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Review

Mobile music recommendations for runners based on location and emotions: The DJ-Running system

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ABSTRACT

Music can produce a positive effect in runners' motivation and performance. Nevertheless, these effects vary depending on the user's location, the emotions that she/he feels at each moment or the type of training session. In this paper, a context and emotion-aware system for the recommendation and playing of *Spotify* songs is presented. It consists in a location-based mobile application that interacts with a novel emotional wearable and a recommendation service that predicts the next song to be recommended. These predictions are performed by an intelligent system that combines artificial intelligent techniques with geodata and emotionally-annotated music. A wide variety of location-based services and music services available in Internet have been integrated into the recommender in order to support the decision-making process in a real environment. The final solution has been customized to be tested in the city of Zaragoza.

Contents

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1. Introduction

Many people listen to music while running. Different studies conclude that music has a motivational effect and can help to mitigate the fatigue and to improve the runners' performance [1,2]. The advances in mobile devices and the proliferation of music streaming services have favoured that runners can listen to live music broadcast by Web radios or playlists based on their musical preferences. Obviously, playing songs without considering the runner's context or the particularities of training reduces the benefits that could be obtained through the music. *Context-aware music recommendation systems* arise as an interesting solution to the above problem by predicting dynamically the next song to be played based on different variables, for example, location [3–7], time [4,8,9], weather [8,10], physiological state [11,12] or physical activities [11,13–15], among others. These systems consider the physical user location, however they do not take all advantages of other important information related to the users' environment and the effects that it can generate in the users.

The features of the natural environment in which the user is running have influence on her/his affective state and, therefore, on the results of the training [16,17]. The combination of user's location and emotions in the domain of outdoor sports is a complex problem and still presents a wide range of open challenges, such as the precise characterization of the environment in which the user runs, the time-varying emotion detection when the user is in motion, the intelligent interpretation of those emotions considering the user's context at each moment, and the personalization of recommendations according to the runner's profile and the type of training session, among others. But, additionally to these challenges, the emotions generated by the music to users must be also considered, and these can vary depending on what she/he feels at each moment or what happens around her/him.

DJ-Running is a research project which goal is to address some of the above challenges in order to develop a new generation of context and emotion-aware mobile applications for runners. As discussed in [18,19], the emotions are a factor that can be considered as part of the user's context. Nevertheless, in our approach, context and emotions are two first-level elements involved into the system's operation and, therefore, these two issues are treated separately. At the beginning of the project, the efforts were concentrated on building an emotional wearable for runners [20] and on developing a Music Emotion Recognition system (MER) able to annotate the songs available in the *Spotify* streaming service [21]. The wearable integrates a set of physiological sensors that monitor to the runner during the physical activity. The sensor data are sent periodically to the runner's mobile phone and, then, locally processed by an emotion interpretation system for determining the user's emotion in real time. On the other hand, the MER consists of a set of machine learning models that annotate emotionally the songs. Unlike others existing approaches, these annotations express what the user feels when listens to a song instead of the emotion associated to the intrinsic characteristics of that song. *Spotify* users' playlists and the emotional descriptions associated with these playlists have been used to determine the users' feelings, and from these to build and train the machine learning models. Then, the recognition process is carried out automatically and without user intervention, making possible the annotation of large-size music datasets from the user's emotional perspective. Therefore, the device helps to detect what the runner is feeling at that moment (for example, as result of the activity or depending on her/his context) and the annotated songs are used to provoke a particular emotion to the runner. These two affective dimensions have a relevant role in the technological framework of the project and, specifically, in the system described in this paper.

In this paper, we present a novel location-based system that consists of (1) a mobile application that interacts with the emotional wearable and plays music from the *Spotify* streaming service, (2) a music recommendation service based on geographic knowledge, emotions and personalized training plans for runners, and (3) a software infrastructure of geographic services and data providers that supports the decision components integrated into the system. The main contributions of the system with respect to the existing approaches are:

- it consists of a complex result of engineering that combines people, mobile computing, intelligent systems, music recommendations algorithms, service-oriented architectures and geographic information systems,
- the runner's location is not directly applied for making the recommendation, but for deducing what she/he is feeling depending on her/his current location,
- a multimodal approach is used to detect the variations of the runner's emotions during the training sessions in order to improve the music recommendations in real time,
- and, finally, the resulting system has been adapted to be deployed in a real environment (in the city of Zaragoza).

The rest of the paper is structured as follows. Section 2 reviews the music recommendation systems based on users' location and/or emotions paying attention in the existing solutions in the domain of sports. Then, the mobile application is presented in Section 3. The architecture of the recommendation system is detailed in Section 4 and the process of predicting the next song to be recommended in Section 5. Section 6 describes the real deployment of the system. And, finally, Section 7 discusses the main conclusions obtained and the future work.

2. Related works

In this section the most relevant music recommendation approaches based on the user's location and/or emotions are presented, especially those that are applied in the domain of sports.

2.1. Music recommendation based on location

The environment in which the user is located can condition her/his predisposition to do certain types of physical activities (running, bicycling, hiking, etc.), as was studied in [22–24]. These works focus on analysing how the landscape or the orography (understood as the variations in the elevation profile of terrain and the speed with which these variations happen) affect the selection of the area to do sport. Despite the interest of these two variables, many other geographic factors could be taken into account in order to characterize the environment perceived by the user. This characterization is interesting to take other type of decisions, for example, to play music according to the user's location and the environment that surrounds her/him.

Many proposals have applied music recommendation techniques in indoor environments with different purposes, like improving the user's experience [25] or modifying the user's shopping behaviour [26]. Nevertheless, these differ widely from outdoor techniques. In general, these outdoor solutions determine the user's location using the GPS system integrated into her/his mobile phone and translate this position (low-level geographic data) to a concrete geographic area [3,27], a ZIP code [28] or a place [7,29] (high-level data). Then, these high-level data are used to do the music recommendations. Exceptionally, in [7,29] the geographic perspective is combined implicitly with the type of activity that the user can be doing. Places are represented by labels (such as home, office, store, library or gym, among others), and the semantics of these labels provides certain information about whether the user is relaxing, moving or doing sport, for example. The systems proposed use this extra information for improving their recommendations.

On the other hand, other music recommendation proposals obtain the user's location applying alternative methods, like processing the listening events posted in social networks [30,31]. These events are analysed for determining the music listened to in the different places, and then for categorizing of music preferences according to the users' location. These preferences are used as a decision variable in the music recommendation process.

Therefore, the existing approaches are based on the user's location, instead of considering the characteristics of the environment where the user is or what the user feels in that environment.

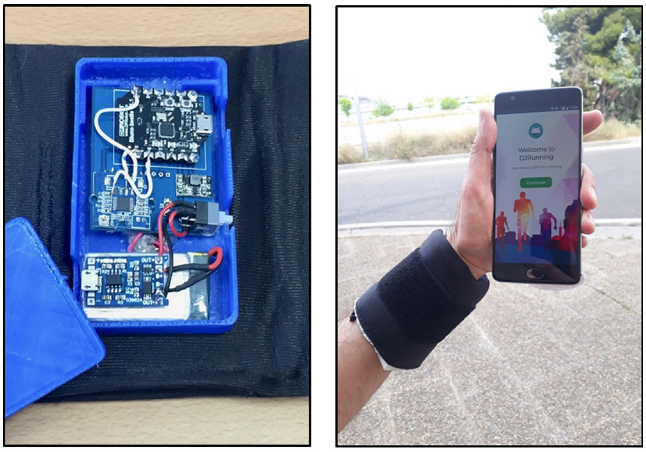
2.2. Music recommendation based on emotions

Due to the important and proven relationship between the music and users' affective states, emotion-based models have been considered in order to improve the quality of the music recommendation systems [32,33]. In these methods, the system recommends music taking into account the user's mood. The emotions perceived by the listeners are registered by self-report measurements [4] or, mainly, by physiological measurements [34]. Artificial intelligence methods are applied to detect and recognize the emotions induced by the music through intrinsic music features [35]. And, in many works, music is stored in databases that are emotionally classified according to the user's perception or to low level acoustic features of the song. In this way, it is possible to search for music that can provoke a particular emotion in order to achieve an specific goal [36].

Personalized music recommendation systems that infer the affective state of the listener have been used for mood's regulation, for improving mood [37] or for reaching an affective goal state [38,39]. In these cases, the selection of the music is carried out only by analysing the physiological response. Other works, instead, focus on analysing the low level acoustic features of the music to detect and classify the emotion that produces in order to create emotional music databases [35]. The music stored is used for selecting songs that match to a specific emotional state [15] or that enhance learning performance in response to user's heart rate variability (HRV) [40]. Finally, in recent works, the recommendation system uses content-based music search engine, while users' emotions are detected and classified from different physiological sensors [12]. However, there are some music recommendation systems that not only consider emotions, but also information about the user profile and the user's listening history [33,41].

Following, emotional music recommendation systems that consider information related with the user's location, are briefly described.

[4] describes a system that recommends the most appropriate music according to the listener's current emotional state in order to reach a desired emotional state. The details about the initial and the goal emotion are provided directly by the user (by self-reporting). This work uses location information (home, job place, market, etc.), also provided by the user, as part of the modelling process for the transition between emotions. Other proposals select the music that best fits a Point Of Interest (POIs) [5,6]. These solutions involve the users in the emotional annotation of songs and of points. Then, a mobile application suggests an itinerary and plays recommended music for each visited POIs. The recommendation process is based on the use of similarity metrics establish a match between the emotions that the user feels when listens to a song and when visits a POI. On the other hand, an application for generating playlists according to the user's context is presented in [42]. At the beginning, the application selects the songs considering the user's location and the weather conditions. These contextual factors are tracked during the playing and, if a change is detected, the application is able



(a) (b)

Fig. 1. The emotional wearable for runners.

to modify the songs included in the playlist in order to improve the user's experience. The users' listening behaviour is recorded and used for filtering the future recommendations.

Despite the advances in music and affective recommender systems, most of the works detect the listeners' emotions through physiological sensors while they are not in motion. Moreover, most of the approaches ignore the variation of listeners' emotions along time and do not recommend music that dynamically adequate to their emotions.

2.3. Music recommendation for sports

Most of the music recommendation systems previously commented are multipurpose [12,15,41]. In this section, music systems specifically developed for motivating physical activity are presented.

There are many music recommendation systems aimed at increasing the motivation and performance while doing physical exercises. IM4Sports is one of the first personalized system that recommends music that suits the user's training programme, based on the music that the user has previously selected for an exercise and the music's tempo [13]. Also, PersonalSoundtrack [14] and TripleBeat [11] are music players developed for runners that relates the user's running pace, detected by his/her heart rate, with the tempo of the music. More recently, [43] presents the application requirements needed to increase runners' motivation and control training, based on heart rate monitoring and using the music for regulating the runners pace. [44], instead, proposed a system to motivate sedentary people to do physical activity, including the user's profile for initial recommendations and considering user interactions and aggregated profiles of group of users to improve the recommendations. All these works consider the motivational effects of the music, and, although the affective state of the user is mentioned in some of them, not one takes into account the emotions felt by the users. They are focused on considering only the user's heart rate to select music with a specific tempo (beats per minute), in order to slow down or speed up the user's performance. Moreover, in these systems other context information is not considered.

However, there are some works that include contextual information, such as [9]. In this work a personalized music playlist is generated considering time, activity doing in the mobile phone, physical activity and user's emotion. Unfortunately, in this case, the emotion is detected through voice and facial expressions, making it almost impossible to use this system for doing sports (although running is included as a possible physical activity).

3. The ***DJ-running*** mobile application

The mobile application plays personalized music considering the runner emotions and the environment in which she/he is running. It interacts with three external systems: an emotional wearable for runners designed as a part of the project, a *music recommendation service* and the *Spotify* streaming service. The wearable integrates a set of sensors to measure different physiological parameters of the runner in order to detect her/his affective changes. The recommendation service determines the next song to be played at each moment, considering a set of contextual factors that will be later described. And, finally, the *Spotify* streaming service is used for playing remotely the recommended songs.

Before describing the application, the wearable built for recognizing the runner's emotions is briefly presented (a more detailed description is available in [20]). Fig. 1-a shows the wearable's hardware components. It integrates three sensors usually used for recognizing emotions in the field of affecting computing [45]: a Galvanic Skin Response (GSR) sensor that measures the electrical conductivity of the skin, an oxygen saturation sensor and a pulse sensor. These sensors

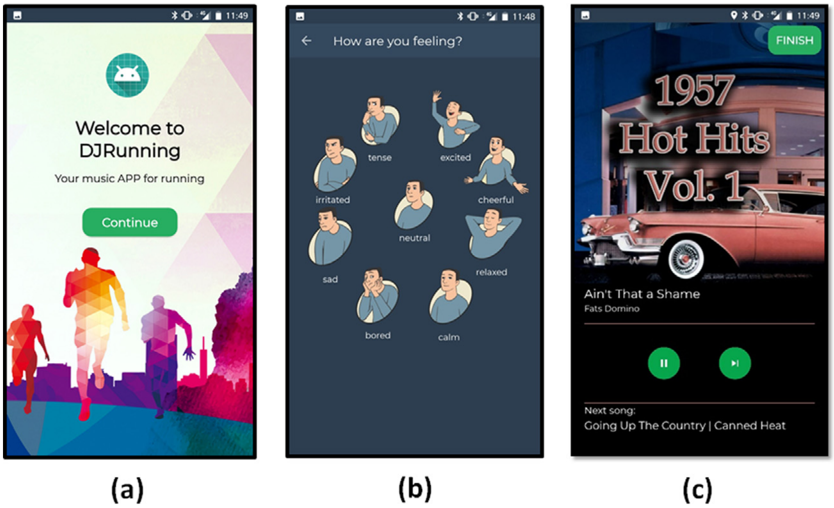


Fig. 2. Interface of the DJ-Running application.

communicate with an Arduino microprocessor that incorporates a Bluno Beetle BLE board for sending the information to the mobile application through a Bluetooth Low Energy (BLE) protocol. The wearable is powered by a rechargeable LiPo battery. On the other hand, Fig. 1-b presents the wearable's design. It is a wristband made of flexible textile material that incorporates an inner box in which the electronic components have been encapsulated. Its design is lightweight in order to be comfortable for runners during their training sessions.

Regarding the use of the application, at the beginning, the runner must sign-up in the *DJ-Running User Profile* service and complete her/his profile. The user profile includes the type of runner (beginner, half-marathon and marathon runner), anthropometric characteristics (measurements of the size, shape and composition of the user's body), demographic data and musical preferences. Currently, the musical preferences consist basically of the genres the user likes and dislikes. Once completed the sign-up, the service generates a user's unique credentials that are required jointly with a *Spotify* premium licence during the installation of the application. Once finished the installation, the application is ready to be used during the training sessions.

Fig. 2-a shows the initial application screen. The application offers different training plans for each type of runner (beginner, half-marathon and marathon runner). A plan consists of a set of training sessions that have been created by running coaches in order to achieve a target performance (for example, to run a half-marathon in 1:30h). Three different types of training sessions are currently supported by the application: easy run, fartlek, and split intervals. Before starting to run, the runner must select a training session of the plan she/he is following. Besides, she/he must also introduce her/his emotional state at that moment (happy, relax, stressed, etc.). Each type of training consists of a different sequence of exercises and, therefore, requires different music recommendations for improving the runner's motivation and/or performance. On the other hand, the screen in which the runner is asked about the emotional state is presented in 2-b, and it is based in the "Pick-A-Mood" (PAM) model [46], a cartoon-based pictorial instrument for reporting moods. This model classifies the possible user's emotional states according to the reference model of affect proposed by Russell [47]. Optionally, the mobile application can be executed without being connected to the emotional wearable. In that case, the runner's affective response will not be taken into account for doing the recommendations. After this initial configuration stage, the application starts to play music provided by the recommendation service, as shown in Fig. 2-c.

The decision about which song must be played at each moment involves three different types of input parameters. Some of these parameters were defined as part of the runner's profile, and there are shown in the left part of Fig. 3. Others are introduced by the runner before starting the training session (upper side of Fig. 3), while the last ones are automatically recorded by the mobile application during the sport activity (specifically, runner location, heart rate and the changes experienced in her/his emotional state) and used for requesting the next song to the recommendation system (see bottom right of Fig. 3). Some of these latter parameters (the physiological and emotional parameters) are obtained through the wearable designed for runners.

The recommendation service works with the *Spotify*'s catalogue of songs. Currently, *Spotify* is the most popular online music provider with more than 30 million songs and 90 million of subscribers. The decision of integrating the *Spotify* data and streaming services in the system has as objective to build an attractive final product which has available a wide and updated variety of songs.

The application also allows the runner to stop the player or to skip the song that is being played. This last action is reported to the system for improving future recommendations. Finally, when the runner ends the training session, the application shows in a Google Maps map the route followed and a summary of the session activity.

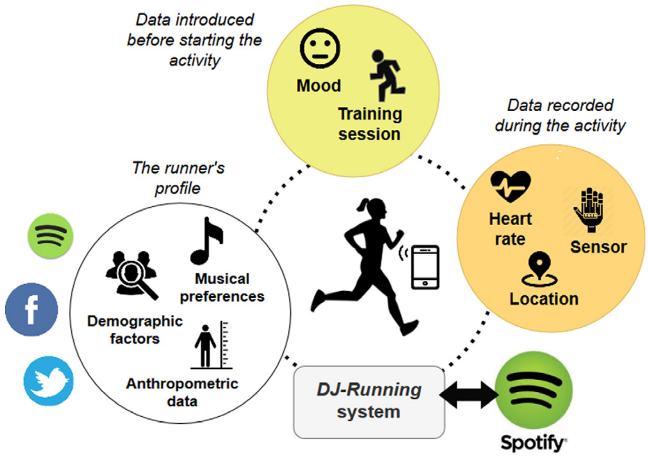


Fig. 3. Factors related to the user's context.

4. Architecture of the music recommendation system

The system has been designed and implemented according to the principles of the *multi-tier architecture* [48,49]. It makes easier the logical and physical decomposition in different tiers of the data management, processing and presentation functionality. These tiers are hosted on several machines or servers, maximizing resources' utilization and taking advantage of a distributed deployment (scalability, availability and manageability, for example). This architecture is compatible with the *service-oriented computing* paradigm [50] and, therefore, it is usual that a tier is composed of a set of net-accessible services.

In particular, the system programmed has been divided in four tiers [51]: the *application tier*, the *business tier*, the *processed data tier* and, finally, the *data provider tier*. The first contains the DJ-Running application, and the second consists of the recommendation service in which the decision and personalization systems are integrated. The last two tiers are composed of the services responsible for getting access and processing the system's data. The decision of dividing the data functionality in two different tiers determines the frontier between the DJ-Running data services and the external services, and is justified by the following three reasons. Firstly, we consider necessary to decouple the services involved in the generation of aggregated and processed data (third tier) from the external providers that offer the raw data (fourth tier). This decoupling allows to hide providers' particularities and to facilitate the maintainability (like change of providers or integration of new providers) and the redundancy of sources that offer the same data. Secondly, the processed data tier's services integrate time-consuming processes and store large-size collections of aggregated data. Therefore, the use of dedicated resources for the execution of these services improves the system's performance. And, finally, the processed data tier's services are reusable and can be integrated into different systems/services that use geographic information or music annotated emotionally (not only into the recommendation service presented in the paper).

In the following subsections the high-level design of the application, the recommendation service and the back-end of data services is presented.

4.1. High-level design of the mobile application

The high-level architecture of the mobile application (application tier) is represented at the top of Fig. 4. Before the training begins, the application registers the type of training that the runner is going to do in the user profile service. From that moment on, the application interacts with the recommendation service (business tier) for requesting the next songs to be played. In order to simplify the interaction protocol between both components, the application stores locally data related to the training session in process (the *Session data*), specifically, the user identifier, the route of the runner, the session's listening history, the skipped songs and the runner's affective changes. This design decision facilitates that the recommendation requests are independent of each other, and the communication can be programmed as a request–response interaction. As it is represented in the figure, each request contains three input parameters: the runner identifier, her/his current location and the affective state. The service response consists of the *Spotify* identifiers of the songs that are recommended (by default, three recommendations are returned).

Internally, the mobile application integrates a music player able to connect with the *Spotify* streaming service and to play the recommended songs. A buffer of pending songs stores the next songs to be played, specifically, their *Spotify* identifiers. When the buffer is almost empty, the application sends a new request to the recommendation service, specifying the runner's current location and emotional state. These parameters are determined from the phone's GPS and the *Sensor emotion recognition* system integrated into the application. The emotion recognition system is connected

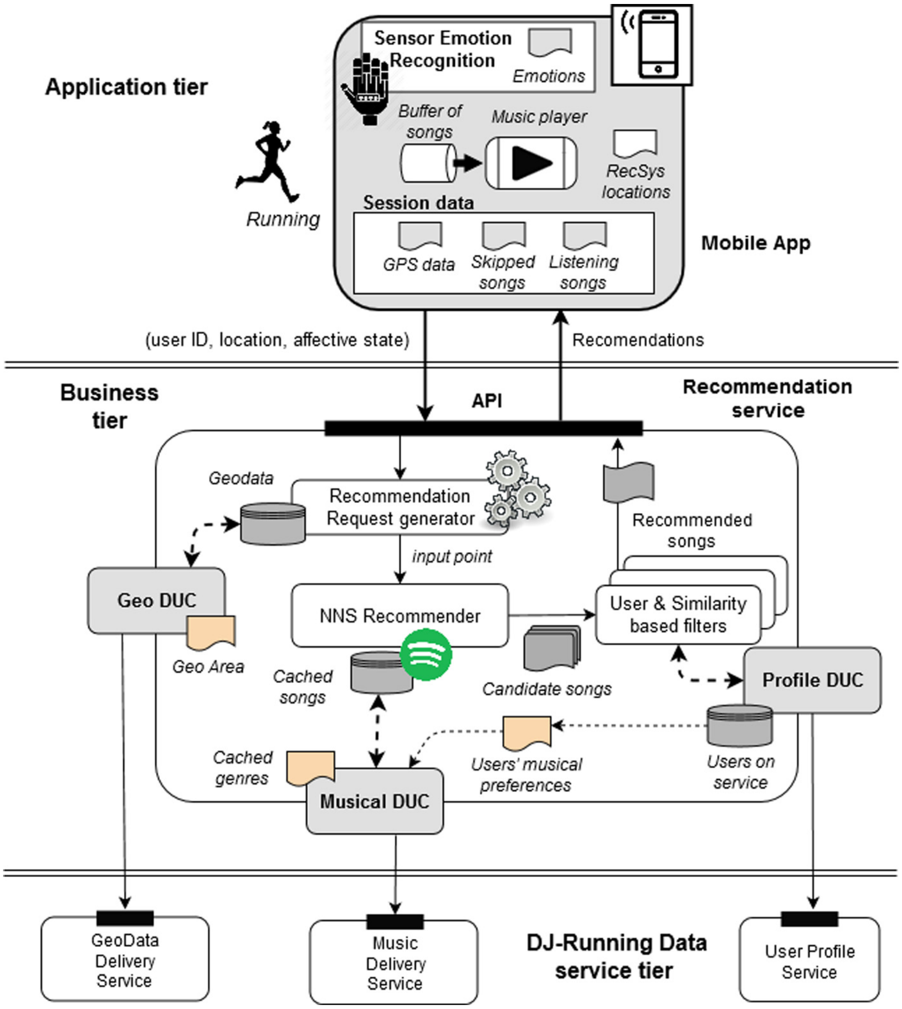


Fig. 4. Design of the application and business tiers.

with the emotional wearable device that the runner wears and detects her/his affective changes during the physical activity [20]. The recognition begins with the preprocessing of the runner's physiological data and the extraction of features of interest. Then, a set of machine-learning models are applied for analysing the runner's affective response and determining her/his emotions. These models are based on affective patterns defined from sensor data. The decision of integrating the recognition system into the mobile application guarantees the privacy of user's data and avoids the unnecessary transfer of low-level physiological data by reducing the network traffic flow.

On the other hand, the session data are periodically stored in local files and used for different purposes during the training, for example: the GPS route (to be shown on a *Google* map at the end of the session), and the listening songs and the skipped songs (to filter the recommendations that were already played during the session).

4.2. Components of the recommendation service

Fig. 4 shows the components of the recommendation service (business tier). When the service receives a new request, it processes the input parameters, executes a recommendation algorithm and applies a set of filters for deciding the songs to recommend. The components responsible for executing these three tasks are the *Recommendation Request generator*, the *NSS Recommender* and the *Personal and Social filters*, respectively. These components need to access to geodata, to the emotionally annotated songs and to the runners' profiles for completing these tasks. These data are stored in different caches that are periodically updated by the corresponding *Data Updating Components* (DUC) invoking the infrastructure's services.

The *recommender* is the core component of the service. Its implementation is based on a *Nearest Neighbour Search* algorithm (NNS). This class of algorithms solve the problem of finding the point in a given set that is closest (or most similar) to a given point. Formally, they are defined from a set of points in a *space M* and a *metric distance* that allows to determine the similarity (or dissimilarity) between these points. In our proposal, each *Spotify* song has been translated to a point of the *space M*. The translation function is based on songs' acoustic characteristics, and a point is represented as a vector of 12 audio features. When working with NNS algorithms is very important to consider the dimension of points (the number of features) and the size of the search space because both have a significant impact in the execution time and resources' utilization (memory and computing resources) [52,53]. In the presented solution, the points have a low dimension (12 features), but the space has a large size (more than 30 million of points, a point for each song available in *Spotify*). In these cases, *Approximate Nearest Neighbour Search* algorithms (A-NNS) are helpful to obtain efficient solutions [54,55], returning neighbours that are an approximation of the true nearest neighbours.

Different A-NNS algorithms have been used for music recommendation [56–58]. Although there is no systematic comparison between all the existing algorithms, we have selected the *Annoy* algorithm [59] due to: it optimizes the memory requirements applying tree-based techniques and reduces the search time by partitioning the space and using tree-based indexes [53]; it provides a good performance and recall in comparison with other A-NNS algorithms [55]; it is able to scale efficiently when the space's size grows [53]; and, finally, it is being used by *Spotify* for making music predictions [58]. Finally, after evaluating different metrics using the benchmarking framework provided by [55], we have decided the use of the *angular distance* as similarity measurement in our implementation of *Annoy*.

On the other hand, the *Recommendation Request generator* is responsible for processing the input parameters of each service request and translating them to a point in the search space. It represents the kind of songs to be recommended as response to that request. This point is called *search point*. In Section 5 the process for calculating this point is detailed.

Finally, the *filters* are responsible for scoring and ranking the returned songs by the recommender in order to personalize the final recommendations. Two kind of filters have been implemented: *user-based filter* and *similarity-based filter*. The former scores each of the recommended songs with a value of interest according to the runner's preferred music genres, that had been introduced by the user during the sign-up. The second searches for users that are similar to the target runner based on similarity of recommendation histories, and, applies collaborative filtering techniques for refining the songs' values of interest. This collaborative filter works with the user-genre matrix, that describes the runner' recommendation ratings according to music genres. These ratings are calculated from recommendations made during the runner's training sessions. The filter computes the cosine distance for measuring the similarity between users, and a nearest neighbour search for finding the most similar users to the target runner. The ratings of these users are subsequently used for refining the songs' values of interest. Finally, the result of applying these filters is a ranked list of recommended songs. The three best ranked songs are returned as response to the recommendation request.

4.3. Data services for supporting the music recommendations

As part of the *DJ-Running* project, we have previously programmed a set of Web services that provide functionality for registering users in the system, storing runners' profiles, managing large-size music databases from an emotional perspective, and providing access to geodata [60]. These services constitute the processed data tier. In this subsection, we will focus on those services involved in the delivery and process of geodata that are used in the music recommendations.

At the top of Fig. 5, different instances of the music recommendation service are represented (business tier). During the system execution each recommender will be periodically interacting with the *DJ-Running* services for updating the geodata stored in its cache. These updates are executed by the recommendation systems' data updating components (*Geo DUC components*). Each updating request contains a bounding box that determines the geographic area of interest, among other parameters. These areas depend on runners' location that are being served for each particular recommendation service.

The *Geodata Delivery Service* responds to the geodata requests sent by the different updating components. Internally, this service integrates two different databases. The first stores geographic information that describes the environment in which the users usually run. These data are represented as vector data (points, lines, and polygons that represent geographic objects and their attributes) or raster data (two-dimensional matrix of cells where each cell contains a value representing information). The data stored are as follows:

- the type of landscape, polygons that are labelled using an enumerated type (parks, gardens, water areas, open spaces, building blocks, etc.)
- the class of soil, polygons that are labelled using an enumerated type (pavement, land, sand, etc.)
- the altitude, raster data where each cell's value is the average elevation above sea level of that area; and the slope, raster data that is calculated from the altitude values for certain routes of interest. The resolution of both data depends on the geographic resources available for each working area.

These data are static and require infrequent updating. The second database stores dynamic information related to the weather, the air quality or the noise pollution that affects the previous geographic areas. These data are represented as vector data (based on polygons) and their attributes are:

- Weather data: the overall conditions (an enumerated type), the temperature (in degrees Celsius), the humidity percentage (based on a 100% scale), the probability of precipitations (a 100% scale), the rainfall intensity (millimetres per hour) and the wind speed (kph, kilometres per hour).

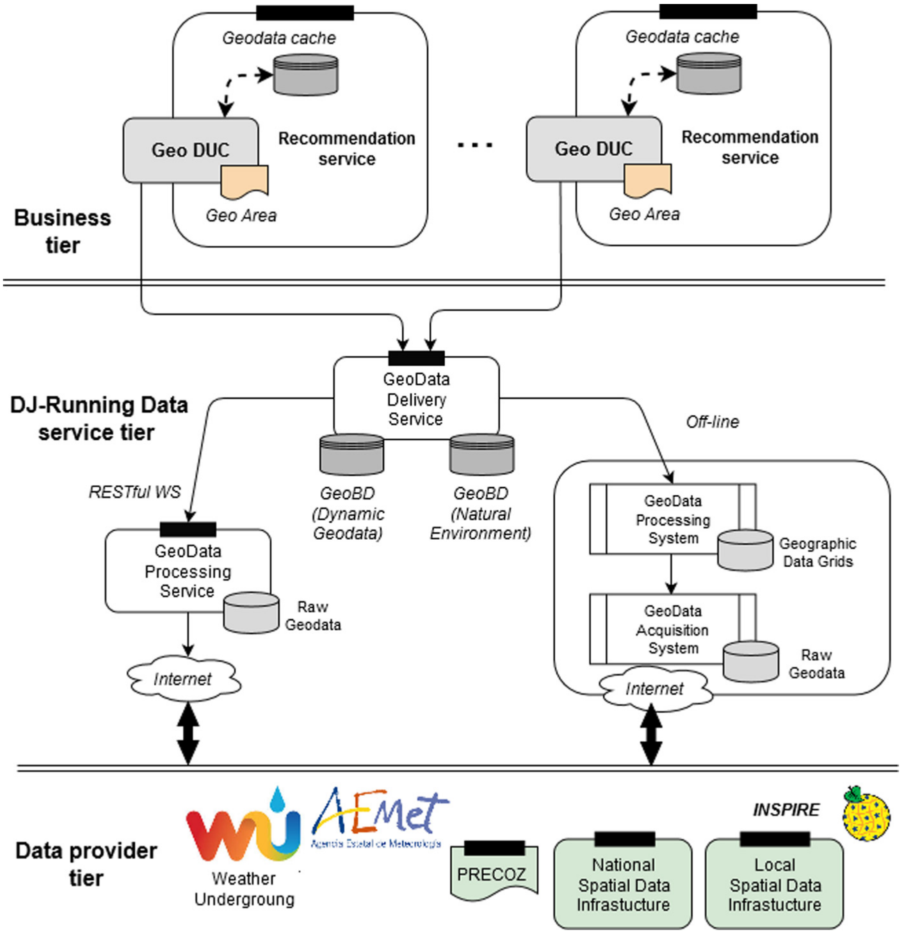


Fig. 5. Architecture of geographic services and processes.

- Air quality: the overall conditions (an enumerated type) and a list of contaminants, such as, O_3, SO_2, CO, CO_2, NO_2, SH_2 and PM10 (ug/m^3, micrograms per cubic metre of air).
- Noise pollution: the sound level and the traffic noise level (dB, decibels).

Obviously, these data change along the time and require a continuous updating. As it is shown at the bottom of Fig. 5, the delivery service's back-end is composed by a set of acquisition and processing systems of geodata that create and update the two previous databases. This back-end is responsible for interacting with data providers (data provider tier) integrated into the *DJ-Running* data infrastructure. On the one hand, an offline system has been programmed to connect with different spatial data infrastructures and geodata repositories for generating the datasets that describe the environment. Despite efforts of the standardization initiatives, such as the *INSPIRE* directive (https://inspire.ec.europa.eu/) and the *Open Geospatial Consortium* (https://www.opengeospatial.org/), and the open geodata policies promoted by international and national geographic agencies, the involved processes are highly complex, compute- and data-intensive, and require user intervention. Additionally, a RESTful Web service has been programmed for interacting with providers of weather data (such as, the *Weather Underground* API or the *State Meteorological Agency* of the Govern of Spain) and with the air quality and pollution monitoring systems available in most of the medium and large sized cities. The service acts as an intermediary that retrieves periodically information of different providers and, then, updates on demand the geodata delivery service's database.

Finally, different data providers must be integrated depending on the geographic area in which the music recommendation service is deployed, as is shown in Section 6 for the case of the city of Zaragoza (Spain). Nevertheless, the geodata processing systems developed as part of the work have been designed for being reused. An integration layer encapsulates the interoperability issues involved in the providers' integration needed for each particular scenario.

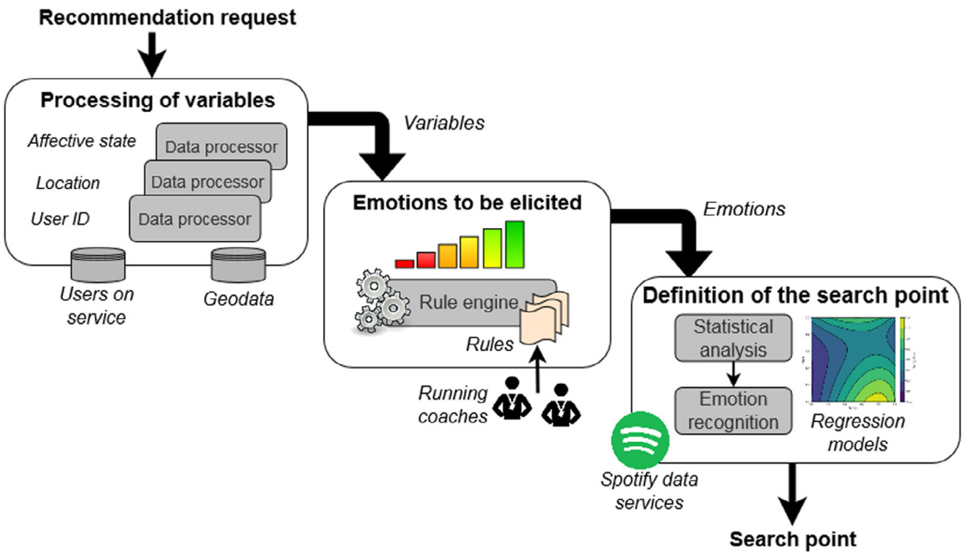


Fig. 6. Process for determining the songs to be recommended.

5. Prediction of the next song based on the runner's context and emotions

As it was described in the previous section, the *Recommendation Request generator* component determines the kind of songs to be recommended (specifically, the *search point* in terminology of recommendation algorithms) from the input parameters contained in each service request. Fig. 6 shows the steps involved in this process. First, the input parameters are processed for obtaining a set of variables that describe the environment in which the user is running and what she/he is feeling. Three different data processors determine the value of these variables. Then, the variables are interpreted by a rule engine for deciding the emotion to induce to the runner through the music at that moment. And, finally, that emotion is translated to a search point that consists of a vector of audio features.

Following, the variables involved in the prediction process and the three steps for determining the search point are detailed.

5.1. Selection and processing of variables of interest

Before implementing the prediction process presented in Fig. 6, it was needed to select the set of variables of interest. Three kinds of variables have been considered: the contextual variables based on the user's location, the emotional variables and the runner model variables. The first describe the characteristics and conditions of the environment in which the user is running. This description can be complex and involve a wide variety of variables. For this reason, as part of the work, we have organized *discussion groups* with runners and published a *Web-accessible survey* for discovering the contextual variables that can affect runners' motivation and performance. On the other hand, the emotional variables describe the affective state of the runner at that moment and the evolution of this state during the training session. And, finally, the runner model variables determine the user's demographic profile, her/his musical preferences and the type of runner.

Firstly, the activities organized for the discovery and the selection of contextual variables are briefly explained. Two discussion groups with runners were done [61]. The first involved 7 runners with some technological background (mainly professors at the engineering school). At the beginning, we asked them about what characteristics and conditions of the environment could affect to the success of their training sessions, and they proposed individually a set of variables. In a second round, they discussed their proposals and agreed on a common set of variables of interest. Besides, they classified them in two types: static variables (do not change during the training) and dynamic variables (can change during the training). Then, the runners prioritized them considering the influence that have on their training sessions. The second discussion group followed the same process, but in this case there were involved 25 runners, with a heterogeneous profile. In both cases, the set of variables was very similar: the type of landscape, the variation of the landscape, the type of soil, the orography (the altitude and the slope, mainly), the weather, the pollution, the noise, and the presence of people.

In a second phase, we used the previous conclusions for publishing a Web questionnaire in order to collect more runners' opinions. It was answered by about 500 runners in the area of Zaragoza (Spain). The questionnaire also enquired into the influence of two concrete issues: the type of soil and the weather conditions. Regarding with the first one, it was considered relevant to take into account the preference of the runner regarding the hardness or softness of the soil. In the same way, on relation to the weather it was considered relevant to offer the possibility of choosing among preferences in running with light/moderate/heavy rain, light/moderate wind, and cold/hot/very hot temperatures. These answers were finally used for deciding the set of contextual variables to be integrate into the system: the type of landscape, the type of soil (according with its hardness/softness), the altitude and the slope, the weather (temperature, humidity, probability of precipitations and rainfall intensity, and wind speed), the air quality and the noise pollution. A detailed description of results obtained in the discussion groups and in the questionnaire can be found online as supplementary material related to this paper.

With respect the emotional variables the current version of the system only considers the emotion that the runner is feeling at each moment. This emotion is determined from the user's affective state which is an input parameter. In our proposal, the emotions are represented based on the Russell's circumplex model [47], one of the most popular dimensional models and widely used in affective computing. On the other hand, the user profile is represented by the runner model variables. These are the user's genre and the range of age, her/his preferred musical genres, the type of runner (beginner, half marathon or marathon runner) and the type of training session that she/he is doing (it was introduced by the runner at the beginning of the session through the mobile application).

Following, we explain briefly the process of setting values to all these variables from the input parameters of each recommendation request (first step of the prediction process represented in Fig. 6). As commented above, three data processor are involved in this stage. A processor uses the runner's location for determining the values of the contextual variables based on the information available into the recommender's geodata cache. This cache contains a wide variety of static and dynamic geodata related to the area in which the users are currently running. The processor acts a simple gazetteer able to extract the geodata needed for setting the variables. An example of cache and of the Web data providers involved in its creation is presented in Section 6. Then, a second data processor is responsible for interpreting the user's affective state at that moment and translating it to a particular emotion. And, finally, a third data processor uses the runner identifier for accessing to the user profile cache and instantiating the runner model variables.

5.2. Rules for the elicitation of emotions

In the second step, a rule engine has been used for determining the emotion to provoke in the runner through the music [62]. The engine receives, as input, the values of variables obtained in the previous step. Internally, the engine integrates a corpus of knowledge composed by two sets of rules that are evaluated using those input values: the contextual rules (C-rules) and the training rules (T-rules). The C-rules determine how the environment in which the user is running affects her/his emotions. These rules were created from the conclusions of the discussion groups and the Web questionnaire, and are evaluated using, as inputs, the values of contextual and emotional variables. On the other hand, different T-rules have been defined for each type of training session with the help of running coaches. The values related to the runner profile (in particular, the type of training session that she/he is doing and the type of runner) are used to select the concrete T-rules to be evaluated.

The two types of rules are condition–conclusion rules that generate as result an assertion. The functioning of the rule activation mechanism is as follows. The C-rules are evaluated first, since their assertions have been included as conditions into the T-rules. Then, a T-rule is selected depending on the type of training and evaluated considering the C-rules' resulting assertions. The result of the T-rule determines the emotion to be produced in the runner at that moment. The current version of the engine integrates rules for three types of training sessions (easy run, fartlek and intervals) and three runners' profiles (beginner, half-marathon and marathon runner) and a set of rules for evaluating the runners' context. The decision of using a rule-based solution was motivated for the following issues [63]: the syntax and semantics of rules are easy to understand by the non-expert users who participated in their definition (running coaches and runners); it is easy to maintain and improve the existing rules (for example, with the results of validating them with real users) and to add new rules (including in the future new types of training); and, there are many engine implementations available and all of them provide a good performance when work with a small set of rules, as is this case. In the following paragraphs the model selected for representing the emotions and some examples of rules defined as part of the solution are detailed.

The Russell's emotional model represents an emotion over a two-dimensional space that is defined by the *valence* (X-axis) and *arousal* (Y-axis) dimensions. The valence represents the intrinsic pleasure/displeasure (positive/negative) of an event, object or situation, and the arousal the feeling's intensity. The combination of these two dimensions (valence/arousal) determines four different emotional quadrants: the *aggressive–angry* (negative/positive), the *happy* (positive/positive), the *sad* (negative/negative) and the *relaxed* (positive/negative) quadrant. Each emotion is mapped to a point in the two-dimensional space and is represented by a pair of real values into the interval −1.0 (negative) and 1.0 (positive).

On the other hand, the following examples illustrate some training rules (T-rules):

- *T-Rule 1*: If a half marathon runner is carrying out a training run that includes a series of five speed intervals (1000-m intervals divided in two parts, with the first 800 m fast and the last 200 m easy), the rule proposes emotions contained in the happy and relaxed quadrants for the fast and easy parts, respectively. Besides, the arousal of the happy emotions must be moderate for avoiding the runner to be over-motivated. Nevertheless, if a beginner runner is carrying out the same training run, the rule proposes the same emotions, but their arousal will be more positive for increasing his/her motivation.

- *T-Rule 2*: If a half marathon runner is carrying out a training run that includes a tempo of three intervals (5 km at a pace of 5:00/km, 5 km at a pace of 4:30/km and, finally, 2 km at an easy/recovery pace), the rule proposes emotions contained into the relaxed, happy and relaxed quadrants for each one of the three parts, respectively. Nevertheless, if the runner is a beginner (in this case, the race paces are easier), the proposal consists of emotions belonging to the happy (with a moderate value of arousal), happy (with a high value of arousal for increasing the motivation) and relaxed quadrants.

The first rule corresponds with a training of intervals and the second with a fartlek training. Both rules can be applied if the user is a half marathon runner or a beginner runner. In the examples the T-rules' contextual conditions have been removed for simplicity, but these are explained below. Before some examples of contextual rules are presented (C-rules):

- *C-Rule 1*: If the user is relaxed and running in a green area, the temperature is moderate and the noise level is low, then his/her affective state is positive and the environment is considered pleasant.
- *C-Rule 2*: If the user is stressed and running in an industrial area, it is raining and there is probably a lot of traffic, then his/her affective state is negative and the environment is considered disagreeable.
- *C-Rule 3*: If the user is motivated and running in an area of complex orography, the temperature is low with a light rain falling and the noise level is low, then his/her affective state is positive and the environment is disagreeable.

The assertions generated as part of evaluating these contextual rules have been incorporated as conditions to the training rules. Basically, these new conditions modify (if it is necessary) the valence–arousal values of the emotions returned by the training rules. For example, if the *T-Rule 1* is matched, the runner's affective state is negative (because he/she is sad) and the environment is pleasant, then the arousal of the emotions proposed for the fast and easy part will be increased. So, in the case of a half marathon runner, the happy emotion will be more motivating and the relaxed emotion more happy. Finally, the engine returns the emotion to be produced in the runner as a pair of (valence, arousal) values.

Finally, the rules are being currently validated with real runners (specifically, with half-marathon runners and triathletes) in collaboration with the Sports Medicine Centre of the Government of Aragón (Spain). We are interested in studying whether the emotional response of runners corresponds with what is expected under each particular circumstance. The preliminary results are helping us to adjust and improve the valence–arousal values of rules.

5.3. Definition of the search point

The evaluation of the rules determines the emotion that must be provoked in the runner. In this third step, this emotion is translated to a *search point* which defines the music audio features that should have the songs to provoke that emotion. Then, this search point will be used by the recommendation algorithm for finding a set of candidate songs. In the field of music recommendation it is usual to use these features for classifying songs according to the effects that they can produce to users when listening to them, and for estimating the similarity among songs. Nevertheless, there is no consensus on which combination of audio features is the most suitable for these problems and, besides, the extraction of these features requires the audio of songs and the use of signal processing tools [35]. These drawbacks complicate to work with large-size music databases.

Our approach requires the audio features of *Spotify* songs for including them into the search space of the recommender. As it is impossible to have the audio of all these songs (more than 30 million of songs) for extracting their features, we decided to obtain directly these features from the *Spotify* data services. This decision implies we have no information about how these features are internally calculated but, instead, the system makes recommendations considering all songs available in the streaming provider. In the provider's data model a song is described by a set of twelve audio features: loudness, energy, tempo, acousticness, valence, liveness, speechiness, instrumentalness, danceability, key, duration, and mode. In the current version of the system, a search point is a vector that includes these twelve features. Some features have probably more influence on provoking emotions than others, but the determination of that influence requires complex analysis with real users that will be made as part of the future work.

In the solution a set of *regression models* are applied for translating the input emotion to a search point. Specifically, twelve statistical models have been created, one for each audio feature of the *Spotify* data representation. Each model determines the value of the corresponding audio feature (the dependent variable) from the emotion's valence/arousal values (the independent variables). The building of these models is a complex problem that requires a large amount of data, as it is explained in Fig. 7.

A large-size database of emotionally-labelled songs is needed for building the regression models. As shown on the left side of Fig. 7, a data extraction process has been programmed for interacting with the *Spotify Web API for developers* in order to access the music database of the provider (list of songs) and to get the metadata (author, album, musical genre, etc.) and audio features of each song. These data are temporally stored into a database and, then, sent to the emotion recognition system developed as part of the project [21]. This system determines the emotions associated with each song from its audio features and translates it into a set of emotional labels. The current version of the emotionally annotated database contains more than 5 million of popular *Spotify* songs.

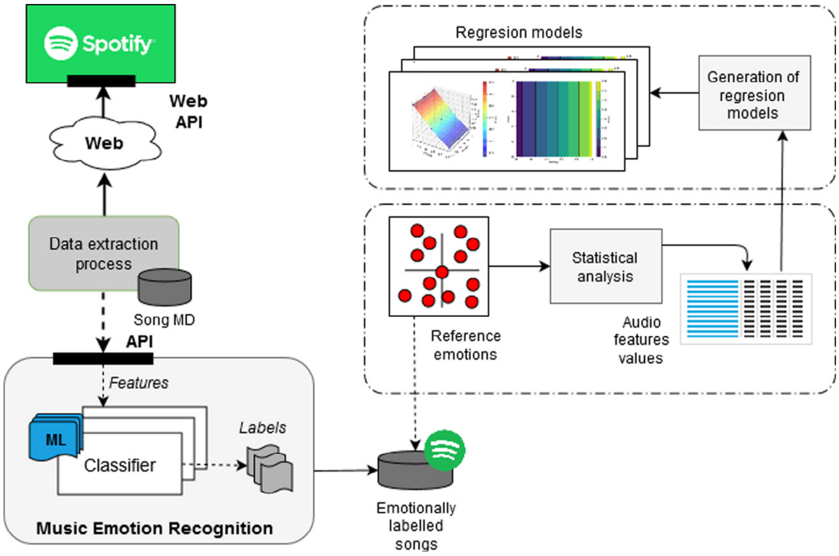


Fig. 7. Process of generating the regression models for the feature prediction.

On the right part of the figure, the building of the regression models from the annotated database is described. Firstly, a set of concrete emotions from the two-dimensional Russell's emotional model have been selected. For each one of these emotions, a set of songs annotated with that emotion have been recovered from the database. For example, the query *"Happy AND Joy NOT Sad NOT Relaxed NOT Angry"* is executed for getting songs that are associated to the *happy* emotion (more than 10,000 songs have been recovered for each emotion). Then, the set of songs of each reference emotion has been analysed for calculating different statistical values of the twelve audio features (mean, media, variance, standard deviation, mode, etc.). All these statistical results have been subsequently used for generating a regression model for predicting each particular audio feature. This generation follows an iterative approach in order to evaluate different regression models and to find the more suitable one for each feature. A linear regression model has been selected and built in most of the cases, therefore, the relationship that exists between dependent and independent variables is good and useful for obtaining satisfactory prediction results.

Finally, the twelve regression models obtained have been integrated into the request generation component for determining the audio features' value that make the search point. This point represents the kind of songs to be recommended by the recommendation algorithm, as was explained in the previous section.

6. Installation of the system in the city of *Zaragoza*

The testing of the music recommendation system has been carried out in the city of Zaragoza, a capital city situated in the north of Spain. Its population is more than 800,000 inhabitants and a land area of 1000 square kilometres (about 400 square miles), ranking fifth in Spain. From 2006, the Zaragoza City Council has promoted the development of a local spatial data infrastructure (IDEZar, https://www.zaragoza.es/sede/portal/idezar/) and, therefore, a wide variety of geodata are available for programming geospatial applications, such as the proposed in this paper.

The main goal of this testing has been to customize the proposed technological architecture in order to be deployed in the selected area and to evaluate the system's operation in a real scenario, as presented in this section.

6.1. Representation and integration of geodata

The recommendation service predicts the next song to be played considering a set of contextual variables related to the runner's location, as it was discussed in Section 5. The value of these variables at each moment is determined from the data stored into the recommender's geographic cache which is periodically updated by invoking the infrastructure's delivery service. Consequently, before starting the recommendation system it is necessary to create the delivery service's databases. In this case, these databases store different geodata about the city of Zaragoza.

At the beginning, the metropolitan area of Zaragoza has been divided in a set of regular grids, as shown on the right side of Fig. 8. Each grid is defined by a bounding box and has associated a set of geodata that describe the region contained into it, specifically, those that are needed for making the predictions. Some of these geodata have been created for the offline processing system (the type of landscape, the type of soil, the altitude and the slope), whereas other will be continuous updated by an instance of the *Geodata processing service* (temperature, humidity, wind speed, probability of precipitations,

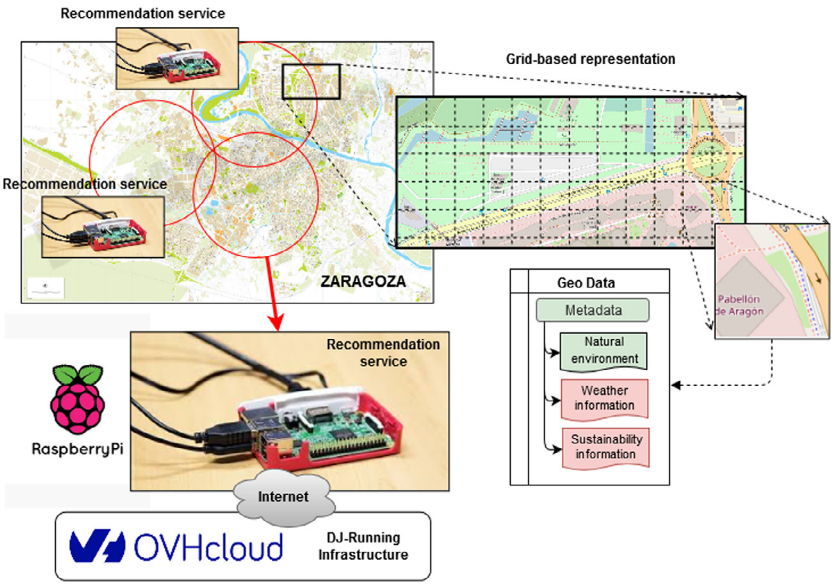


Fig. 8. Representation of geodata.

and different parameters related to air quality and noise pollution). Besides, each grid has also a versioning number that is used for controlling the caching processes. Following, the Web data providers used for creating the grids of Zaragoza are detailed:

- The *type of landscape* is related to the land use (a natural environment, an industrial zone, the city centre, etc.) and, therefore, has been obtained from the data published by the *Spanish Cadastre Office* (http://www.catastro.meh.es/). This office has available a set of SOAP services for accessing to their data which are compliant with the INSPIRE schemes. Nevertheless, in some areas these data do not provide complete information about the use of parcels. For solving this problem we have also used some data provided by the *Zaragoza City Council Open Data portal* (https://www.zaragoza.es/sede/portal/datos-abiertos/) and by the SIOSE system (*Sistema de Información sobre Ocupación del Suelo en España*), mainly, data related to parks and green areas of the city, areas with presence of water or locations of business activities.
- The *type of soil* has been inferred from the type of land use. Currently, it has been assumed that industrial, residential and commercial areas have a hard soil, meanwhile parks and green areas have a soft soil. Obviously, this approach should be improved, for example, some green areas have pavement in their paths or some industrial areas under development still have soft soil. These improvements have not been included in the current version of the system, but solutions based on the use of *LiDAR* data such as those proposed in [64,65] will be considered.
- The *altitude* and the *slope* have been obtained from the *Digital Elevation Model* provided by the *Spanish National Center for Geographic Information*, specifically, from the model with 2 m of resolution.
- The *meteorological data* are periodically acquired from the *Weather underground* (https://www.wunderground.com) and from the *Spanish National Weather Agency* (AEMET, https://opendata.aemet.es). Both providers offer a RESTful service for accessing weather data and predictions.
- The *air quality* data are periodically requested to the *Spatial Data Infrastructure of Zaragoza* (IDEZar). The city has a network of monitoring stations and their data are published through Web services based on the *Open Geospatial Consortium* standards.
- Finally, the *noise pollution* data are periodically downloaded from the *Zaragoza City Council Open Data portal*. These datasets are available in JSON format and require an extra preprocessing for extracting the information of interest.

The service infrastructure's back-end has been customized for integrating these data providers. Then, the processing components have been executed and deployed for creating and updating the delivery service's geospatial databases.

6.2. Deployment of the system

Before deploying the recommendation system, a Web questionnaire was published for determining the areas where citizens of Zaragoza usually run. This questionnaire was answered by about 500 runners and helped us to determine the three most common areas. These are close to the banks of the Ebro river, to the largest park in the city and to a recently built neighbourhood on the outskirts of the city. These areas are geographically separated. We decided to

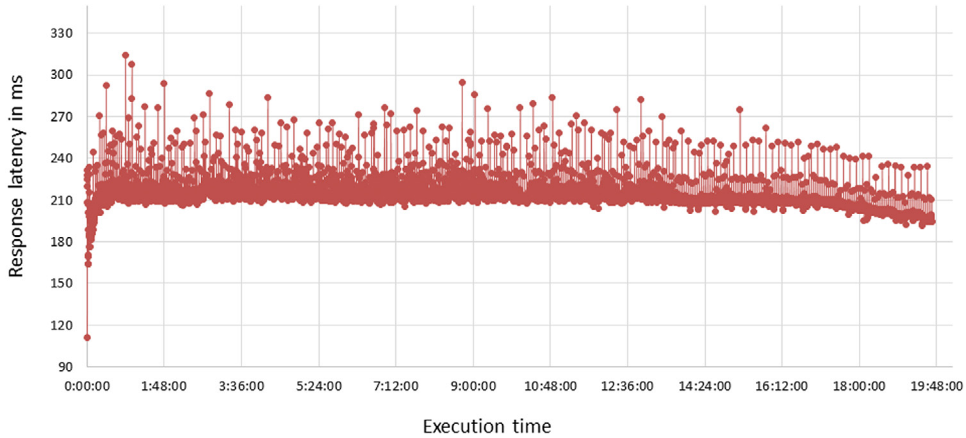


Fig. 9. Response time of recommendations in the worst case.

deploy three instances of the music recommendation service, one in each of those areas, as it is shown on the left side of Fig. 8. The mobile application invokes the functionality of the instances via Internet (more specifically, 4G mobile Internet connections are being used in the first experiments). The decision of which instance is invoked at any given time depends on the user's location. The application stores locally a configuration file that contains the instances' location and IP address, and uses this information for connecting with the nearest according to the runner's current location. Besides, as the recommendation requests are independent of each other, the application is able to interact with different instances during the same training session.

Before starting the recommendation instances, their data caches were configured and created: the grids stored into the geodata cache depend on the geographic area in which each instance was deployed, and the songs stored into the music cache were selected depending on the profile of users that run in each area (the data of 300,000 *Spotify* songs were stored at the beginning in each cache). Then, these service instances were deployed in low-performance computing servers, specifically, in *Raspberry Pi 3 Model A+* computers.

On the other hand, the geodata delivery and processing services of the infrastructure were deployed in the *OVH cloud* (https://www.ovh.com/fr/). Two general purpose virtual computing instances *VPS b2*, with two 2 GHz CPU cores, 16 GB of memory and 80 GB of disk space were hired for executing these services and storing the data involved into the system. These computing resources are connected to Internet for interacting with the data providers integrated into the solution and offering their functionality to the recommendation instances.

6.3. Performance of the recommendation instances

Apache JMeter has been used to programme different load tests and to analyse the behaviour and the performance of the recommendation service when it is running at a *Raspberry Pi 3 Model A+* computer. These tests are executed in a computer configured with a Windows 8.1 Pro x64 operating system and composed of an Intel Core 2 Quad Q8200 processor at 2.33 GHz and 8 GB of RAM. This computer is physically connected to the same network as the *Raspberry* server.

The goal is to measure the number of clients that the recommender is able to attend in different execution scenarios and the response time of the service in these scenarios. Two different scenarios have been studied: the first represents when the runners are continuously skipping the recommended songs (the worst case), and the second when the runners listen to the recommended songs and skip occasionally some of them (the normal functioning of the system).

Regarding the first scenario, at the beginning, we analysed the maximum number of clients who could be constantly invoking the recommender without it experiencing response failures. The result was around 80 clients. Using this result, the next experiment consisted in measuring the response time of recommendations when 75 clients are executing in the worst case during 20 hours. Fig. 9 shows that the recommender was able to attend correctly to the clients and the average response time was 221 ms. These times ranged over [185-317] ms, except of beginning of the experiment due to the clients were launched progressively.

On the other hand, similar experiments have been carried out for analysing the normal functioning of the recommender. In this case, the clients make a new recommendation request each interval of [150-210] ms. It has been observed that from 12,000 clients the recommender fails frequently. For this reason, the response time was measured for the case of 10,000 clients executing during 30 min (the capacity of computer for managing concurrent threads restricted the duration of the experiment). Fig. 10 shows that sometimes the response time is not as expected (when a large number of requests are simultaneously received, the performance degrades), but the recommender still works. The response time in critical periods can ranged over 1 and 2 s. Nevertheless, the average response time in non-critical times is 54 ms. As conclusion,

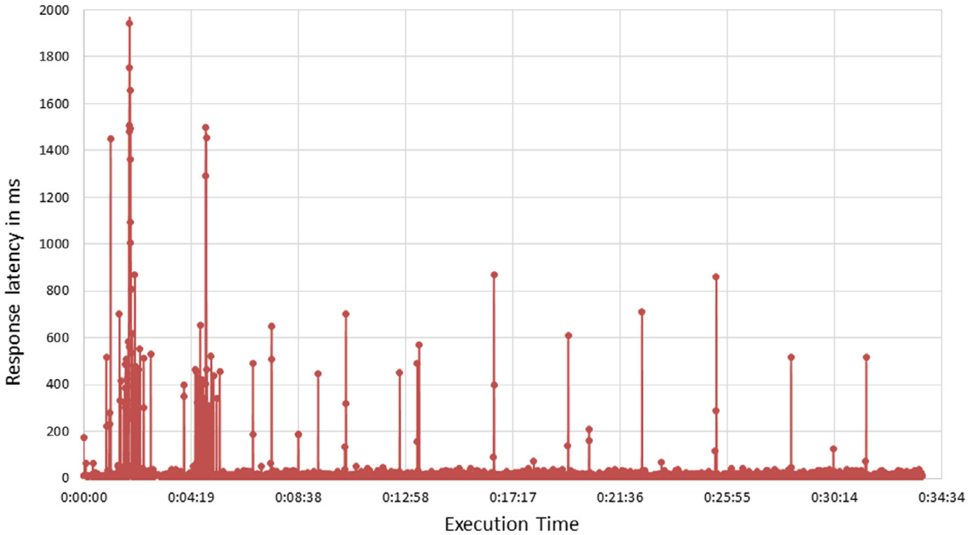


Fig. 10. Response time of recommendations in an usual scenario.

despite the restricted capabilities of the *Raspberry* computers, these could be used in the future for attending a large number of runners.

7. Conclusions and future work

In this paper, a location-based mobile application that monitors the runner's physical activity and plays *Spotify* songs during the training sessions have been presented. The recommendation of songs is based a set of contextual and emotional variables that describe the environment in which the user is running and what she/he is feeling at each moment. A rule-based system evaluates these variables from the perspective of each particular type of training and predicts the songs to be recommended. In these predictions geodata play a relevant role, and for this reason it was necessary to integrate an infrastructure of the geographic services and providers into the solution. The resulting system is a complete solution that combines proposals of different engineering fields.

As part of the ongoing project, the application is being tested by real runners in collaboration with the Sports Medicine Centre of the Government of Aragón (Spain) and local athletics clubs. On the one hand, we are analysing the emotions that the runners feel through different music recommendations. These emotions are monitored using the wearable developed as part of the project and corroborated through the questionnaires fulfilled by participants at the end of each session. The results obtained will be used for improving the system's decision components, mainly, the rules for provoking emotions, the recommendation algorithm and the filters. On the other hand, an online system has been also programmed for discovering the effects that the songs produce in the listeners. These effects will be used for improving the songs' emotional labels and the users' experience. Therefore, we are currently focused on understanding the runners' emotional response to certain music and integrating that knowledge in the recommendation strategies. In the future we will also evaluate how the recommendation algorithm selected affects the runners' experience. As discussed in [66], this kind of evaluation is complex and involves the analysis of a set of properties through different types of experiments.

On the other hand, we are also interested in including new type of sessions/profiles in the application (for sedentary people, for instance). The medium-term goal is to publish a version of the application in some digital distribution market, such as *Google play*, and to find investment for launching in the future the product (or part of the product) on the market. And, finally, we are studying the creation of new location-based applications in the domain of smart cities (recommending music depending on where the user are walking) or workplace health (promoting the wellness by combining music and physical exercises), for instance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.pmcj.2020.101242.

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