Mood-based On-Car Music Recommendations

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Abstract. Driving and music listening are two inseparable everyday activities for millions of people today in the world. Considering the high correlation between music, mood and driving comfort and safety, it makes sense to use appropriate and intelligent music recommendations based on the mood of drivers and songs in the context of car driving. The objective of this paper is to present the project of a contextual mood-based music recommender system capable of regulating the driver's mood and trying to have a positive influence on her driving behaviour. Here we present the proof of concept of the system and describe the techniques and technologies that are part of it. Further possible future improvements on each of the building blocks are also presented.

Key words: Contextual Music Recommendations; Car Based Computing; Music Mood Recommendations; Connected Car; Car Mobile Apps

1 Introduction

Since the advent of the first car radios, listening to music has always been one of the favorite activities carried out by people while driving their cars: as reported in [4], about 70% of the drivers do so. Driven by their tastes, attitudes and moods and by the nature of the trips, people have always selected the most adequate songs from their libraries creating their own customized playlists. In [19] the authors attempt to answer the question "Why do people listen to music?". Their finding is that the three most common motivations for listening to music are *Self awareness*, *Social relatedness* and *Arousal and mood regulation*. These findings reveal a strong correlation between listening to music and self regulation of mood. Thus, people may want to confirm the mood state they are in by listening to music in accordance with it; conversely, they may want to get out of a bad mood by listening to songs capable of encouraging opposite feelings. In the automotive domain there are many psychological studies that reveal connections between the played music and the actual behavior, concentration or performance of people driving their cars. Obviously, an appropriate background music stimulus may be an useful instrument to enhance the human performance and comfort in driving [15, 21].

On the other hand, the evolution of music recommender systems in the last decade has encouraged a high percentage of music listeners to rely on suggestions given by such applications. Music mood recommendations are embedded in many music social communities such as *Last.fm*, *TIMmusic* or *Spotify*. This article presents the proof of concept of a Mood-Based On Car Music Recommender System that uses various sources of information for tuning the recommendations: physiological information about the heart rate dynamics of the driver obtained from wearable sensors; user's saved musical preferences to take into account his/her musical tastes; telemetry of the current drive to consider the actual driving style of the user; location and time information to adapt the chosen playlists to the driving context. Using a tag-based folksonomy we classify the musical tracks in four categories: *Happy*, *Tender*, *Sad*, *Angry*. Four sets of tracks are fed inside the recommendation module together with the other data and the most convenient playlist is generated and recommended to the user. The rest of the paper is organized as follows: section 2 provides the necessary background about the principal building blocks of the project; section 3 illustrates the design of our project, with the choices we have made for each building block and the motivation behind them; finally, section 4 gives some hints for future extensions of the project.

2 Background

In this section we give insights about the state of the art of the components of this project. First we present some models for mood representation, both for people and songs. We continue providing some relations between mood, music and driving safety. Then we describe what recommender systems are, and identify what contextual data can be utilized by them and how. Finally we give some information about in-car music infotainment systems, where our project of mood-based music recommendations will eventually be deployed.

2.1 Modeling Emotions

There are various definitions of mood in the works of psychiatrists that have relevance to this project. For example, while trying to point out the differences between *Affect*, *Emotion* and *Mood* (which seem to be highly interrelated), the author in [6] provides the following:

– **Affect** - a neurophysiology state consciously accessible as a simple primitive non-reflective feeling most evident in mood and emotion but always available to consciousness;
– **Emotional episode** a complex set of interrelated sub-events concerned with a specific object;
– **Mood** - the appropriate designation for affective states that are about nothing specific or about everything - about the world in general.

Obviously a key difference between Moods and Emotions is the fact that moods usually last longer. What matters from our perspective is to use well-defined models which represent the mood states of a person and the mood categories of songs. One of most used in literature is Russel's planar model [17] shown in Fig. 1.1. This model is based on two dimensions: *Valence* (pleasant-unpleasant) and *Arousal* (aroused-sleepy). Valence represents how much an emotion is perceived as positive or negative whereas Arousal indicates how strongly the emotion is felt. A prominent categorical model for the mood of songs is [8], which uses

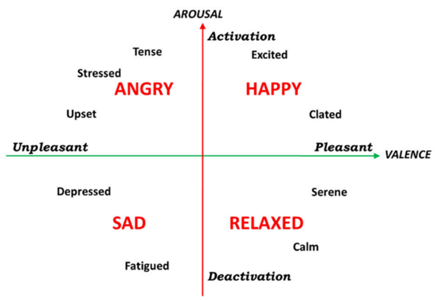

Fig. 1. Circumplex model of mood

Angry	Sad	Tender	Happy
angry	sad	tender	happy
aggressive	bittersweet	soothing	joyous
visceral	sentimental	sleepy	bright
rousing	tragic	tranquil	cheerful
intense	depressing	good natured	happiness
confident	sadness	quiet	Quirky
anger	spooky	calm	gay
exciting	gloomy	serene	amiable
martial	sweet	relax	merry
tense	mysterious	dreamy	rollicking
anxious	mournful	delicate	campy
passionate	poignant	longing	light
quirky	lyrical	spiritual	Silly
wry	miserable	wistful	boisterous
fiery	yearning	relaxed	fun

Fig. 2. Representation of Folksonomy

66 descriptors categorized in 8 groups. A more recent approach we found is a folksonomy with four clusters of social community tags described in [12]. It is the one we use in this project.

2.2 Mood Recognition and Context

Psychologists evaluate the impact of music listening in one's mood using a standard method called Musical Mood Induction Process (MMIP). It consists of replaying mood-eliciting music to research participants. In [23] the authors outline several MMIP techniques for estimating the effects on mood given by music. Some of the most important ones are *Self-reports*, *Behavioral measures* and *Physiological measures*. For this project we base the driver's mood recognition in physiological measures obtained from wearable sensors. The physiological parameters provided by wearables can be combined and used as valuable emotion-related data sources. For example, in [16] the authors present one such system capable of recognizing emotions which is based on heart rate, skin conductivity, and skin temperature. In this project we utilize heart rate dynamics to assess the arousal and valence the driver perceives when listening to the recommended songs. His/Her mood can be considered as a contextual parameter. In context-aware systems research, one of the definitions of context-aware computing is the ability of a mobile user's application to discover and react to changes in the environment (i.e. driver's mood state) they are situated in [20]. Context is defined by different concepts or factors such as time and/or date, weather conditions and user's emotional state.

One approach used to consider the contextual factors in providing recommendations is the multidimensional model which considers dimensions as Cartesian products of some attributes and the recommendation space as Cartesian product of the dimensions [1]. In a music recommender based on mood the dimensions could be ***User*** $\subseteq$ *Uname x Age x Proffession*, ***Item*** $\subseteq$ *SongTitle x Artist x Genre x MoodLabel*, ***Context*** $\subseteq$ *Time x Location*, ***Mood*** $\subseteq$ *DrivingStyle x HeartRate x SkinConductance*. The other side of the coin is to detect or recognize mood categories inside musical tracks. In the literature this problem is addressed using the following approaches:

– **Social Tags** - many tags (such as *passionate*, *autumnal*, *witty*, *cool*) may be useful for mood or genre recognition in songs;
– **Lyrics** - song lyrics can also be used to classify music tracks into mood categories [10, 25];
– **Audio** - audio processing techniques were the earliest employed to recognize mood in music using features like timbre, harmony, register, rhythm;
– **Multimodal** - to attain better predictive accuracy many studies combine the above three approaches in different ways building multi-modal algorithms [9, 26].

There are also several studies which try to shed light on the moods that different structural properties of music induce to people. According to [5] *mode* is the highest important music property followed by *tempo*, *register*, *dynamics*, *articulation* and *timbre*. All these properties of music exhibit certain correlations with mood categories.

2.3 Mood and Driving Style

Several studies show correlations between a driver's mood and his/her behavior while driving: for instance, [7] shows the influence on driving cautiousness given by moods like anger or depression; [22] shows the outcomes of an experiment conducted on drivers in which the sad and relaxed moods were found as connected to a safer driving; conversely, [15] highlights the correlation between an angry mood and an aggressive style of driving. Regulative efforts should take place when the current driver's mood is not safe for driving: [22] shows the effectiveness of changing the mood of the listened songs in doing so and underlines that gradual shifts can obtain such result more efficiently. In general, the actions that can be performed on the driver's mood through music recommendations are:

– **Mood Regulation** - a target desired mood, different from the current one, is set as goal;
– **Mood Maintenance** - the driver is already in a suitable mood, thus actions have to be taken to try to maintain it.

Driving style can be retrieved dynamically gathering telemetrics from the car. To do so, the OBD-II technology can be leveraged, since it provides access to a set of diagnostic information about the car functioning. Recently, a vast assortment of OBD-II adapters (the so-called *dongles*) has been made available in the market. They may provide APIs to mobile applications, so they can telemetrics service and keep track of the driver's behavior. An alternative to the use of OBD-II adaptors, as discussed in [13], is the use of approximations done by the smarphones themselves, leveraging data collected from GPS, accelerometers and gyroscopes. Such measures, however, are vulnerable to external interference and provide little accuracy in short time windows. Once telemetric data are extracted and used to characterize the driver's behavior, they can be used to check whether the playlists recommended by the system have accomplished the objective of making the driving style shift to a safer one.

2.4 On-car Infotainment technology

Lately, a rapid growth and diffusion of on-car infotainment platforms [24] has been witnessed. Car dashboards are now being connected to the Internet and/or integrated with driver's hand held devices, thus enabling finer music listening experiences than just the plain classic radio playback. What follows is a quick overview on some available solutions for the access to music streaming on car:

– *Direct use of the smartphone* - The simplest solution is to connect the smartphone to the car speakers (via AUX or Bluetooth cables), and make use of it to provide the only human-machine interface with which the users will interact. "Auto" versions of renowned streaming music players (e.g., Spotify or Pandora), car-oriented music players accessing playlists stored in the smartphone, as well as prototypes of music recommendation apps [2] are available in the market.
– *Android Auto Integration* - Once a device is connected via a USB cable or bluetooth to a compatible car dashboard, it allows the use of applications installed on it as providers of music playlists to be played from the car speakers. The connectivity of the smartphone can be used to stream playlists. Once connected, the smartphone screen goes black and user interactions are performed with the car dashboard only. Android Auto mandates a common very minimal user interface for all the applications working with it.
– *Proprietary applications installed on dashboards* - Some automakers have signed partnerships with music streaming services provider, thus native streaming applications are installed on their dashboards.
– *Mirrorlink* - It performs a mirroring of compatible applications installed on the smartphone. All human-machine interaction is performed through the car dashboard. The guidelines for the application graphics are really strict, and both the smartphone and the car must be MirrorLink-enabled.

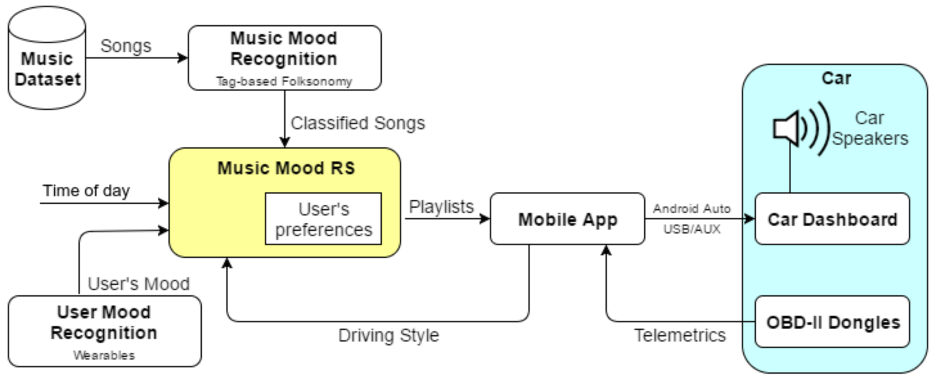

Fig. 3. Schematic view of the system.

3 System Description

The architecture of the system is presented in fig. 1.3. The main module is the Music Mood RS, which is responsible for providing the appropriate playlist of songs recommended for the driver. This module analyzes many data such as driving style patterns, contextual factors, mood labeled musical tracks and driver's mood state. User Mood Detection is the module responsible for providing the driver's mood representation. It takes in mood related physiological data provided by wearable sensors (e.g., heart rate dynamics), computes the *Valence* and *Arousal* values and feeds the driver's mood state in the RS module. The OBD-II module is responsible for providing car telemetry data from which driving style patterns are extracted. Music Mood Recognition module adds mood labels to the musical track the system uses. The Mobile App module is an Android application which shows up the user interface and enables media playback. The application may be used on the smartphone itself or may be integrated with the car-dashboard after having connected the smartphone to it.

3.1 Music Mood Recognition

This module works on the many songs obtained from public music datasets such as last.fm, Yahoo Music Ratings, or Million Song Dataset. These datasets are very important for training and testing purposes and are further described in [3]. We use a classifier that is based on a semantic mood model described in [12]. The model was derived from social tags of songs collected from last.fm music community. It is in consonance with many other existing mood models. The four categories *angry*, *sad*, *tender* and *happy* can be seen as the representative mood categories of each of the four subplanes in the planar model of Russell. Other studies such as [18] also confirm that tag based semantic mood models are effective to predict perceived mood of the songs. The top tags of each category are presented in fig. 1.2.

3.2 User Mood Detection

We use the system presented in [21] to recognize the mood state of the driver. The authors use cardiovascular dynamics (Heart Rate Variability) observations on short-time emotional stimuli. They utilize the images of International affective picture system (IAPS) described in [11] to provoke emotional stimulus and observe the physiological consequences. The emotional model used in their work is the Circumplex Model of Affect (CMA) which is basically the same model we adopt. Using only heartbeat dynamics they effectively distinguish between the two basic levels of both arousal and valence, thus allowing for the assessment of four basic emotions. An important advantage of their framework that has relevance for us is the fact that it is fully personalized and does not require data from a representative population of subjects.

3.3 Driving Style Recognition

To track user's driving style, we have chosen to rely on the OBD-II adapter approach. In particular, we do a simple estimation of the driver's aggression in his/her driving style by calculating the jerkiness of the speed and acceleration profile of the car. To obtain the necessary telemetry data we leverage the *stats* API provided by Dash: the call provides the average speed in a finite time interval so the acceleration can be computed based on two subsequent measurements. A heuristic threshold is utilized to discriminate between calm and aggressive driving style, based on estimations of the jerk (the first-order derivative of acceleration). We consider the thresholds provided by [14], obtained as the average jerk values on a number of drive cycles in typical scenarios. The driving style is tagged *aggressive* if the actual jerk is greater than the threshold correspondent to the scenario where the drive is having place. The derived driving style is computed by the mobile application that is running the player and is then used as a flag inside the recommender to confirm or dissent the mood estimation of the wearables endorsed by the user (since an aggressive driving style is related to a high level of arousal, and in particular to an angry mood). Moreover, the driving style itself is used as a direct proof of the effectiveness of the recommendations, as they are used with the aim of relieving the driver from stress and aggression.

3.4 Music Mood RS

The recommendation module collects the different contextual, user and song data, analyzes them and generates the most appropriate playlist. Time of day is a contextual parameter related to the rate of arousal the driver needs. We assume that during the day there is no need for extra stimulation of the driver. For this reason the default recommended mood category is *tender* which based on the driving literature background (2.3) is the most favorable to a comfortable and safe driving. On the contrary, during a night drive it is usually better to avoid

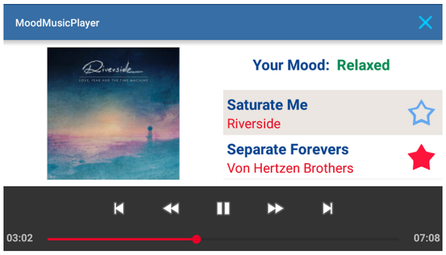

Fig. 4. Mobile Application interface.

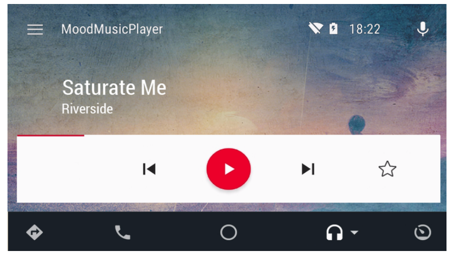

Fig. 5. Android Auto interface.

a sleepy state of mood and keep the driver more alerted, thus recommending *happy* music.

We use the two values (arousal and valence) provided by the wearable sensors to identify the mood category the driver is in. The objective is to keep the driver in a relaxed state of mood by recommending music of his/her tastes. When the user is already in relaxed mood the recommender gives more priority to his/her past musical preferences. The driving style is obtained from the telemetric data of the OBD-II module and provides insights about how safe the car being driven. It falls in two categories, *aggressive* and *non aggressive*. The last data that goes in the recommendation module are the musical tracks which have already been classified in the four mood categories by the tag-based classifier. The recommender considers the contextual data and the user's past preferences to generate the playlist. The driver is free to chose which song to play. If no selection is made the top ranked song is played automatically.

3.5 Mobile App

The main outcome of the project is an Android application providing a music player Service. Since the intended use of the app is inside an in-car environment, we made the application compatible with the Android Auto platform. However, full functionalities are also available if the car dashboard is not compatible to Android Auto. The phone should anyhow be connected via AUX/USB-cable to the car dashboard to enable music playback through the car speakers The mobile app is targeted to Android 5.0 Lollipop and presents a simple landscape interface through which the user can give traditional music playback inputs and express his/her approval about the recommended songs. The application also shows information about the user's estimated mood. The user interface (see fig. 4) is designed to provide minimum distraction to the driver.

The app is compatible with the Android Auto platform for the in-car streaming. To the standard interface, a button allowing to express appreciation for a recommended song has been added. The interface of the application can be seen in fig. 5.

4 Discussion

A great amount of the music streamed from the Internet today is suggested by intelligent recommender systems embedded in popular music portals such as TIMmusic, last.fm or Spotify. We have considered using a music recommender system also in a car environment, using the driver's mood and other contextual data to recommend musical tracks able to adjust the driver's mood for a comfortable and safe drive. In this work we presented the proof of concept of the system and its building blocks. The work is still in progress and we expect to have improvements or module extensions in the near future. We are working to adopt a finer grained mood representation model with more categories. Also the driver's mood recognition can be based on more than just heart rate dynamics (for instance, facial expressions and skin conductance can be additional alternatives) and can take into account external factors, like the speed of the vehicle compared to the speed limits of the road percurred (with a higher speed taken as a consequence of an excited mood, and a lower speed as a possible proof of drowsiness). Moreover, we are experimenting with multi-modal music mood classifiers which consider audio and textual feature of songs for better predictive and recommendation accuracy.

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