the song could potentially be part of their life soundtrack. The third question of the evaluation is related to memories. We reported the summed percentage of songs that were rated as bringing “good memories” or just “memories (neither good nor bad)”. The last question of the evaluation is related with the willingness of the subject to listen the songs again. So that, we reported in Table 4.1 the positive listening intentions answers of the subjects.

List Type	Number of Songs	Familiarity	Name Retrieved	Liking	Memories	Listening Intentions
All	240	87.500	72.083	80.833	72.917	83.750
A	59	89.831	89.831	89.831	84.746	93.220
B	62	90.323	90.323	85.484	74.194	88.710
C	95	86.316	56.842	76.842	67.368	80.000
D	12	91.667	58.333	75.000	67.368	66.667
E	12	66.667	25.000	50.000	50.000	58.333

Table 4.1: Percent of songs rated per category and list type.
(A= Preferred Songs, B= Preferred Artists' Songs, C= Preference Similarity Songs, D= Youth Hits, E = Folk)

Considering the previous categories as the relevant aspects to be taken into account when retrieving and building the life soundtrack of an individual, in the case of evaluating the inclusion of a song in it, this song would have to meet all these conditions. In this sense, all of the songs included in each of the playlists have been evaluated in these terms. So that, if the subject rated the song as familiar, liked it, the song brought some memories and the listening intentions were positive, the song was considered as being part of their life soundtrack. This evaluation was done in two different ways, considering the “name retrieved” results and without considering them. While the rest of conditions are essential, name recall may be sensible to other parameters such as the personal ability to remember names or the lack of exposure to the song in a long time. In Table 4.2, the percentage of songs considered to be part of the life soundtrack for the subjects are reported and divided into categories and list types, with and without the name recall condition.

In Table 4.3, we report the results for each of the individual subjects who participated in the evaluation. The number of songs that were inferred are shown along with the number of songs that were extracted from the direct musical data. Table 4.3 along with the graphs below are shown in order to understand whether the number of inferences made by the algorithm has an influence in the overall rating of the playlist.

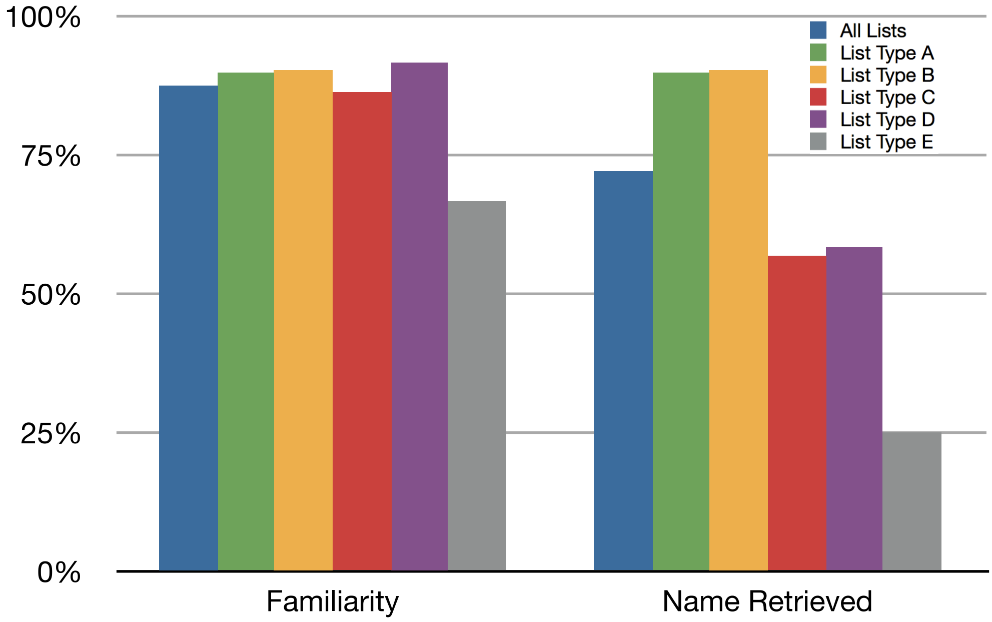

Figure 4.1: Percent of songs rated as familiar (left) and percent of song titles or artist names retrieved (right) by list type

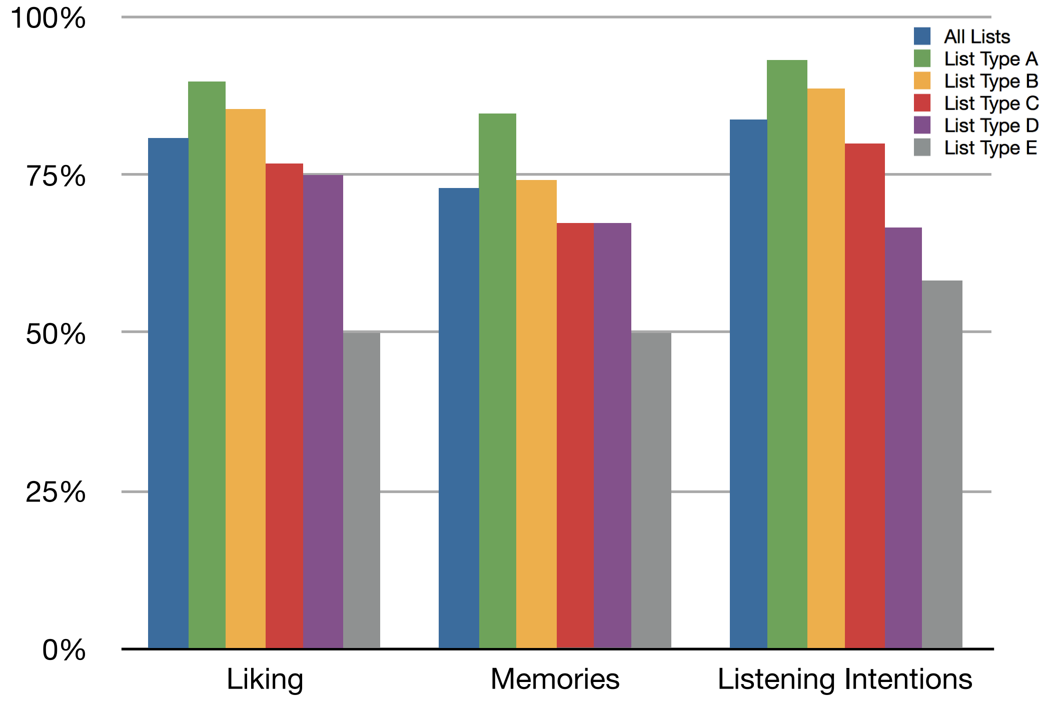

Figure 4.2: Summed percent of songs rated as "I like it a lot" and "I like it" (left), summed percent of songs rated as bringing "good" or "neutral" memories (middle) and percent of songs rated as "I would like to listen the song again" (right) by list type

List Type	Life Soundtrack Songs (considering Name Retrieved)	Life Soundtrack Songs (not considering Name Retrieved)
All	57.500	65.417
A	74.576	76.271
B	67.742	67.742
C	45.263	61.053
D	58.333	58.333
E	16.667	41.667

Table 4.2: Percent of songs considered to be part of the subjects' life soundtrack, considering results with and without the Name Retrieved condition.
(A= Preferred Songs, B= Preferred Artists' Songs, C= Preference Similarity Songs, D= Youth Hits, E = Folk)

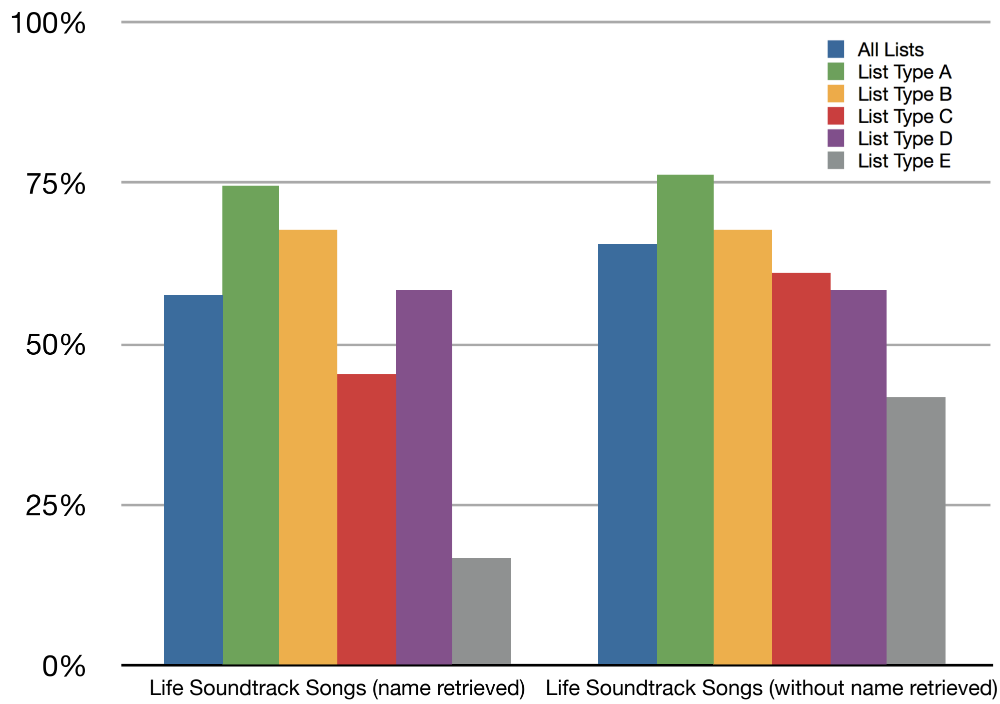

Figure 4.3: Percent of songs considered to be part of the subjects' life soundtrack by list type

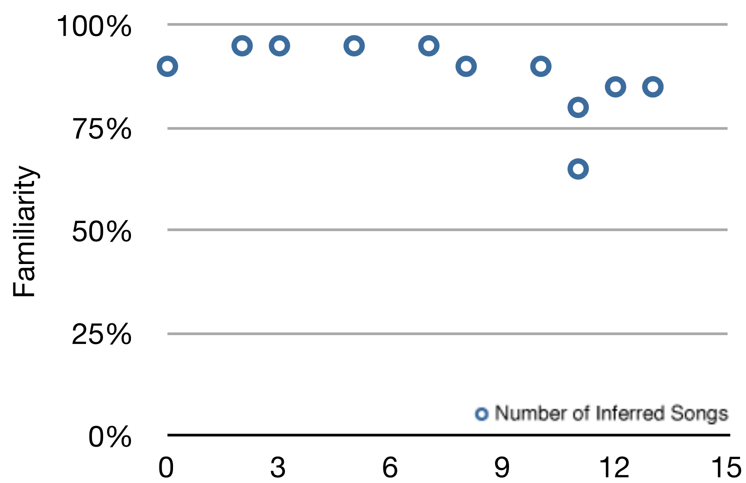

Figure 4.4: Percent of familiar songs per number of inferred songs for the playlists evaluated

User / Subject ID	Number Songs (Type C)	Number Songs (Type A & B)	Familiarity	Name Retrieved	Liking	Memories	Listening Intentions	Life Soundtrack Songs
u01	3	15	95	90	90	100	85	80
u02	8	10	90	70	85	65	75	60
u03	2	16	95	85	85	65	100	55
u05	7	11	95	85	85	90	100	70
u06	11	7	65	50	70	40	60	35
u07	13	5	85	65	60	70	60	55
u08	10	8	90	55	90	95	90	55
u09	0	18	90	95	90	60	90	60
u11	11	7	80	50	75	30	80	20
u12	12	6	85	65	85	85	100	65
u14	5	13	95	90	85	95	85	80
u20	13	5	85	65	70	80	80	55

Table 4.3: Percent of songs rated per category and user,
specifying the number of inferred songs (type C) for each subject's playlist

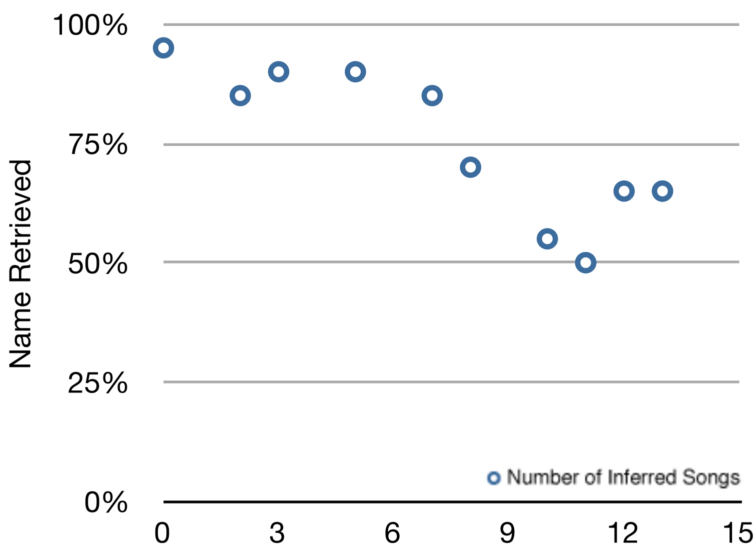

Figure 4.5: Percent of retrieved song titles or artist names
per number of inferred songs for the playlists evaluated

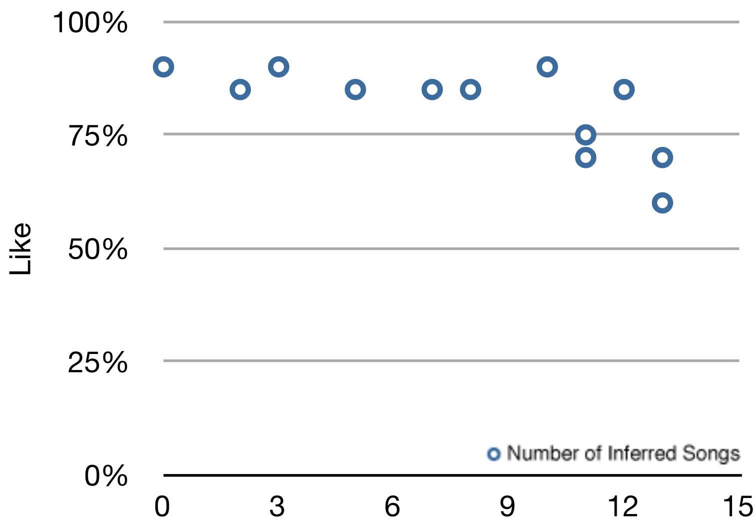

Figure 4.6: Summed percent of songs rated as “I like it a lot” and “I like it” per number of inferred songs for the playlists evaluated

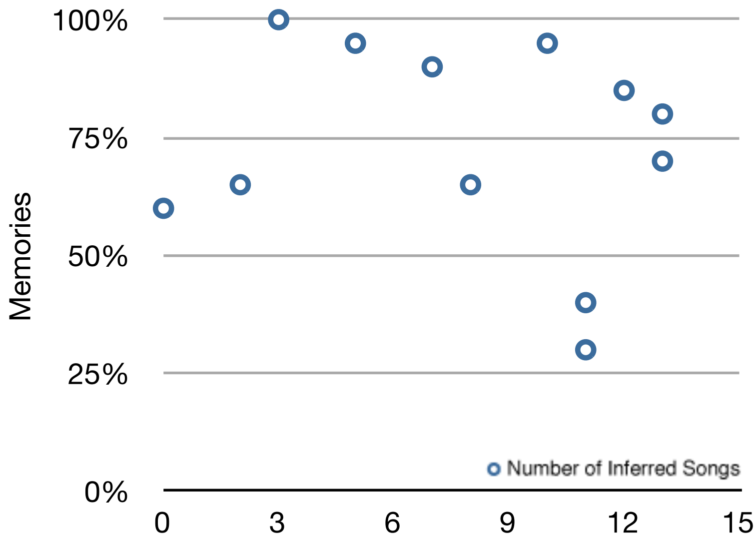

Figure 4.7: Summed percent of songs rated as bringing “good” or “neutral” memories per number of inferred songs for the playlists evaluated

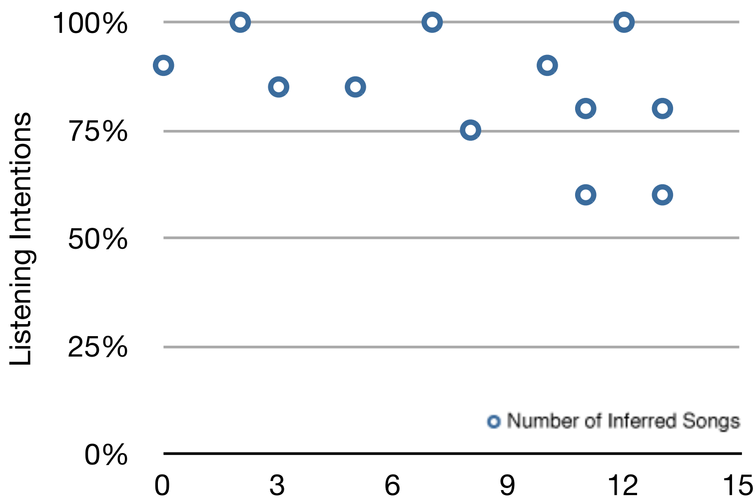

Figure 4.8: Percent of songs rated as "I would like to listen the song again" per number of inferred songs for the playlists evaluated

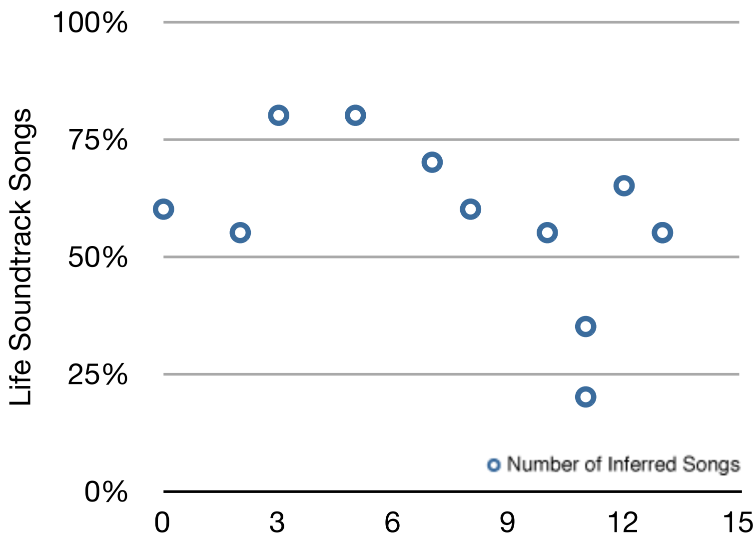

Figure 4.9: Percent of songs considered to be part of the subjects' life soundtrack per number of inferred songs for the playlists evaluated

4.2 Discussion

In this section the analysis of the previous results is provided. The discussion is divided into the different categories explained: familiarity, liking, memories and listening intentions. An additional subsection is included to analyze whether the songs are considered to be part of the subjects' life soundtrack. Another aspect included is the influence of inferences in the overall playlist rating.

Familiarity

In terms of familiarity (see Table 4.1), the types A (89.8%) and B (90.3%) are rated the highest along with the youth hits (type D, 91.6%). For types A and B, those are expected results, being the preferred songs and artists that the subjects gave in the *Musical Preferences Online Questionnaire*. For youth hits, the songs are shown to be generally very familiar to the subjects. In the case of musical inferences based on similarity made by the algorithm, they are mostly rated as familiar (songs of type C, 86.3%). Regarding folk music original from the place of birth or places the subject lived in, the percentage decreases in comparison with the other types (songs of type E, 66.6%). In terms of song titles and artist names recall, the percentage is exactly the same as for familiarity for types A (89.8%) and B (90.3%). However, recall decays substantially for types C (56.8%) and D (58.3%) when comparing it to the familiarity percentage. So that, even if the songs were familiar to them they could not recall the name for many of these songs. For type E only 25% of the songs were correctly named. In Figure 4.1, the bar graphs show these results, where a lower overall percentage of retrieved names can be observed due to the lower recall in types C, D and E. Regarding the relation between the familiarity results and the number of inferences, we observe in Figure 4.4 that there is a slight decrease when the inferences are higher than 10. This is more pronounced when considering the amount of titles and artist names recalled, as Figure 4.5 shows.

Liking

As expected, the percentage of songs rated as "I like it a lot" or "I like it" was higher for songs in lists of type A (89,8%) and B (85.4%). It is interesting to remark the fact that for songs in list type A (preferred songs of the subject) not all of them were rated as "I like it a lot" or "I like it". This may have to do with the version of the song chosen for the playlist. Since the subject only gives the title of the song (with or without the artist name) sometimes the chosen version or the artist who sings the song is not the expected by the subject, as reported in some of the optional comments and suggestions written by the subjects in the questionnaires. A lower percentage is reported as “I like it a lot” or “I like it” for the inferred songs (type C, 76.8%) and for the youth hit songs (type D, 75%). Folk songs are reported as the lowest percentage of liked songs by the subjects (E, 50%). In Figure 4.2 (bar graph in the left) the summed percentage of songs rated as “I like it a lot” and “I like it” is presented for each of the different list types. In Figure 4.6 we observe that for most of the playlists that had more than 9 inferences, the liking percentage was below 75%.

Memories

Regarding memories, 84.7% of the songs of type A where considered to bring memories. For type B (74.1%), we observe the highest percentage difference (-10.6%) in relation to type A, taking into account the previous categories familiarity, name retrieved (both 0.5%) and liking (-4.4%). Songs of type B are from subject’s preferred artists, but chosen by the algorithm in terms of popularity. So that, for some cases it may be the most popular song of the artist, but the song itself may not be so relevant for the subject. Regarding inferences (C, 67.3%) and youth hits (D, 67.3%) we get the same percentage value of songs bringing memories. The lowest percentage of songs bringing memories is for folk songs (E, 50%). In Figure 4.2 (bar graph in the middle) the summed percentage of songs rated as bringing “good” and “neutral” memories is presented for each of the list types. In Figure 4.7 we observe that there is no clear relationship between the number of inferences in a playlist and the memories brought by the songs.

Listening Intentions

Regarding listening intentions, higher values are reported for types A (93.2%) and B (88.7%), but type C shows similar results as well (80%). Then, types D (66.6%) and E (58.3%) show the lowest percentage results in this aspect. This might be due to the fact that for youth hits and folk songs, musical preferences are not taken into account, only biographical data. This is also shown in Figure 4.2 (bar graph in the right), where the percent of songs rated as “I would like to listen the song again” is presented for each of the list types. In Figure 4.8 we observe that for the playlists which had 11 and 13 inferences the listening intentions are the lowest. However, for high overall listening intentions no pattern is observed.

Life Soundtrack Songs

When evaluating the results for each of the songs, i.e. whether the songs could be considered part of the subject's life soundtrack, we observe different results when taking into account song title recall. In this case, considering song title recall, less than half of the suggested songs (type C, 45.2%) can be considered part of the life soundtrack. Interestingly, for song titles provided by the subjects as preferred songs, the results did not show the totality of these songs as part of it (type A, 74.5%). This may be caused by the version of the song chosen, or the artist playing the song, since subjects provided some song titles without the artist name. A second hypothesis for these results, is that the combination of conditions that we have set for a song to be considered part of a life soundtrack may be too demanding. We have determined familiarity, liking, memories and listening intentions as essential properties for a song to be considered part of a life soundtrack. However, name recall may be depending on other parameters such as the personal ability to remember names or the lack of exposure to the specific song for a long time. So that, the results have been provided also without considering the name recall. In this second case, we do not observe relevant differences for types A (76.2%), B (67.7%) and C (58.3%). However, not considering the name recall improves the results substantially for the inferences (type C, 61.0%) and for traditional and folk music (type E, 41.6%). Figure 4.3 show the percent of songs considered as being part of the subjects' life soundtrack for each of the list types in both modes. In addition, Figure 4.9 we can observe that the lowest amount of life soundtrack songs are presented in the playlists with 11 inferences. However, for the playlists with 12 and 13 inferences the results were comparable to those with 2 or 0 inferences, so there is no evidence that the number of inferences has influence in this sense.

We can observe that the algorithm generates musical suggestions that are evaluated similarly in terms of familiarity, liking and listening intentions to the songs that are provided by the subjects. However, regarding song titles and artist names recall, the results are lower for music suggested by inference. When evaluating the songs that can be considered part of a subject life soundtrack, we obtain higher performance results for the inferences and traditional or folk music when not taking into account the song title or artist name recall. Generally, the algorithm is generating and reconstructing part of the life soundtrack of the subject by relying on preference similarity suggestions. However, we consider that these results may be improved by increasing the number of conditions for the algorithm to include a song as a suggestion, such as audio content-based similarity with other preferred songs. Currently, the algorithm is choosing many “most popular” songs by preferred and similar artists, and that may be a weakness of our system. On the other hand, the difference of results shown in Table 4.2 bring the question of whether recalling the song title or the artist name is important for a song to be considered part of the life soundtrack of an individual. In terms of future work, setting a minimum number of preferred song titles and an improved integration of the musical preferences with the biographical data may help drawing more accurate inferences.

Chapter 5

Life Soundtrack Recovery within a Clinical Context

In this chapter we provide details about how the adaptation to a clinical context could be made from the work developed in this thesis. First, an overview about this problem is given. Secondly, details about different aspects that need to be considered for the adaptation are shown and explained.

5.1 Overview

One of the main goals of this thesis is to study the possible adaptation of current MIR approaches to the needs of AD patients in therapeutic sessions within a clinical context. For this work, the evaluation of our approach had to be done with non-AD users for two main reasons. First, the concept of a life soundtrack can be extrapolated to the whole population. Second, due to the difficulties that implies attempting to study objectively the results of the evaluation for AD patients considering their challenging situation. So that, the different aspects that have to be taken into account for adapting this system are provided in in this chapter.

5.2 Clinical Context Adaptation

This section is dedicated to explore in depth the aspects of this thesis that are sensible to be adapted in the case of a clinical context situation. Some of the key concepts developed in this thesis are universal such as the life soundtrack of an individual. However, the way we gathered the data of our non-AD subjects is not completely applicable in a clinical context. This is due to the general challenges associated with the dementia, and those which are dependent on the condition of each individual patient. For this reason, we explain in this section the adaptations needed for the questionnaires, database, algorithm and evaluation that were developed in this thesis with non-AD subjects.

5.2.1 Musical Preferences Questionnaire

The musical preferences questionnaire would not be online as it was for the development of this thesis. In a clinical context, this questionnaire would be given to the patient by the therapist, caregivers, family or friends, and they would guide the patient through it. Other extra questionnaires may be filled by the therapist, family or friends in order to complete missing information about both biographical and musical preferences information.

5.2.2 Database

Updating the database with new songs that are provided in new questionnaires and entries is a process which is independent from the adaptation to the clinical context. The same applies to the management and access of the database in iTunes. However, interesting possibilities could be explored within the automatization of the process for future work. For instance, suggesting songs that are missing in the database through an online form or a mobile application. Those suggestions could be made by the therapists, family or even the same patients.

5.2.3 Algorithm and Playlist Evaluation

One of the most important aspects to be considered for the adaptation of the algorithm is to incorporate the relevance feedback taken from the playlist evaluation in order to improve the musical selection. On the other hand, the evaluation would have to be changed for a clinical context in which therapists, caregivers and family would play a crucial role. In this subsection we focus in these two points.

In the case of the evaluation for this thesis a fixed number of 20 songs was selected for each playlist. However, that would not be the case for a clinical context application. In this sense, each patient would have a personal playlist that would be improved in each algorithm iteration. The first iteration would actually generate 20 songs for the AD patient to evaluate. For the evaluation, the different categories (familiarity, liking, memories and listening intentions) taken into account for this thesis would be considered, adapting the questions if needed. All songs will be filtered by the conditions set in order to consider a song part of the life soundtrack of the patient. Then, the algorithm could be asked again to generate new suggestions to evaluate based on the results of the first iteration. Different weights could be applied, generating more songs per artist or genre, or recommending more similar artists per preferred artist, depending on the needs. In addition, it would be interesting enabling the possibility for therapists and family to tag songs with specific comments about memories or emotions that the patient experiences when listening to them.

Regarding the playlist evaluation within a clinical context, possibilities include making the questionnaire playful, flexible or more abstract depending on the needs of the patient. Other possibilities include the use of cameras and sensors when exposing the patients to music. Through cameras the facial expression of the patient could be recorded when listening to music. Heartbeat rate, sweat rate or body temperature could also be interesting ways of evaluating if the music generates some type of reaction on the patients. On the other hand, exposing the patients to music in different ways such as headphones or loudspeakers, quiet or loud volume, could be considered for other evaluation conditions. There are also long-term aspects that could be evaluated regarding the daily life of the patient. Being exposed to their life soundtrack on a daily basis, therapist and family could report the effects of it; whether the patient walks more during the day, feels more active or talkative, or any changes in situations that are usually stressful for the patient.

5.2.4 Other Considerations

Other considerations may include having a framework that family, therapist, caregivers and friends can share and improve. That means, having access to the music, folders and forms for updating or entering new information. It would also be important for the patients to have the chance of listening to the music in different places: therapy center, friends' places or home. In this sense, accessibility and portability of the music are relevant aspects to be considered in this context.

Chapter 6

Conclusions and Future Work

In this last chapter an overview about the work carried out in this thesis is provided along with conclusions and contributions. In addition, we provide a discussion on the issues that need further investigation for future work projects.

6.1 Summary of the work

First, an overview of the problem is given setting the different motivations and goals of the thesis. It has been studied in different psychology related works that music therapy helps patients of AD improving their daily life. However, the selection of music for therapy is generally manual and lacks of user-oriented approach, being difficult to match patient's musical taste as a result. In this sense, the main motivation of this thesis is to help AD patients and adapt to their needs the MIR technologies that have been proved effective and useful for general population.

The review on the literature is focused on the different aspects of Alzheimer's disease as a dementia and its relations with music, emotion and memory. Relevant concepts such as "the musical self" or the "reminiscence bump" were introduced and used later on. Then, a review on MIR technologies was done regarding the strategies commonly used for music recommendation systems. Another section of the review was devoted to previous work with technologies and therapy.

In this work, the concept of the life soundtrack of an individual has been introduced. Using this concept, a database of music that has been considered of interest for our target group has been built. We have based the musical selection on different sources such as specialized websites, blogs and user-based information gathered in different questionnaires. In this sense, the questionnaires have been very relevant and useful for gathering the information, being the basis for our work. The subjects who participated in the *Musical Preference Online Questionnair*e evaluated a playlist of 20 songs generated by our algorithm. The algorithm generated them considering different musical preference aspects such as genre, preferred instruments, mood or language and biographical information such as birth place and birth year.

The results gathered the impressions and evaluation from all the subjects. Those are presented divided into the different types of lists and the different categories considered relevant for a life soundtrack. We also dedicated a chapter to how this work could be adapted for a clinical context situation, giving different ideas about how to implement it.

6.2 Main conclusions

In this work, the problem of adapting MIR technologies to the context of AD has been addressed. For this purpose, the questionnaires taken helped to know what data is possible to get from subjects in order to plan the functioning the algorithm. So that, an important source of information is the subject itself, who empowers the algorithm for querying personalized information. On the other hand, one of the challenges when building the database was to obtain information about spanish music from the decades 1940s to 1960s. Not much information about this type of music was found and not many commercial compilations were available in the market. So that, the process of building this database consisted mostly on manual research. For the database to be useful, it needs to be flexible and be updated based on the preferences and inputs of new subjects or patients.

The algorithm developed was supervised and mostly manual. In this sense, the queries were done using last.fm manually providing details on how the algorithm would work in a more automatized process. This was to give more importance to the design of the algorithm first, in order to facilitate the future work of automatizing it. Moreover, focusing mostly on the algorithm design made possible to give more insight on the needs of it, being flexible to new ideas about how to implement it.

The results of the playlist evaluation were presented in terms of familiarity, liking, memories, listening intentions and amount of life soundtrack songs. These were divided by list type depending on whether the songs were picked by the subjects or suggested by similarity or biographical data. Results were positive generally in terms of familiarity, liking and memories. However, when recalling names of artists and song titles the performance decreased for songs suggested by similarity and biographical data. It was interesting to observe that the results for songs suggested by similarity and the results for songs suggested by popularity in the subject's youth were very similar in terms of familiarity, liking and memories. This may suggest that the inferences made taking into account several musical preferences aspects do not generate better results than just taking into account the birth year of the subject. However, in terms of listening intentions results for inferred songs are higher than for youth hits. On the other hand, each song evaluated by the subjects was filtered when meeting all positive conditions: being familiar, name of the song correctly retrieved, liked by the subject, the song brought memories and positive listening intentions. The highest rate of songs considered to be part of the subjects' life soundtrack was found in songs preferred by the subjects and songs of artists preferred by the subjects. Then, more than half of the youth hit songs suggested were part of the life soundtrack of the subjects. Less than half of the songs suggested by similarity met the conditions to be considered part of the life soundtrack. The lowest rate of songs of their life soundtrack was for traditional or folk music. So that, according to these results, taking into account biographical data such as the birth year generated similar accurate inferences than considering the musical preferences of the subject. However, when discarding the artist names and song titles recall, improvements in the results were observed for the inferences by similarity and folk or traditional music. This brings the question of whether the name recall is relevant for considering a song part of the life soundtrack. Moreover, these results suggests that a combination of both musical preferences and biographical data may generate more accurate inferences for future implementations. Finally, we consider that these results show that the approach is of interest for the field and for its future development and exploration.

6.3 Future work

Further work on this topic includes automatization possibilities such as questionnaire automatic parsing, the use of last.fm API for metadata processing or the use of Essentia and Gaia for audio content-based similarities.

With questionnaire automatic parsing, subject's musical preferences, titles of songs or artist names could be automatically retrieved. However, new challenges appear such as understanding certain written expressions or correcting wrong or misunderstood song titles and artist names. This could be supported by a more structured form of a questionnaire, so that it would be simpler to automatically parse in future developments.

Regarding the use of last.fm API[8], the same functions used in this thesis could be automatized. So that, similar artists, songs, genres, tags and other metadata could be retrieved through the API. Then, further musical suggestions by audio-content similarity could be done using Essentia and Gaia[9] within the framework of our database. This would generate new suggestions based on relevant songs included in the subject's life soundtrack.

Other future possibilities include working with sound, field recordings, family tapes and other media. For instance, to work about a life soundtrack not only in terms of music that the patients like, but also about sounds that bring memories to them. This is an interesting challenge in terms of how to gather the information about the sounds or soundscapes for which the patients have memories associated with. On the other hand, retrieving sounds, recording and recreating soundscapes or researching interesting ways of reproducing them will be other aspects in this new branch of work. In addition, the use of visual material attached to sound and music could be of special interest in order to trigger memories and improve the therapy sessions in which this material is thought to be provided.

[8] http://www.lastfm.es/api

[9] http://essentia.upf.edu/

6.4 Contributions

In terms of contributions, a database made of 1790 songs has been built. This can be used for further investigation in topics that need to be focused in music published in Spain, or played in spanish radio, in these decades. Moreover, the concept of a life soundtrack has been addressed and develop, so that future work can be implemented on this topic. In this direction, several questionnaires and surveys have been developed that can serve as an orientation for future projects. Regarding the general outcome of this thesis, a theoretical approach has been developed for the use of MIR tools within the context of AD, which can be of interest for future work in this field willing to merge technology with therapy.

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Annex A

Life Soundtrack Survey

Música, emoció i memòria: La banda sonora de la teva vida

Gràcies per la vostra col·laboració en aquesta sessió. Si us plau, ompliu aquest full i deixeu-lo sobre la taula abans de sortir. En algun moment de la sessió d'avui parlarem de l'activitat que us proposem aquí. Si ja la teniu omplerta serà molt millor!

Any de naixement:

Lloc de naixement:

Recorda quin va ser el primer disc (vinil, cassette, CD, etc.) que vostè es va comprar?

Enumeri fins a cinc cançons o peces musicals que pertanyen a la banda sonora de la seva vida (si recorda l'artista, cantant o compositor escrigui'l també)

1.

2.

3.

4.

5.

Moltes gràcies!

Annex B

Musical Preference Online Questionnaire

Datos personales

Fecha de nacimiento (DD/MM/AAAA):
(ejemplo: 19/02/1937)

Lugar de nacimiento
(ej.: Vilanova i la Geltrú)

Lugares donde ha vivido durante su vida
(ej.: Vilanova i la Geltrú (1937-1957), Tarragona (1957-1990), Barcelona (1990-hoy))

Profesión
(ej.: panadero)

Relación con la música

¿En qué tipo de lugares ha trabajado?

- [ ] Oficina
- [ ] Fábrica
- [ ] En casa
- [ ] En el campo
- [ ] Tienda / Trabajo de cara al público
- [ ] Otro:

Cuando trabajaba, ¿cantaba y/o se escuchaba música?

- [ ] Cantaba
- [ ] Se escuchaba música
- [ ] Se escuchaba música y cantaba
- [ ] No había música
- [ ] Otro:

¿Toca o ha tocado algún instrumento?

- [ ] Guitarra
- [ ] Piano
- [ ] Violín
- [ ] Saxofón
- [ ] Percussión
- [ ] Voz cantada
- [ ] Otro:

¿Le gusta cantar?

- Me gusta mucho
- Me gusta
- No me gusta
- No me gusta nada

¿Ha cantado en una coral o en un conjunto?
(ej.: Sí, en la coral de Sant Jordi.)

¿Le gusta bailar?

- Me gusta mucho
- Me gusta
- No me gusta
- No me gusta nada

¿Le gusta algún tipo de música en especial?

- ☐ Música clásica
- ☐ Sardanas
- ☐ Flamenco
- ☐ Copla
- ☐ Rock
- ☐ Jazz
- ☐ Soul
- ☐ Canción ligera
- ☐ Jota
- ☐ Música tradicional / folclórica
- ☐ Otro:

¿Le gusta algún compositor, autor o cantante?
(ej.: Frédéric Chopin, The Beatles, Nat King Cole, Joan Manuel Serrat...)

¿Le gusta alguna pieza musical en especial? (canción, concierto, ópera...)
(ej.: "Mediterráneo" de Joan Manuel Serrat...)

¿Prefiere música con melodía que pueda cantar o música con ritmo?

- ○ Música con melodía que pueda cantar
- ○ Música con ritmo
- ○ Música con melodía (instrumental)
- ○ Todas por igual
- ○ Otro:

Cuando escucha música, ¿prefiere música movida o música calmada?

- ○ Música movida
- ○ Música calmada
- ○ Las dos por igual
- ○ Otro:

Cuando escucha música, ¿prefiere música alegre o melancólica/triste?

- ○ Música alegre
- ○ Música melancólica
- ○ Las dos por igual
- ○ Otro:

Cuando escucha música, ¿le gusta algún instrumento en concreto?

- ☐ Piano
- ☐ Guitarra
- ☐ Violín
- ☐ Instrumentos de viento
- ☐ Percusión
- ☐ Voz cantada
- ☐ Otro: ____________

Cuando escucha música, ¿prefiere música en algún idioma en concreto?

- ☐ Catalán
- ☐ Castellano
- ☐ Inglés
- ☐ Francés
- ☐ Italiano
- ☐ Otro: ____________

Recuerdos y música

¿Recuerda música de su infancia?

- ○ Mucho
- ○ Poco
- ○ Nada

¿Qué canciones recuerda de su infancia?
(ej.: canciones que cantara su madre, sus hermanos, en la escuela...)

¿Iba a bailar cuando era joven?

- ○ Si, iba a menudo
- ○ Si, alguna vez
- ○ Nunca

¿Recuerda alguna música de los bailes?

¿Recuerda escuchar música en la radio?

- Mucho
- Poco
- Nada

¿Qué le gustaba escuchar en la radio?

¿Recuerda haber visto programas de música en la televisión?

- Mucho
- Poco
- Nada

¿Qué programas musicales le gustaba ver en la televisión?

¿Recuerda qué música sonó o bailó en su boda?

¿Hay alguna canción que le traiga buenos recuerdos?
(ej.: Sí, "Un beso y una flor" de Nino Bravo.)

¿Hay alguna música que le traiga recuerdos desagradables?

Datos de contacto

Nombre

Correo electrónico

Enviar

Annex C

Life Soundtrack Playlist Evaluation

Lista de canciones de [redacted] (1/4)

¡Hola [redacted]!

Bienvenido al cuestionario de evaluación de su lista de canciones. Es una lista de 20 canciones que han sido seleccionadas según sus recuerdos y preferencias musicales indicadas en el "Cuestionario de preferencias musicales" que rellenó.

Las canciones están nombradas con un número (01.mp3, 02.mp3, 03.mp3...), no hay datos de título ni artista por razones de evaluación para este experimento.

Hemos dividido la lista en cuatro partes (cinco canciones en cada parte) de forma que pueda más cómodamente responder a las preguntas en distintas sesiones. Esta es la 1ª parte de las 4.

A continuación, le haremos una serie de 4 preguntas para cada una de las canciones de la lista. Le pediremos que escuche la canción antes de responder a las preguntas.

¡Esperamos que lo disfrute!

Music Technology Group
Universitat Pompeu Fabra

Pulse 'Continuar' para comenzar.

Continuar »

Canción 1

En el siguiente link encontrará la canción '01.mp3'. Al hacer clic se reproducirá la canción en una ventana nueva de su explorador:
https://dl.dropboxusercontent.com/u/46355191/LSR_usr001/01.mp3

Escuche la canción como desee, si desea saltar alguna parte de la misma o escucharla varias veces, ¡no lo dude!

Una vez la haya escuchado, conteste a las siguientes preguntas:

¿Le resulta familiar esta canción? *

- Me resulta familiar
- No me resulta familiar

¿Le gusta la canción? *

- Me gusta mucho
- Me gusta
- Ni me gusta ni me disgusta
- No me gusta
- No me gusta en absoluto

¿Le trae recuerdos? *

- Me trae buenos recuerdos
- Me trae recuerdos que no son ni buenos ni malos
- Me trae malos recuerdos
- No me trae recuerdos

¿La escucharía de nuevo? *

- Sí
- No

(Opcional) Si lo recuerda, escriba el nombre del artista y de la canción:

(Opcional) Otros comentarios:

Pulse el botón 'Continuar' para continuar a la siguiente canción.

« Atrás   Continuar »