Filtering Fitness Trail Content Generated by Mobile Users

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Abstract This paper proposes a novel trail sharing system for mobile devices that deals with context information collected by sensors, as well as users' personal opinions (e.g., landscape beauty) specified by ratings. To help the user in finding trails that are more suited to her, the system exploits a collaborative filtering approach to predict the ratings users may give to untried trails, and applies a similar approach also to context information that can significantly vary among users (e.g., lap duration).

1 Introduction

Regularly performing physical activities such as jogging provides a variety of benefits: it improves physical fitness, it helps to prevent pathologies such as obesity, it may be an opportunity to meet other people, and it may also be fun.

Since people, especially those who do not exercise regularly, may need support before, during, and after physical activity, we recently proposed [1,2] a wearable training system to support users with tailored advice during sessions, and a visual tool to help them with post-session performance analysis.

This paper focuses instead on a users' need that precedes the actual jogging activity, i.e. finding trails that satisfy specific requirements such as suitability for the current physical fitness of the user, possibility to meet other people, purity of the environment or beauty of the landscape.

While motivating and training people requires knowledge that can be elicited from domain experts such as physiologists and personal trainers, fulfilling the above need requires information about the different available trails and their features, including users' personal opinions on them. Since there are millions of possible trails spread around the world, it would be very difficult and expensive for a small group of people to collect all the required information. On the contrary, a Web 2.0 approach would allow a community of users to generate that content, possibly using mobile devices equipped with sensors such as GPS and heart rate monitor. For this reason, some communities, companies, and researchers (e.g., [3,4,5]) have proposed trail sharing systems which invite users to collect context information about themselves (e.g., heart rate) and the trails where they jog (e.g., waypoints), and share such content with other users through the Web.

Position information about trails, represented as the latitude and the longitude of a set of waypoints, has been the first kind of user-generated content considered in the fitness domain. Waypoint information can be enhanced with altitude and timestamp, if available, and can be generated by asking users to manually place the waypoints on a map [3], by automatically collecting position information in the field by means of a GPS device [4], or by combining the two approaches [5].

Besides position, users' heart rate is an important information associated to fitness trails, and is indicative of users' physical fitness as well as trail difficulty. Two of the existing proposals allow to record such information: Nokia Sport Tracker [4] allows users only to manually add average heart rate to the automatically collected position information, while SlamXR [5] can automatically acquire heart rate information, together with synchronized information about position, acceleration, atmospheric pressure, and temperature, by means of a dedicated wrist-wearable device which integrates different sensors.

Unfortunately, existing systems do not consider users' personal opinions on trail features, such as the beauty of the landscape or the purity of the environment. To overcome such limitation, we propose a trail sharing system for mobile devices that deals with data collected by sensors (GPS and heart rate monitor) as well as users' personal opinions, and employs a collaborative filtering approach to help the user in finding the trails that are more suited to her.

2 Our proposal

The mobile trail sharing system we propose deals with two different types of trail features:

– *Objective features* are those features directly measured by means of sensors or derivable from sensor measurements. Our system exploits (i) a GPS device to collect *waypoints*, (ii) a Bluetooth pulse oximeter to measure users' *heart rate* at each waypoint, and (iii) the internal time of the mobile device to measure the duration of a jogging session (*total duration*) and the duration of a lap (*lap duration*). From the collected information, the system can derive: (i) *total length* (by summing waypoint-to-waypoint distances), (ii) *lap length* (by summing waypoint-to-waypoint distances in a lap), (iii) *mean slope* (by calculating the ratio between the sum of waypoint-to-waypoint differences in altitude and the total length), (iv) *mean speed* (by calculating the ratio between the total length and the total duration), (v) *mean heart rate* (by averaging collected heart rate values), and (vi) *difficulty* (by calculating the ratio between mean heart rate and mean speed). Moreover, the system computes the *popularity* of trails (by considering how many times users jogged there), and the *distance* between a trail and the current location of a user.
– *Subjective features* are those features that depend on users' personal opinions. The system explicitly asks users to specify them using numeric ratings on a 1 to 5 scale. Considered subjective features are: (i) *beauty of the landscape* (e.g., is there anything the user likes to see while jogging such as trees

or rivers?), (ii) *crowding* (e.g., how many people will the user meet while jogging?), (iii) *purity of the environment* (e.g., is there waste or smog around the trail or is it a clean open-air environment?), and (iv) *safety* (e.g., can cars cross the trail? is it a crime-related area?).

We further classify objective features in: (i) *user independent features*, such as waypoints and lap length, and (ii) *user dependent (UD) features*, such as lap duration and difficulty, that can significantly vary according to the user.

Our system provides the user with a mobile tracking application to measure objective features of the trail where she jogs, collect her ratings about trail subjective features, and access a password-protected Web service for sharing trails. Besides storing content, the Web service calculates derivable objective features from the measured ones.

To search for a shared trail, existing systems ask users to specify some objective features. However, a search based only on objective features is not enough to find the trails that are most suited for each individual user, since users may like or dislike trails based on their personal opinions. A real-life scenario where users' opinions are fundamental to find the most suited trail may be the following (Scenario 1): two users (User 1 and User 2), who live in the same town, are looking for a nearby trail with a desired lap length and mean slope. User 1 likes trails with beautiful trees, while User 2 prefers jogging near clean rivers. Among the nearby trails satisfying the specified objective features, there is a trail (Trail T) with several beautiful trees, but no rivers at all. Since existing systems do not consider users' personal opinions, recommended trails for both users will include Trail T. As a result, if both users decide to try that trail, User 1 will appreciate the recommendation, while User 2 will be dissatisfied.

To deal with users' personal opinions, we adopt an approach based on collaborative filtering (see [6] for a recent survey about collaborative filtering), i.e. we collect the ratings that different users give to the subjective features of trails, and exploit such ratings to predict how much each user would like a trail she never tried. More precisely, our system is inspired by the GroupLens architecture [7] and the item-based recommendation algorithm proposed by [8]. We predict the rating a particular user would likely give to a subjective feature of an untried trail by proceeding as follows:

– for each subjective feature f, the system computes, on a regular basis, the adjusted-cosine similarity (Equation 1) between each possible pair of trails $(i,\ j)$ by considering ratings for f given by the users who have tried both trails (we denote this set of users as $RB_{i,j,f}$) as well as the mean rating of each user $u \in RB_{i,j,f}$ for f (we denote this mean as $\overline{r_{u,f}}$);
– for each user u, trail i, subjective feature f, where u has not rated f of i, the system calculates the rating u would likely give to f of i as the weighted average of the ratings u has given to f of other trails (we denote the set of trails for which u has rated f as $R_{u,f}$), where weights are the adjusted-cosine similarities between i and the other trails for f (Equation 2).

$$AdjCosSim(i,j,f) = \frac{\sum_{u \in RB_{i,j,f}} (r_{u,i,f} - \overline{r_{u,f}})(r_{u,j,f} - \overline{r_{u,f}})}{\sqrt{\sum_{u \in RB_{i,j,f}} (r_{u,i,f} - \overline{r_{u,f}})^2} \sqrt{\sum_{u \in RB_{i,j,f}} (r_{u,j,f} - \overline{r_{u,f}})^2}} \tag{1}$$

$$PredRat(u,i,f) = \frac{\sum_{j \in R_{u,f}} AdjCosSim(i,j,f) \cdot r_{u,j,f}}{\sum_{j \in R_{u,f}} AdjCosSim(i,j,f)} \tag{2}$$

Applying this technique to Scenario 1 will produce the following results: since users who like trees are likely to give high ratings to the beauty of Trail T (and of other trails with beautiful trees), and users who instead prefer rivers are likely to give low ratings to the beauty of Trail T (and of other trails without rivers), the similarity among T and other trails with beautiful trees and no rivers for the beauty feature will be very high. As a result, the predicted rating of the beauty feature of Trail T for User 1 (who likes trees) will be strongly influenced by the ratings she gave to other trails with beautiful trees and so it is likely to be high. For User 2 (who likes rivers), the predicted rating of Trail T will be influenced by those she gave to other trails without rivers, and is likely to be low. Therefore, if both users query the system for a trail with the specified objective features and a high rating for beauty, recommended trails for User 1 will include Trail T, while recommendations for User 2 will not.

UD features, such as lap duration and difficulty, are strongly dependent on users' physical fitness. As a result, if a user looks for a trail with a particular value for one of these features in existing trail sharing systems, she may be misled by the shown value, since it may have been derived from content collected by users with completely different physical fitness. Consider the following scenario (Scenario 2): an untrained user (User 3) has shared a trail (Trail R) whose lap duration, as measured by her, is 25 minutes, and a well trained user (User 4) is looking for a trail with that particular lap duration. Since existing systems do not personalize recommendations based on users' physical fitness, the recommended trails for User 4 will include Trail R. However, since differently trained users are likely to take an amount of time inversely proportional to their physical fitness to complete a lap of the same trail, User 4 will likely be disappointed after trying Trail R, because she will have taken much less than the shown 25 minutes to complete a trail lap.

To adapt the values of UD features to the individual users, we applied the collaborative filtering technique also to information collected by means of sensors. However, while ratings of subjective features can be considered stable over time, values of UD features are likely to change even within a few months. For example, with appropriate training a user can increase her mean speed or exercise at a lower heart rate without reducing the speed. Therefore, the collaborative filtering technique, which would consider all the collected values, is not well suited for these features. To overcome this problem, we consider only the most recent trails for each user (last 6 months) in the computation of the similarities and the predicted values for UD features, and we invite users to share their information associated to each trail everytime they jog in it. As an additional benefit, regular update allows us to count how many times each user has jogged in each trail, so that we can compute the total number of visits for each trail and determine its popularity.

By applying collaborative filtering to UD features, recommendation in Scenario 2 changes as follows: the system considers lap durations of the same users in different trails to compute the adjusted cosine similarity for the lap duration feature among all the possible pair of trails. Then, the system predicts lap duration of Trail R for User 4 as the weighted average of the values measured for User 4 in similar trails, where weights are the adjusted cosine similarities for the lap duration feature. Since User 4 is more trained than User 3, lap durations measured by her in trails similar to Trail R are likely to be lower than 25 minutes, so predicted lap duration of Trail R for User 4 will be lower than 25 minutes as well. As a result, recommended trails for User 4 will not include Trail R, but other trails whose lap duration is well-suited to User 4's request and physical fitness.

To test the proposed technique, we developed a mobile application (Figure 1) to browse filtered content by specifying a range of values for each feature.

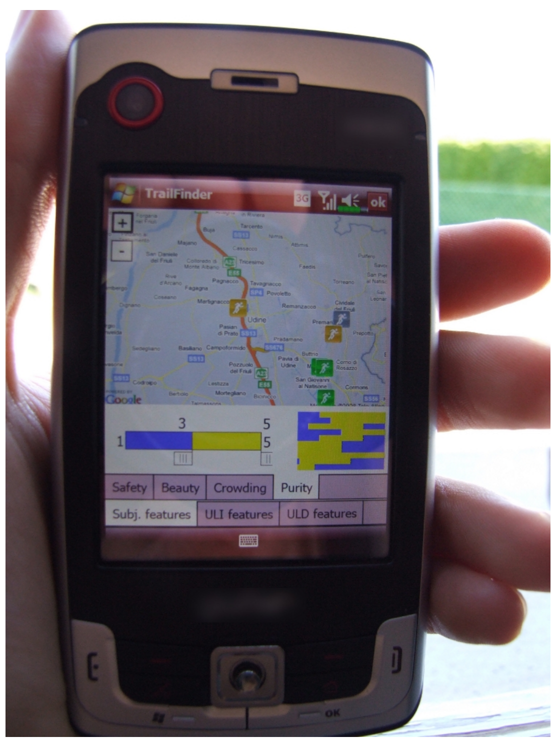

Figure 1. The proposed mobile application to browse filtered content.

3 Discussion and future work

As any collaborative filtering system, our system is affected by the cold start problem, i.e. users can be reluctant to share their content and give ratings, expecially during the initial phase after the deployment of the system. Once the system has collected enough content, the users who share more are rewarded with more tailored predictions for their untried trails, but during the initial phase the system may not be able to predict some feature values even for the users who have shared more. To motivate users to share their trails, we are integrating our proposal in a mobile fitness game to provide fun, training, and motivation, while generating content for the trail sharing system.

We will also extend our system to consider more context information. At present, the system filters the content by considering current location and collected information about heart rate and position. Moreover, it implicitly collects also timestamp information about the waypoints, that can be exploited to determine the season and the time of the day. Considering also current season and time of the day in the prediction of ratings will allow the system to further tailor the filtering of the content.

4 Acknowledgements

We acknowledge financial support from the Italian Ministry of Education, University and Research (MIUR) within the FIRB project number RBIN04M8S8.

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