A Pervasive Mobile Assistance System for Health and Fitness Scenarios

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Abstract

Many commercial mobile applications or "apps" have surfaced in the past few years, such as Polar, Suunto, etc., to assist hobby runners in their personal fitness training. Although they partially consider vital parameters such as heart rate, blood pressure, etc., they do not consider the specific health constraints and requirements of rehabilitation patients. Nevertheless, the hobby scenario is also important for long-term, self-responsible rehabilitation training. As motivation is a key success factor in this phase, personal interests of the user have to be considered. The work presented in this paper tackles this problem context from a design science perspective, and derives a new concept for pervasive mobile assistance in the aforementioned scenarios. The approach covers specific route characteristics, its impact on the user and the user's personal preferences. The paper concludes with a description of an implemented proof-of-concept as a personal health system for self-motivated and self-controlled disease management.

1. Introduction

Many mobile applications like Polar and Suunto [1] that assist mobile fitness training by taking into account sensors monitoring body functions and vital parameters have emerged in the past few years. However, such applications do not live up to their full potential, as they do not take into account other important aspects such as context information. For health applications such as running and biking, it is less important to get from A to B, than to meet specific requirements (e.g. taking into account bus stops as described in Yu et al. [2]), such as the hilliness of a route, specific interests of the user, points of interests (POIs), etc. In this context, these recommendations are similar to recommendations for location-based services, e.g. mobile tourist guides. Personalization in recommending running routes is more similar to approaches for location-based services than to traditional routing problems. However, for the ability to react to context changes of a user in real-time, traditional routing problems have to be dealt with.

For patient-centered e-health (PCEH), it is not sufficient to focus solely on Health Information Systems and Health Portals. A combination of patient focus, patient activity and patient empowerment improves the user acceptance and allows users to integrate a health aspect into their everyday life [3], [4].

Context in pervasive systems does not only include the user's location, but also temporal characteristics of the involved entities and their relationships [5]. In our case, this includes character and accessibility information of POIs and routes. For example, a POI might not be accessible 24 hours a day, but may be restricted to certain opening hours. A route might contain mud sections, which are not suitable to use after a rainy day. This paper prioritizes context characteristics, which are specific for running routes.

This paper investigates the requirements of a specific, personal health system for runners with a hybrid approach: combining recommendation mechanisms of location-based services with traditional routing concepts, i.e. simulation techniques as proposed in [6] will be applied to PHS for runners. The former allows the assistance system to provide personalized recommendation of routes, the latter allows for dynamic route adaptation due to context changes, i.e. in-/decrease of heart rate. Some of these context parameters are interdependent and have a strong impact on energy consumption and training success [7]. The envisioned application will target both fitness and health scenarios. Thus, medical requirements and lifestyle aspects will be considered. An assistance system offering these functionalities must be able to define multiple criteria in a personalized way, in order to fulfill these requirements.

The research in this paper follows a design-oriented research approach [8]. According to design-oriented methodology, an artifact is being created in a prototypical approach in order to meet collected requirements fitting to a specific problem description. In section 2 different approaches from literature are being discussed, in order to identify gaps for location-aware assistance of outdoor training situations. Section 3 is concerned with the derivation of requirements for such an assistance system. Section 4 describes the recommendation mechanism of the assistance system, which incorporates the detected requirements. Furthermore, the prototypical evaluation is presented to provide a proof-of-concept. The paper concludes with a conclusion and an outlook.

2. Related Work

The following overview of related work is divided into three approaches. They are either based on optimization and combination of route segments, approaches for recommendation of routes and POIs as location-based services and eventually personalized approaches and requirements in the eHealth and mHealth domain.

2.1. Route adaptation and recommendation

In the area of dynamic route adaptation, Chen proposes a system in which optimal path candidates are pre-computed offline, but the final route is calculated on the fly by utilizing heuristics respecting the driver's preferences [9]. With the same goal, Pang uses a fuzzy-neural approach to orientate a route selection on the driver's preference. Given a route map and a user-selected route and based on enough training sessions, the selection function is able to adapt to the actual decision making of the use [10]. Hitoshi uses a genetic algorithm mimicking viral infections to optimize the route selection based on travel time [11], [12].

In the following, related papers for route recommendations are analyzed in terms of applied filtering and ranking mechanisms, incorporation of user feedback and real-time adaption to context changes, i.e. handling of live data and configurable rankers.

Zenker and Ludwig [13] conclude that route recommendation becomes more complex when reaction to live data is incorporated. They examine the combination of pedestrian navigation with event recommendation and live public transportation. Their system consists of three components, recommendation, route generation and navigation. They are loosely coupled, i.e. the results of the recommendation (goals) are input to the route generation and the results of the route generation (way) is the input for the navigation. However, unexpected changes, e.g. missing the bus, are not covered by this approach. Van Setten et al. [14] propose an application for a tourist scenario. It depicts a selection of nearby buildings, friends and other objects, viewable on a map and in a list on the mobile phone. Vicinity to the user is a hard criterion for filtering. Ranking is designed modular and combines different methods. Not every ranking method is used with each request, but methods are combined depending on the request. User feedback is incorporated by the system considering factors such as “last time visited”.

Tumas and Ricci [15] describe a tourist guide which combines recommendation of points of interest with recommendation of routes in a transit network (network that bridges at least two different types of networks). Several routes are generated which exhibit different features, e.g. fastest route, walking route, route consisting of central streets, etc. According to a user profile an overall satisfaction score is generated for each route. The ranking function is a sum of sub-functions, which evaluate different attributes and their adherence to the user profile. The sub-functions are not necessarily equal for each user since they vary with the preferences specified by the user.

Priedhorsky et al. [16] talk about using collaborative filtering mechanisms for estimating ratings of unrated byways for personalizing bikeability ratings in a geowiki for bicyclists. Preferences of a user are specified in the search interface where a user orders attributes for the preferred bike route in accordance to their relevance. Thus, only session-specific preferences are specified as opposed to an approach defined by Ricci and Nguyen [17] which defines a user model with session-specific preferences and long-term preferences.

Regarding data acquisition Völkel and Weber [18] develop a system for personalized multi-criteria routing for mobility impaired pedestrians. They investigate user-driven map annotation as well as the development of routing methods utilizing the acquired data. Here, environmental conditions such as availability of road segments are collected in a collaborative manner. Changes over time of environmental conditions are considered by assigning lower priority to older ratings and higher priority to recent annotations when creating the overall rating value for the attribute. Adaptation is realized by providing a 5-point Likert scale, one for each criterion to be rated regarding its individual importance. These ratings are correlated with weights in the costs function. Baus et al. [19] and Schmidt-Belz [20] provide more extensive surveys of location-aware mobile guides. Their work can be used as starting point for extending the related work section based on our applied evaluation scheme. Only the most relevant articles have been included in this overview. In terms of modularity Bellotti et al. [21] compute final scores for items based on the results of several evaluation models. The way these models are combined can be specified in a set of rules, or inferred from the user’s context.

2.2. POI recommendation

In terms of ontology-supported route and POI recommendations Tomai et al. [22] describe a context matching algorithm for trip planning for tourism which generates a mapping between a user profile ontology and an ontology containing tourism information. The specification of the actual profile of a user is limited by the predefined user profile ontology, i.e. a user can only chose from a list of alternatives that correspond to the sub-concepts of the “interests” concept. Filtering removes services that do not match the service type selected by the user. The second step involves finding the correspondences between concepts and properties in the user profile and those in the tourism ontology. Additional information such as projected length of stay is used to further filter out services. Ranking is better described as grouping since results are classified into exact and approximate results.

Ontologies are also used for configuration purposes. Van Setten et al. [14] describe a mobile tourist application which uses different recommendation strategies for different classes of POIs. As the semantics of POIs are described by an ontology, the recommendation engine is aware of the class hierarchy of each POI. So, if a prediction strategy exists for the actual class of a POI, then that strategy is chosen, otherwise a parent class with an associated recommendation strategy is used. Furthermore, ontologies are used to create semantically rich queries.

2.3. Related approaches in e/mHealth

There is some related work in the areas of eHealth and mHealth (mobile health), that focuses on similar application areas as the presented approach. As such, the depicted solution can be seen as an mHealth solution.

Ontologies can be used to correlate health phenomena with context information, for example route characteristics and personalized training plans. McGuinness et al. [23] describe how semantic web technologies can improve the data integration and visualization in health portals.

Koay et al. [24] evaluate the pervasiveness of a remote patient management system (RPMS). They describe a use case scenario, in which a patient suffering from an embolic stroke needs to take medicine and participate in rehabilitation measures. The RPMS is supposed to act as a warning system for any deterioration of the patient’s health status. To find the optimal mobile device for a patient’s condition, they derive non-functional requirements by exploiting several ontologies.

The study of Fisher et al. [25] shows that the aspect of personalization is crucial to improving a user’s search experience and the resulting recommendation quality in a health information portal.

While those findings provide hints for the design of a patient-centered health application, they do not go into detail about a specific service. Our goal is to seamlessly integrate a solution in the patient’s everyday life with the help of available mobile devices. This allows an easy adaption and lowers barriers for the usage.

3. Requirements Analysis

Based on the analyzed related work, requirements for the envisioned solution are elicited. The references from section 2 are used to justify the relevance of such requirements. However, it is evident that existing approaches for health- or fitness-related recommendations take into account location-based factors very sparsely. Especially, the interdependencies between the aforementioned aspects call for an integrated view on the assistance problem in mobile health and fitness scenarios. This section provides a coherent set of requirements for a system that combines the benefits of the different approaches.

Returning to the reviewed papers in section 2 only the paper of Zenker and Ludwig [13] describes a simplified approach to combining location-based services recommendation with traditional route recommendation. However, unexpected changes, e.g. missing the bus, road characteristics, etc., are not covered by this approach. Additionally, several requirements can be derived for the mHealth aspect. This primarily includes the need for personalization and the importance of a remote monitoring functionality for critical health cases.

In the following the derived requirements for the envisioned system are set out. It is a hybrid system from a recommender systems point of view, as it comprises collaborative, content-based and knowledge-based filtering and ranking mechanisms (cf. [26]).

Requirement 1: Consideration of domain-specific route features: A route model needs to not only provide traditional features such as length and average traversing time for route segments, but also to cover domain-specific aspects such as underground, environment, walking aspects, etc. [15]

Requirement 2: Consideration of points of interest: For a hybrid approach which also incorporates recommendation of location-based services as in tourist scenarios, a route model needs to incorporate relevant points of interest, which can be related to routes [15].

Requirement 3: Location-based filtering: Location as in vicinity to a user or a user-specified location is a hard criterion and, thus needs to be a main filtering criterion [14].

Requirement 4: Consideration of user-preferences: Selecting a suitable route is a multi-criteria decision problem. Each criterion needs to be evaluated in relation to user preference (resulting in a final evaluation score for each route (cf. [15], [18], [21]). Taking into account the user's preferences and accepted customs helps to improve the user acceptance, which is important to provide additional usage value as a personal health system (cf. [24], [25]).

Requirement 5: Just-in-time evaluation of ranking criteria: Short-term (e.g. current situational context) and long-term user attributes (e.g. interests) need to be considered (cf. [16], [17]) when evaluating potentially suitable routes for a user.

Requirement 6: Evaluation of complex, semantic interdependencies: Incorporation of ontology matching mechanisms provides an additional evaluation criterion based on semantics (cf. [14], [22]).

Requirement 7: Pluggable & easy ranking extension: Configurability of evaluation functions enables easy extension. (cf. [14], [21]).

Requirement 8: Interface for event monitoring & direct feedback: Direct and indirect user feedback needs to be incorporated (cf. [18], [19], [14], [18]). This is especially important regarding critical vital data in a remote monitoring environment.

Requirement 9: Collective intelligence based on collaborative filtering: Collaborative filtering provides additional evaluation possibilities, taking into account the actions of similar users or profiles of similar routes [16].

4. Concept for Route Recommendations

An integrated assistance system that integrates the information from explicit user or physician feedback, situational data gathered by the mobile device and externally collected information addresses the aforementioned requirements.

The basic concept for route recommendations is visualized in the following figure:

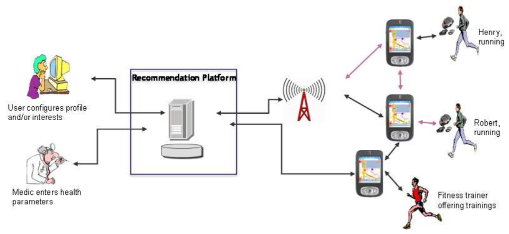

Figure 1. Concept overview

The overall idea comprises a central recommendation platform that acts an assistance system towards the mobile users, i.e. runners, fitness coaches or medics that supervise the users' training and configure related health statistics, treatment and training plans accordingly. Besides direct user feedback, like ratings of routes or POIs on-the-go and configuring their profiles and interests explicitly, indirect context-information can be monitored. This includes current location and certain vital parameters such as heartrate and blood pressure, which is collected by the mobile device and associated sensors. The mobile device acts as a proxy for these external sensors. Regarding sensor integration we use state-of-the-art approaches, as described e.g. in [27], [28]. Some of the information has to be interwoven with associated information sources such as map services (e.g. Google Maps, OpenStreetMap, weather services), in order to consider important context information in real-time. Figure 2 visualizes the information gathered while running a certain route.

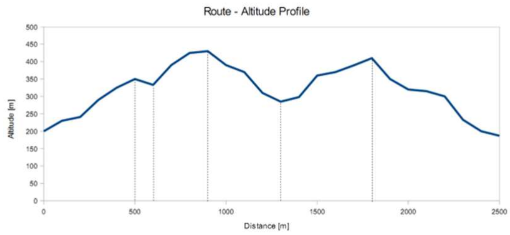

Figure 2. Segmented route

Based on the GPS information of the user's mobile device, information like altitude information or route surface characteristics (e.g. is the route a dirt track, a street, etc.) can be gathered by accessing external services. This information can be used to forecast the possible energy consumption for the training and the projected change of certain vital parameters (e.g. in some rehabilitation scenarios it might make sense to limit the heart rate, thus resulting in avoiding steep ascents, etc.).

The following subsections will explain, how the data is modeled, acquired and how the data are analyzed, in order to provide location-based, mobile assistance for scenarios in the health and fitness domain.

4.1. Data Acquisition and Route Model

The definition of our route model provides the basis for user-driven annotation of running routes. Here, we distinguish between automated and manual annotation. An example of automated annotation is the generation of running route segments through the analysis of GPS traces received from the user's mobile device.

During route creation, a user who carries a mobile device measures the route by walking. Wireless connectivity, e.g., Wi-Fi, or UTMS, is necessary to establish a connection to the destination host, the server that collects and evaluates the GPS data. To extract the information on the user's actual position we use the Google Maps API that provides the data that is modeled in the Route Definition.

Parts of the route can be annotated by the user as shown in Figure 2. For instance, we modeled the Terrain Segments which are defined by the user. Here the user manually assigns the type of terrain to a route segment by choosing a new terrain from a list-box. Another possible annotation is the change of the route environment. It makes a difference if one jogs at 8 pm in winter through a lit and inhabited district or a dark forest. Since we use time-based recommendations, such parameters can improve the quality of recommendations to the user. The modular design allows us to include further segments later on.

Another variant of annotations are automatically generated annotations that are computed by the system for segments of a route that lie between two altitude differences. Altitude changes can be defined by mathematical rules and are easy to compute as contrasted with the manual annotations described above.

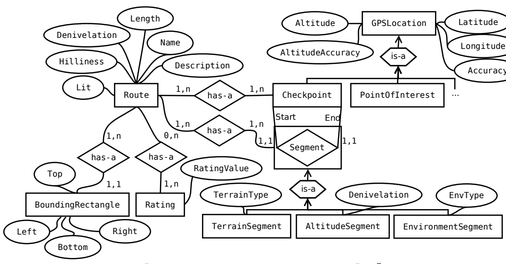

Figure 3. Data model

A Route (see Figure 3) is created by an admin user and contains a name and a short description (e.g., "Campus Route: a well-frequented moderate running route across the Campus"). The denivelation describes the difference in level between the highest and lowest point of the track. Hilliness projects the collected GPS data of one track on the properties flat, intermediate, or hilly. Lit says if the route is illuminated. Finally, a Route is rated by users on a Likert scale between 0 and 5.

The Route entity consists of multiple Checkpoints that represent the GPS data, collected during Route creation. The GPSLocation maps the data provided by the Google Maps API. We decided to abstract from this entity because we wanted to avoid having one table with a large quantity of GPS coordinates. Such an amount of data would slow the speed of database responses. Thus, GPSLocation represents a theoretical construct and is not implemented in the database. Only objects of interest (e.g., Checkpoint, PointOfInterest) are specified.

We decided to aggregate Checkpoints in a construct we call Segment. Segments have one start and one ending Checkpoint. Those RouteSegments help us to accelerate computation during recommendation processes where not all Route-related GPS information is necessary. TerrainSegment represents one way to use Segments: they define changes of a Route's floor type. Therefore, a Route's creator presses the button 'surface change' and selects a new surface type from a list (e.g., tar, grass, forest). TerrainEnvironment behaves in the same way for Route environments (e.g., pedestrian area, fields, sea-side). AltitudeSegment is used to define parts of a Route that lies between two points of inflection where the slope is changing. E.g., if a Route's slope is continuously ascending from the start to the end, the system generates one Segment. To avoid operating on all data sets when a request for a certain GPS location arrives, we developed the BoundingRectangle. This entity represents a box that surrounds one Route. BoundingRectangle is used during the filtering to find objects of interest in the neighborhood of the user. Requirement 1 and 2 are covered with this definition of a route data model.

4.2. Location-based Filtering

Location-based filtering represents a crucial part of the route recommendation, because it reduces the amount of data that has to be processed by the ranking mechanism, thus significantly improving the overall performance. The filtering only keeps routes in the result set which are located in the vicinity of the user or user-specified location. This vicinity is represented by the BoundingRectangle object, which represents a rectangular area of interest around a geographic location, defined by its four sides. Since the shape of the Earth resembles an ellipsoid, the BoundingRectangle does not represent a simple two dimensional geometric figure but a curved surface. For this reason, it is defined by the corresponding longitudes of its east and west sides and the latitudes of its north and south sides, thus reducing the magnitude of calculation errors even for very large areas.

Filtering of nearby routes is performed by using the routes' corresponding BoundingRectangles. Only routes with BoundingRectangles intersecting with or contained in the vicinity's rectangle are considered as nearby (see Figure 4). Since in our particular case we are not interested in the intersection points or whether we have an intersection or inclusion, the checks needing to be performed can be simplified, thus the overall performance of this filtering mechanism can be improved.

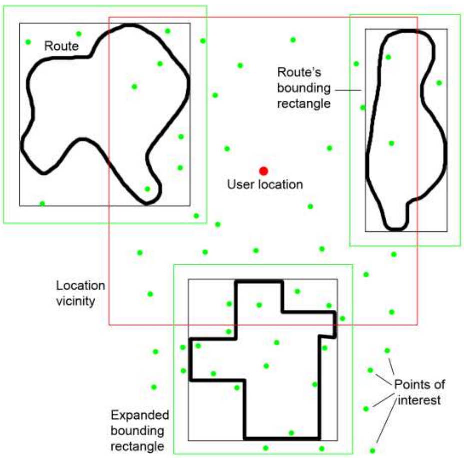

Figure 4. Location-based filtering

In addition to route filtering, the filtering process performs aadditional filtering of POIs. Since the points of interest on or near a route represent an important parameter used by the ranking mechanism, they have to be related to a particular route and then examined by the ranking mechanism. This task is highly computation demanding and may greatly reduce the overall performance of the ranking mechanism, because of the large number of available points of interest. For this reason, the matching of points of interest to particular routes is pushed down to the filtering process. It is performed as a second phase of the filtering process and uses the result set produced by the preceding filtering of nearby routes. In this phase, we iterate over all relevant routes and filter out points of interest, which are not contained in their BoundingRectangle or in its vicinity. This vicinity is represented by the route's BoundingRectangle expanded to an area, which contains potential relevant points of interest (cf. Figure 3). Requirement 2 and 3 are covered with the described approach.

4.3. Ranking

The ranking system is following a plugin-based approach. This approach allows the implementation of a single plugin per ranking feature, programmatically separated from the core system. This allows each plugin to be evaluated and weighted individually, and the ranking function can be easily expanded and adapted without touching the core code. Details on this configuration adaptation can be found in [29]. For each data type in the system, e.g., a route, a point of interest, etc., a specific ranking configuration exists. By separating the configurations, we can define which plugins are to be used for entities of certain data types and how the plugin should be weighted. This allows us to easily extend and adapt our system (see requirement 7). For the following descriptions of the ranking mechanism and the individual plugins we are using the term *"object (θ)"*, which can be any object of a valid data type.

The final score for an object is composed by several partial scores (see formula 1 and requirement 4). Depending on the ranking operator (*add* or *multiply*) of the plugin, a partial score is used to determine the multiplier (first component) or is added to the second component of the formula. Be n the amount of *MULTIPLY*-Plugins, m the amount of *ADD*-Plugins and $\mathbf{r_i(\theta)}$ part-score by a single plugin.

$$score(\theta) = \prod_{i=1}^{n} r_i(\theta) \cdot \sum_{j=n+1}^{m+n} r_j(\theta) \quad (1)$$

Formula 2 shows the calculation of a partial score by such a plugin. $\mathbf{P_i(\theta)}$ is the score assigned to the object by the plugin's internal algorithm, and $\mathbf{p_{weight(i)}}$ the plugin's weight as specified in the configuration.

$$r_i(\theta) := p_{weight(i)} \cdot P_i(\theta)$$
$$p_{weight(i)} \in R_0^+; P_i(\theta) \in [0,1] \quad (2)$$

Location Ranking Plugin. The location ranker will determine the distance to the start of a route (or the POI respectively). Origin can be any GPS coordinate or address, including the user's current location provided by his / her mobile device (see Formula 3).

$$P_{loc}(\theta) := \frac{d(origin, \theta)}{LocationRange} (3)$$

Time Ranking Plugin. We extract relevant time information from the query, which can either be a concrete time (like "4 pm" or "August 5th") in the query terms or the point in time at which the query was executed. The object must provide time information for accessibility or a start / end date (e.g. one time running events) and this information needs to fall in a certain configurable time range to be evaluated in the time ranking plugin (see Formula 4). The time and location ranking plugins meet requirement 5.

$$P_{time} := \frac{|Date_{Query} - Date_{\theta}|}{TimeRange} \quad (4)$$

Boolean Keyword Ranking. The Boolean Keyword Ranker will match semantic concepts in the ontology representation of the user profile with potentially related concepts of the object.

Lucene Full Text Search. This plugin is intended to be a backup mechanism if the concept matching fails or does not return any results. It will perform a simple full text search over the objects description containing all available profile information and search query terms. The Boolean Keyword Ranker and Lucene full-text search address requirement 6.

Point of Interest Ranking. The first consideration is the distance between route and POI (see Figure 5). To compute the distance we split the route into segments of a fixed length, defined by the amount of checkpoints included in the segment.

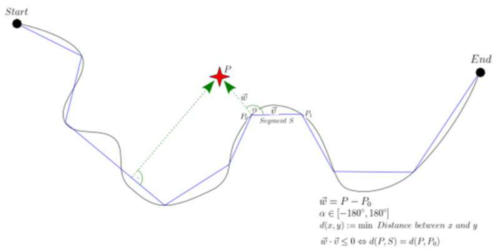

Figure 5. POI ranking

This will impair accuracy, but helps to achieve a better performance. Due to the vector-based calculation, this approach also works in a 3-dimensional space, i.e. taking altitude into account. Furthermore, the relevance of a given POI to the user's profile needs to be considered. Therefore, some ontology matching is also needed at this point.

Rating Ranker. This plugin considers the average user-rating on the aforementioned Likert scale between 1 and 5.

Usage Ranker. Usage refers to the amount of times an object was used. So the score is calculated by dividing the usage indicator of the evaluated object by the global maximum usage indicator (cf. Figure 9).

$$P_{usage}(\theta) := \frac{usage_{\theta}}{\max usage} \quad (5)$$

Length Ranker. The Length Ranker ranks routes by its length according to the user's preferences. If a user is a long distance runner, e.g. training for a marathon, the system computes the most appropriate routes. Therefore, the distance between the average length of a route in the user's running history and the routes that come in to question for recommendation is calculated.

Duration Ranker. The system allows the users to set the duration of their next training session explicitly. Therefore, the users' average duration per unit of length is used to calculate the individual's running time for a specific route.

Hilliness Ranker. As mentioned above, routes are categorized into three slope categories, namely *flat*, *intermediate*, or *hilly*. Routes are sorted into these categories according to their denivelation.

Normalization. Finally, we normalize the output scores of every single plugin to prevent outliers from distorting our results. To do so, we first split the set of scores into quartiles. Then we recalculate the score relative to the quartile borders, as shown in formula 6.

$$f(x) = \begin{cases} q_l & \text{, if } b_u = b_l \\ q_l + ((x - b_{min}) \cdot \frac{q_u - q_l}{b_{max} - b_{min}}) & \text{, otherwise} \end{cases} \quad (6)$$

Be x *the original score,*
q_l/q_u *the lower/upper border of the quartile (e.g. 0.25 and 0.5)*
and b_{min}/b_{max} *the minimal/maximal score in the quartile*

Therefore, each original score is mapped to a new score between 0 and 1 and this solves the problem of outliers. Figure 6 shows the normalization results for a concrete example.

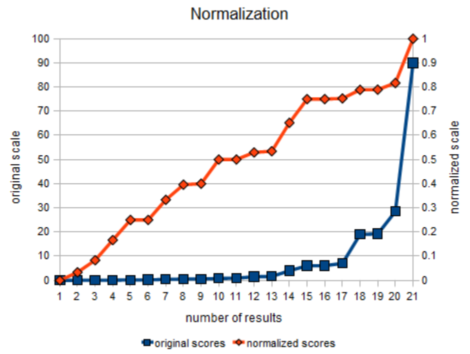

Figure 6. Ranking score normalization

4.4. Implementation

In order to address the limitations of mobile devices like limited computational power or slow and expensive Internet access, a client/server architecture is realized. Figure 7 shows the data flow of route recommendations. The mobile side is implemented using jQuery Mobile.

A user has the possibility to actively search for routes via specifying the location and length of the route or other terms. A REST interface ensures data exchange between client and server. First, the filtering mechanisms reduce the number of suitable routes and then the ranking mechanisms assign a ranking score to each remaining route to derive an ordered list of suitable routes. Filtering and ranking run encapsulated. This led us to the decision to use Java Enterprise Edition (JEE) which separates the business logic from the data tier and the client side. Expensive calculations are moved to the server. Every module on the server is implemented as an enterprise bean. Due to the fact that this approach provides the envisioned modularized structure, it is easy to leverage the power of the JEE platform. Furthermore, only a fixed number of recommendations are transferred to the user interface. Remaining recommendations are saved in a cache to reduce computation efforts for the client. If the user clicks on “More results” additional routes can be loaded quickly from the cache. The same approach is applied for route information. Initially, only basic information such as name, rating, or distance is shown to the user.

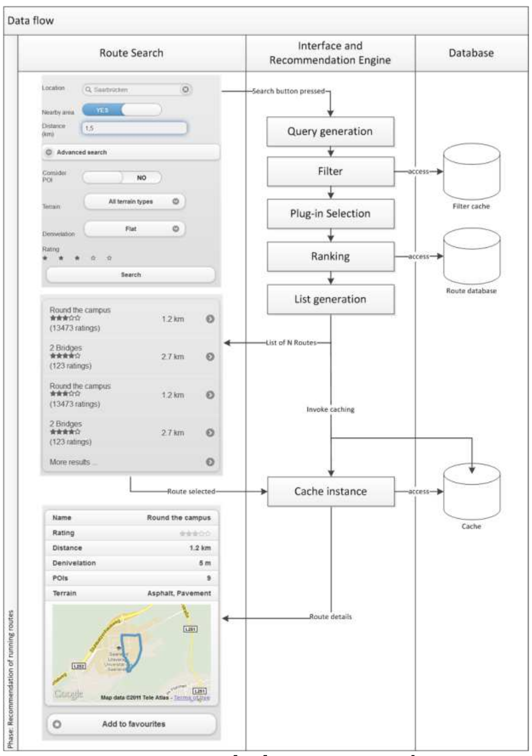

Figure 7. Recommendation process/prototype

Detailed information about a route such as denivelation, terrain, POIs, etc., are loaded from the cache. This approach decreases the amount of data to transfer between server and client. Initial tests have shown that response time is decreased significantly.

Figure 7 shows the overall recommendation process and screenshots from the implemented solution. A search is triggered from the mobile client application on a user’s mobile device. The internal recommendation processes the query, converts it into an internal representation and performs the filtering and ranking operations as described in the preceding subsections. The results are returned to the user for selection. The selection of the result as well as any other explicit or implicit actions of the user on a specific route are tracked in the backend and used to improve subsequent searches. As a final step all relevant information about the chosen route such as a map, terrain description, adjacent POIs, etc., are pushed to the user’s mobile device.

5. Conclusion & Outlook

This paper has presented an integrated concept for a location-aware assistance system for scenarios assisting outdoor sports activities for both the health (e.g. in rehabilitation) and fitness domain. A proposal for an architecture of an assistance system has been developed and a process for recommendations has been designed that covers the core analysis and recommendation system, as well as web-based and / or mobile clients for gathering data and pushing recommendations to the user.

Based on an analysis of influence factors for assistance in outdoor scenarios, requirements have been mapped to analytic features that resulted in the design of specific ranking functions. Routes are considered as objects with certain features, which need to be matched to a runner’s profile and context. Initial evaluations have shown, that relevancy of route recommendation is well received. POIs near or on routes are of particular benefit to runners, being tailored to their demands (e.g. rest points such as benches or restaurants, nice viewpoints). However, routes are not solely considered as objects but are described using segments which is similar to traditional routing problems with the difference that we also describe additional information valuable for runners such as terrain type (soil, concrete, etc.) or route environment (lit, urban, etc.). As a result, dynamic route changes during a run are possible. Such changes can be based on distance or other user criteria.

Overall, the depicted approach represents a major step forward compared to current fitness applications: It is capable of catering to both fitness and health scenarios. Furthermore, it also considers motivations, that may not correlate with the training per se, e.g. a rehabilitation patient who is interested in specific POIs can be recommended routes which include these. By and large, this approach enables a more natural interaction of hobby runners and rehabilitation patients and fosters their willingness to train on a permanent basis. In terms of data acquisition, initial evaluations have shown that the recorded GPS data can be very noisy. Naive solutions so far considered include filtering out GPS data that can be clearly identified as outliers. Other segment types have to be captured manually by the user. Due to the increasing information about route features made available by map providers and increasing capabilities of sensors and image recognition, we expect the latter to be recordable with a user's smart phone automatically in the near future. Following design-oriented methodology [30] the created artifact has to be evaluated against several criteria in future work:

- *user acceptance*: Especially in self-motivated rehabilitation training, technology acceptance and adoption are crucial factors, to ensure that important advice is followed by the patient. [31]
- *real time responsiveness*: Following the work of [32], health-critical situations (e.g. surpassing a certain threshold in heart rate) have to be dealt with in real-time.
- *(mobile) network reliability*: As the communication among devices and people is carried out via a mobile or wireless network, reliability is crucial to prevent possibly hazardous situations for patients (cf. [33]).
- *integration of medical personnel*: Evaluation has to be carried out in clinical studies, in order to evaluate the integration of physicians in caretakers in the monitoring and treatment process (cf. [34])

Further direction for future work is personalization of the ranking function. In order to achieve this, we will apply linear regression on the parameter weights of the ranking function. This will emphasize different ranking plug-ins in relation to individual user feedback, e.g. clicking on the route description, scheduling a run on a particular route, positive rating or negative rating of a route or no action. Cold-start problems regarding new users will be solved by automatic clustering of users. This will allow to group users with sparse data with others users, thereby allowing the system to use the data of other, similar users to guide its recommendation for new users. The identification of similar users will also be used to inform a runner about other runners with a similar fitness level in their vicinity during a run.

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