# Context-Aware Music Recommender System Based on Automatic Detection of the User's Physical Activity

Alejandra Ospina-Bohórquez, Ana B. Gil-González(✉), María N. Moreno-García, and Ana de Luis-Reboredo

Department of Computer Science and Automation, Science Faculty, University of Salamanca, Plaza de los Caídos. s/n, 37008 Salamanca, Spain
{ale.ospina15,abg,mmg,adeluis}@usal.es

**Abstract.** The large amount of music that can be accessed in streaming nowadays has led to the development of more reliable music recommendation systems. To this end, context-aware music recommendation systems, capable of suggesting music taking into account contextual information, have emerged. Studies have shown that music helps to improve mood while can change the focus of attention of users during the performance of some activity, helping to make this activity more bearable. This work presents a music Context Aware Recommender System in order to motivate users in their daily activities. Its main purpose is to suggest to the user the most appropriate music to improve the performance of the physical activity at recommending time. The conducted experiments along a case study prove that this system is useful and satisfactory when the activity does not require a great deal of concentration. During activities that required movement, most users indicated that the perceived effort decreases when using the recommendation system proposed. They also indicated that their mood had improved after using this system. This demonstrates the usefulness of this recommender system while doing physical activities.

**Keywords:** Context-aware recommender systems · Music · Physical activities · Entrainment · Emotional state

## 1 Introduction

There are studies that show that listening to music improves performance when doing some type of exercise, as well as motivating and distracting users from fatigue [1]. It is impractical to choose these songs that are suitable for listening while doing exercise. In this scenario, the technological solution would be to implement an application with an intelligent an intelligent music recommender system to minimize the effort spent by the user in the search for music customized according his/her activities while minimizing the interaction effort.


Y. Dong et al. (Eds.): DCAI 2020, AISC 1237, pp. 142–151, 2021.
https://doi.org/10.1007/978-3-030-53036-5_15

Recommender systems are designed to provide users with personalized products, being music an important field [2]. In the last years, new recommender systems have emerged taking into account not only the user's tastes but also her/his environment, the so-called Context-Aware Recommender Systems (CARS) [3] as described in more detail in the following sections.

A context-aware music recommender system is proposed in this work, which takes into account the user's activity in order to recommend music that may motivate her/him to continue such activity. To strengthen the knowledge about this proposal a mobile application that detects the posture and movement of listeners has been developed to make music recommendations.

The reminder of this paper is organized as follow: previous research on CARS in music are stated in Sect. 2. Section 3 elaborates the proposal of the physical activity detection, including the recommendation strategy along the data-driven architecture and shows the experimental development while provides some experimental results. Finally, the conclusions are presented in Sect. 4.

## 2 Context-Aware Recommendation Systems in Music

Prior to the recommendation process, a set of ratings given to items by users, are obtained and stored in the matrix $R$ then, this matrix is used by the recommendation method to predict the ratings that the user would give to the items not rated by him/her, and finally the $k$ items with the highest predicted ratings are recommended to the user.

$$R : User \times Item \rightarrow Rating \tag{1}$$

There are different ways to make the recommendation to the user, one of them is just to make a prediction of ratings for a specific item that a user would assign to that item. On the other hand, there are also the *top-N* recommendations, which recommends an ordered list of N items. Classical recommender systems are classified into three categories according to the methods they use: content-based, collaborative filtering and knowledge-based. In many cases, recommendation systems not only analyse users' preferences, but also take into account the context in which they find themselves. With the help of current mobile devices, different personal, social and contextual factors can be integrated into the recommendation process, so that a more appropriate recommendation can be given to a specific user at the right time based on their current activity or some other factor that can be deduced from the data obtained by the device [4]. The importance of incorporating contextual information into these systems, has led to the emergence of Context-Aware Recommender Systems (CARS). This specialisation on recommenders has begun to be studied by extending the dimensional model ($User \times Item$) and proposing a new multidimensional rating function:

$$R : User \times Item \times Context \rightarrow rating \tag{2}$$

They can be classified into three categories according to how they incorporate contextual information. They are explained below:

**Contextual Pre-filtering.** With the pre-filtering approach, contextual information is incorporated before the calculation of recommendations by eliminating data that do not correspond to the context being recommended. Context information is used during the selection and construction of data sets. Ratings are then predicted using the two-dimensional recommender systems for the selected data.

**Contextual Post-filtering.** At these approaches contextual information is ignored when the recommendation is being generated and then the list of recommendations is adjusted in the way that those considered irrelevant for a given context are discarded.

**Contextual Modeling.** The contextual modeling approach is the one that uses contextual information directly in the multidimensional function as part of the prediction of ratings.

There are a big amount of music recommender systems. Nowadays with the increased capabilities of mobile devices and the immediate availability of different types of information on the Web, the opportunities to include additional contextual information has steadily increased [5]. Some approaches are detailed below.

### 2.1 Related Work

In this section, we give a description of some approaches to music recommender systems with context feed, their advantages and limitations.

Greenhalgh *et al.* [6] propose the recommendation of songs (*geotracks*) and playlist (*geolists*) aligned and adapted to specific routes, such as the route to the workplace. Reproduction aspects of *geotracks* and the transition between them may be influenced by the user's progress, activity and context. Geotracks are chosen because they are somehow appropriate for the place where they are to be listened to.

Braunhofer *et al.* [7] proposed a location-based recommendation system. The idea is to recommend music that fits with places of interest. For this, they used tags about emotions that users assigned to both songs and places of interest. With this goal in mind, they developed a mobile application that suggested a route and played the music recommended for each place of interest visited.

Moens *et al.* [8] proposed a musical system called *D-Jogger* that uses the movement of the body to select music dynamically and adapt its tempo to the user's pace. They conducted a pilot experiment that suggested that when most users synchronize the musical tempo and the user's step. In addition, a user questionnaire indicated that participants experienced this as both stimulating and motivating.

Oliver *et al.* [9] proposed a mobile personal system (hardware and software) that users could use during physical activity. The hardware of this system includes a heart rate monitor and acceleration wirelessly connected to the mobile phone that the user would carry. The software allows the user to enter an exercise routine, then help the user achieve the objectives of the routine by constantly monitoring heart rate and movement as well as selecting and playing music with specific characteristics that would guide him to achieve the objectives of the routine.

Sen *et al.* [4] proposed a musician recommender system aimed to recommend to novel music users based on contextual information obtained from sensors.

Based on these works, we have selected four characteristics that summarizes the requirements considered interesting for a music recommendation system on the context of physical activity: minimal user interaction, entrainment (BPM), need for a smartphone only and recommendation during physical exercise.

### 2.2 Adding the Context: Influence of Music on Activity Performance

Establishing contextual information on the use of music will give us the opportunity to develop a tailored and accurate recommendation system. Music as a natural form of expression is fundamental to human beings. Also has been shown music to have a motivational effect that encourages people to exercise more vigorously or for longer periods of time [11].

There are few defining properties of rhythmicity [12]. We point out three of them for the proposal, which are relevant in the task of studying the linkage of music in physical activity. First of this elements is the phenomenon of *entrainment* [8], which talks about how two or more independent rhythmic processes synchronize with each other. For example, during dances in which people perform rhythmic movements in synchrony with the perceived musical pulse or in the case of users who listen to music while performing some activity. It is said that they try to synchronize their activity with the musical tempo, improving the experience.

The second property is the called *Rate of Perceived Exertion scale* (RPE) [13], that recently has been proposed to explain the performance during the exercise. RPE measures the entire range of effort that an individual perceives The RPE scale runs from 0–10. This individual perception is really important, allowing us to implement ways to personalization. It has been noted that some psychological manipulation techniques alter the RPE response during constant exercise.

We ended up with the third and final, the called *Extended parallel process model* (EPPM) [14] which is a model that suggests that when music is listened to during exercise, there is competition from cognitive information, where this information comes from different sources (external conditions, such as music, and internal conditions of the body, such as respiratory rate, ventilation, among others) that compete for attention.

Several works and research suggests that music has very positive effects when you engage in physical activity [9]. Some of these works are referenced below.

Simpson and Karageorghis [15], examined the effect of music on performance during 400-m speed races while controlling mood before the race. Runners who listened to music were shown to perform better during the race. Styns [16] observed that participants in his study walked faster with music than with metronome ticks. In addition to the motivational factor, it is believed that exercises that are repetitive in nature benefit more from music that is synchronized with the rhythm of the exercise movement, with it the endurance of those who exercise can increase and can be exercised with greater intensity when they move in synchrony with the musical stimulus. It has been suggested that the effect of using synchronized music during exercise is because it has the ability to reduce the metabolic cost of exercise by improving neuromuscular or metabolic efficiency [17]. It is a fact that music is directly associated with emotions. Although the field of emotions is quite subjective, different investigations conclude that music influences people's emotional reactions [10]. Music affects mood in a positive way, increases confidence and self-esteem. All these elements analized so far motivate our proposal that we will detail in the following point.

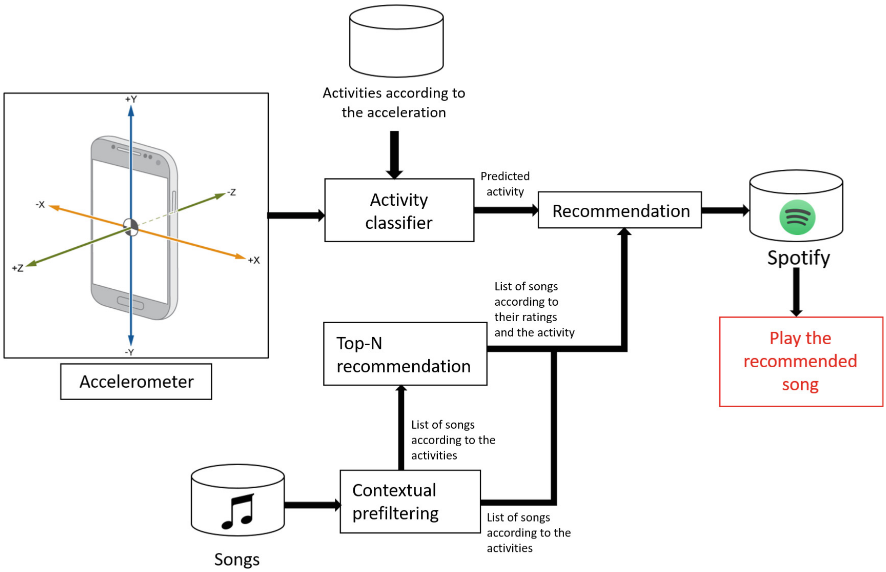


**Fig. 1.** Architecture of the proposed system

## 3 Case Study: CARS in Music Streaming Services

A CARS in music is proposed taken in account the daily activities of the users in order to motivate them to continue with that activity. Different studies indicate that listening to music while doing some type of activity may be beneficial. With this in mind, the proposal is a mobile application that implements a music recommendation system that can predict the user's activity and to make a recommendation while taking into account the user taste. As the idea is to recommend music while the user is doing some activity, it's required the system a low level of interaction. The purpose is to use a data set that relates acceleration data to the physical activities that a user performs based on it. By applying an automatic learning algorithm to this data set, it is possible to obtain as output the activity that the user is performing from the described contextual data. The model obtained will be used within a mobile application where physical activity first will be predicted with the help of this model by giving it as input the values returned by the accelerometer in the mobile phone [18].

It would also be important to recommend songs that had an appropriate BPM, and would also please the user. Therefore, we will also use a data set that contains ratings of the songs where applying a top-N technique. Finally, the song recommended to the user will be played from the Spotify repository. Our proposal, shown at Fig. 1, has all characteristics that were considered desirable in previous studies, detailed in Sect. 2.1.

### 3.1 Classification of Physical Activity

In order to achieve the objective of this system, it is necessary to know the activity that a user is carrying out. This activity can be inferred from the mobile accelerometer that measures the acceleration in the three spatial dimensions.

**Table 1.** Results for automatic learning algorithms

| | Accuracy | Precision | Recall |
|---|---|---|---|
| Nearest centroid | 0.28 | 0,27 | 0,42 |
| Bayesian classifier | 0.23 | 0,235 | 0,51 |
| Multiperceptron neural network | 0.66 | 0,65 | 0,52 |
| Decision tree | 0.98 | 0,99 | 0,98 |
| LTMS neural network | 0.95 | 0,96 | 0,97 |

For the materialization of this application, a data set provided by the laboratory of *Wireless Sensor Data Mining (WISDM)* [19] will be used. This dataset without unknown values, has 1098207 tuples and 6 attributes: *user*, *activity*, *timestamp*, *x-axis*, *y-axis* and *z-axis*. The class attribute in this case would be the activity to be predicted. The attribute *timestamp* indicates the time when the data was taken. On the other hand, *x-axis*, *y-axis* and *z-axis* are attributes that show the accelerations in each of the spatial axes ($x$, $y$ and $z$).

Several algorithms were trained to build the activity classifier Table 1. The results were good for decision Tree and LSTM (Long Short Term Memory) neural network. Due the library *TensorFlow* was used to implementation, LTSM was the algorithm selected to export it to the Android application with a recall of 0.97, a precision of 0.96 and an accuracy of 0.95. This network has cyclic connections between the nodes, this leads to them being able to use their internal states to process input sequences. Table 2 shows the progress during training for LTSM.

**Table 2.** Progress during training

| Epoch | Accuracy | Recall |
|---|---|---|
| 1 | 0,77 | 0,99 |
| 10 | 0,94 | 0,56 |
| 20 | 0,96 | 0,39 |
| 30 | 0,97 | 0,29 |
| 40 | 0,97 | 0,25 |

### 3.2 Classification of the Songs According to the Activity

For the classification of the songs the data-set provided by Gomes *et al.* [20] was used, which relates the songs with a series of attributes. The attributes used were:

- $N$: indicates the numbering of the dataset tuples.
- *artist*: the names of the artists of each song are shown. This will be used to display the names of the artists in the interface.
- *bpm*: indicates the BPM of the songs, that as it has been said before, is the property that will be used to choose the songs based on the activity that the users are carrying out.
- *song_id*: indicates the song identifier in this dataset.
- *image*: this attribute refers to the image that is associated with each song. These images are taken from a Spotify repository; it used to display that image during song playback.
- *preview_url*: this attribute are URLs to fragments of songs also taken from the Spotify repository. These will be the ones that will be played in the application.

For the incorporation of contextual information, prefiltering approach is used. BPM associated with the entrainment is linked to the intensity and rhythm in which an activity is carried out. For this purpose the song data set is divided into different ranges according to the BPM. As many divisions are made as activities are able to predict, as follows: Sitting: 0–80 bpm; Standing: 80–100 bpm; Walking: 100–120 bpm; Downstairs: 120–140 bpm; Upstairs: 140–155 bpm and Run: more than 155 bpm. Based on this, the system play songs with a more intense musical tempo (a higher BPM) when the user is performing activities that require movement (walking, going down and up stairs and running), and it will be higher depending on the intensity of the activity while on activities where user needs relax, concentration or less activity, plays songs with a lower BPM, calmer songs.

### 3.3 Recommendation to the User

The ratings were obtained from the same data-set provided by Gomes *et al.* [20] along the songs associated with. The main attributes used at this procedure where *Song_id*, *Rating* and two new attributes were added to this data set, *Count* and *Mean*:

- *Count*: attribute that indicates the number of times a song has been rated. It was used both to get the average rating and to calculate the top-N table as will be seen below.
- *Mean*: attribute that indicates the average rating of each song. This was used to calculate the top-N table.

Because the ratings are not enough, at this prototype a simple recommender system was made. The Weighted Rating (WR) formula was used to take into account the average of the ratings and the number of votes of the songs:

$$WR = (\frac{v}{v+m} \cdot R) + (\frac{m}{v+m} \cdot C) \tag{3}$$

where $v$ is the number of votes for the songs, $m$ is the minimum number of votes required to be included in the table, $R$ is the average of the song ratings and $C$ is the average of all ratings. Once ratings are computed, the system provides the top-N list of songs.

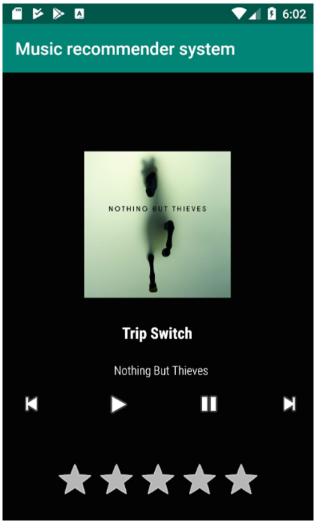


**Fig. 2.** Application interface

The Android application, shown at Fig. 2, obtains data from the smartphone accelerometer, as inputs to the neural network that predicts the activity of the user. Once the classifier shows the user activity as an output, works for song selection. The recommendation is made by choosing the song that is within the top-N list and fits with the activity that has been predicted. Then the song selected is *previewed* and reproduced directly from Internet through the url associated in the dataset.

The simple interface makes possible for the user had the minimum interaction with the system so that she/he didn't have to interrupt his activity. It is based on a well-known music player interface and also includes a way to provide ratings to the songs (using the stars).

### 3.4 User Testing Evaluation

The application was tested with a small number of users at this stage. These users carried out activities with and without the use of the application in order to make a comparison. The RPE model was applied, through which the users were asked to indicate the perceived effort during the activities that required movement (walking, running, climbing and descending stairs). However, for activities that do not require movement, such as sitting or standing, the user was first asked to indicate what he/she was doing while the activity (relaxing or some activity that required concentration). With this in mind, he or she was asked whether they considered that they was able to concentrate or relax adequately on a scale of 1 to 5. Finally, for all cases, we asked about their mood after doing the activity (improved, the same or worsened). The perceived effort rate decreased using the recommendation system in most cases, and the mood improved in the majority of cases. This demonstrates the usefulness of this recommendation system for this type of activities. In the non-moving activities, where the activity carried out required concentration, users indicated that they achieved greater concentration without music. On the other hand, for the activities that had to do with relaxation, user opinion was split. But all those who performed a relaxing activity while using the recommendation system indicated that their mood improved. Based on this, it could be concluded that this recommender system is more suitable for activities that require movement.

## 4 Conclusions and Future Lines

In this paper, we proposed a CARS applied to music recommendation while performing physical activities. The proposal is able to detect the user activity and make the music recommendation according to it. Some parameters are considered, such as RPE, entrainment and PPM in order to contribute to the improvement of the physcical activity. Along the user's activity detection, LSTM type neural network proved to give good results as a classifier of activities, taking into account both the results of its quality metrics and the tests of the experimental study. The case study allowed to demonstrate that the phenomenon of *entrainment* is very useful to link the activities of the users with the music while improving their mood. The research would have to continue to implement the model with another learning algorithm and to extend functionalities. A new method for predicting ratings in order to obtain user implicit feedback. At a higher level, a playlist generation technique could be applied aligned with kinds of activity.

**Acknowledgments.** This research has been supported by the project RTI2018-095390-B-C32 (MCIU/AEI/FEDER, UE).

## References


1. Karageorghis, C.I., Priest, D.L.: Music in the exercise domain: a review and synthesis (Part I). Int. Rev. Sport Exerc. Psychol. **5**(1), 44–66 (2012)
2. Song, Y., Dixon, S., Pearce, M.: A survey of music recommendation systems and future perspectives. In: 9th International Symposium on Computer Music Modeling and Retrieval, vol. 4, pp. 395–410, June 2012
3. Adomavicius, G., Tuzhilin, A.: Context-aware recommender systems. In: Recommender Systems Handbook, pp. 217–253. Springer, Boston (2011)
4. Sen, A., Larson, M.: From sensor to songs: a learning-free novel music recommendation system using contextual sensor data (2015)
5. Bonnin, G., Jannach, D.: Automated generation of music playlists: survey and experiments. ACM Comput. Surv. (CSUR) **47**(2), 1–35 (2015)
6. Greenhalgh, C., Hazzard, A., McGrath, S., Benford, S.: GeoTracks: adpative music for everyday journeys (2016)
7. Braunhofer, M., Kaminskas, M., Ricci, F.: Location-aware music recommendation (2013)
8. Moens, B., Van Noorden, L., Leman, M.: D-Jogger: sycing music with walking (2010)
9. Oliver, N., Kreger-Stickle, L.: Enhancing exercise performance through real-time physiological monitoring and music: a user study (2007)
10. García Vicente, J., Gil, A.B., Reboredo, A.L., Sánchez-Moreno, D., Moreno-García, M.N.: Moodsically. Personal Music Management Tool with Automatic Classification of Emotions (2019)
11. Fang, J., Grunberg, D., Lui, S., Wang, Y.: Development of a music recommendation system for motivating exercise (2017)
12. Priest, D.L., Karageorghis, C.I., Sharp, N.C.: The characteristics and effects of motivational music in exercise settings: the possible influence of gender, age, frequency of attendance, and time of attendance (2004)
13. Lopes-Silva, J.P., Lima-Silva, A.E., Bertuzzi, R., Silva-Cavalcante, M.D.: Influence of music on performance and psychophysiological responses during moderate-intensity exercise preceded by fatigue. Physiol. Behav. **139**, 274–280 (2013)
14. Popova, L.: The extended parallel process model: illuminating the gaps in research. Health Educ. Behav. **39**(4), 455–473 (2012)
15. Simpson, S.D., Karageorghis, C.I.: The effects of synchronous music on 400-m sprint performance. J. Sports Sci. **24**(10), 1095–1102 (2006)
16. Styns, F., van Noorden, L., Moelants, D., Leman, M.: Walking on music. Hum. Mov. Sci. **26**, 769–85 (2007)
17. Van Dyck, E., Moens, B., Buhmann, J., Demey, M., Coorevits, E., Bella, S.D., Leman, M.: Spontaneous entrainment of running cadence to music tempo. Sports Med.-Open **1**(1), 15 (2015)
18. Sassi, I.B., Mellouli, S., Yahia, S.B.: Context-aware recommender systems in mobile environment: on the road of future research. Inf. Syst. **72**, 27–61 (2017)
19. Dash, Y., Kumar, S., Patle, V.K.: A novel data mining scheme for smartphone activity recognition by accelerometer sensor. In: Proceedings of the 4th International Conference on Frontiers in Intelligent Computing: Theory and Applications (FICTA) 2015, pp. 131–140. Springer, New Delhi (2016)
20. Gomes, C., Moreno, M.N., Gil, A.B.: Sistema de Recomendación de Música Sensible al Contexto, pp. 65–80. Avances en Informática y Automática, Duodécimo Workshop (2018)