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Review

Mobile recommender systems in tourism

Damianos Gavalas [a,b,*], Charalampos Konstantopoulos [b,c], Konstantinos Mastakas [b,d], Grammati Pantziou [b,e]

[a] Department of Cultural Technology and Communication, University of the Aegean, Mytilene, Greece
[b] Computer Technology Institute & Press "Diophantus", Patras, Greece
[c] Department of Informatics, University of Piraeus, Piraeus, Greece
[d] Department of Mathematics, University of Athens, Athens, Greece
[e] Department of Informatics, Technological Educational Institution of Athens, Athens, Greece

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ABSTRACT

Recommender Systems (RSs) have been extensively utilized as a means of reducing the information overload and offering travel recommendations to tourists. The emerging mobile RSs are tailored to mobile device users and promise to substantially enrich tourist experiences, recommending rich multimedia content, context-aware services, views/ratings of peer users, etc. New developments in mobile computing, wireless networking, web technologies and social networking leverage massive opportunities to provide highly accurate and effective tourist recommendations that respect personal preferences and capture usage, personal, social and environmental contextual parameters. This article follows a systematic approach in reviewing the state-of-the-art in the field, proposing a classification of mobile tourism RSs and providing insights on their offered services. It also highlights challenges and promising research directions with respect to mobile RSs employed in tourism.

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* Corresponding author at: Department of Cultural Technology and Communication, University of the Aegean, Mytilene, Greece. Tel.: +30 2251036643.
E-mail addresses: dgavalas@aegean.gr (D. Gavalas), konstant@unipi.gr (C. Konstantopoulos), kmast@math.uoa.gr (K. Mastakas), pantziou@teiath.gr (G. Pantziou).

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1. Introduction

The explosive growth of online environments has made the issue of information search and selection increasingly cumbersome; users are overwhelmed by options which they may not have the time or knowledge to assess. Recommender Systems (RSs) have proven to be a valuable tool for online users to cope with the information overload. RSs use details of registered user profiles and habits of the whole user community to compare available information items against reference characteristics in order to present item recommendations (Adomavicius and Tuzhilin, 2005; Ricci et al., 2010). Typically, a RS compares a user profile to some reference attributes and seeks to predict the 'rating' or 'preference' that a user would give to an item she has not yet considered.

RSs originally found success on e-commerce web sites to present information on items and products that are likely to be of interest to the user (e.g. films, books, news, web pages, etc.). Lately, they have been increasingly employed in the field of electronic tourism (e-tourism), providing services like trip and activities advisory, lists of points of interest (POIs) that match user preferences, recommendations of tourist packages, etc. (Kabassi, 2010; Werthner and Ricci, 2004). Existing RSs in e-tourism typically emulate services offered by tourist agents where prospective tourists refer to seeking advice for tourist destinations under certain time and budget constraints (Berka and Plönig, 2004; Ricci, 2002). The user typically states her needs, interests and constraints based upon selected parameters. The system then correlates user choices with cataloged destinations annotated using the same vector of parameters.

A relatively recent development in e-tourism lies in the use of mobile devices as a primary platform for information access, giving rise to the field of mobile tourism. The unique characteristics of mobile tourism bring forward new challenges and opportunities for the evolution of innovative personalized services which have no place in the field of e-tourism. For instance, the knowledge of the exact user location develops appropriate ground for the provision of location-based services. Furthermore, user mobility allows exploiting the knowledge of user's mobility history and taking advantage of a user's social environment lying in geographical proximity.

The most prominent outcome of recent research efforts in mobile tourism has been the substantial number of mobile electronic guide systems, which have been on the spotlight over the past few years (Kenteris et al., 2011). Most of those systems go far beyond from being mobile electronic versions of printed tourist guides, as they incorporate personalization features and take full advantage of the sensing capabilities of modern mobile devices to infer user, social and environmental context in order to provide advanced context-aware services (Höpken et al., 2010).

The first systems that coupled mobile guides functionality with RS technologies appeared soon after (we use the term 'mobile tourism RSs' to refer to those systems). Mobile RSs can increase the usability of mobile tourism applications providing personalized and more focused content, hence limiting the negative effects of information overload (Ricci, 2011). In addition to offering personalized recommendations through employing sophisticated user modeling methodologies, mobile tourism RSs may also take advantage of usage and application context in providing improved, context-aware recommendations for attractions or tourist services (Adomavicius and Tuzhilin, 2011; Gavalas and Kenteris, 2011; O'Grady et al., 2007).

This article follows a systematic approach in reviewing the state-of-the-art in the field of mobile tourism RSs. It offers a detailed insight on typical recommendation tasks and the corresponding support functions commonly offered by existing mobile tourism RS prototypes, categorized in attractions recommendations, tourist services recommendations, collaboratively-generated recommendations, routes/tours and multiple-days itinerary planning. The main contribution of the article lies in the proposed classification of mobile tourism RSs, undertaken on the basis of three different aspects (their chosen architecture, the degree of user involvement in the delivery of recommendations and the criteria taken into account for deriving recommendations). Last, we highlight challenges and promising research directions with respect to mobile RSs employed in tourism.

The remainder of the article is structured as follows: Section 2 provides the required background on the recommendation techniques supported by contemporary RSs. Section 3 summarizes the main features of popular web-based e-tourism RSs. Section 4 provides a detailed view of services offered by mobile RSs in tourism, while Section 5 presents three classification viewpoints for existing mobile tourism RS prototypes. Section 6 provides insights on open issues and research opportunities in the field, while Section 7 summarizes the main issues tackled in the paper.

2. Types of recommender systems

Recommender systems are essentially information filtering systems aiming at predicting the 'rating' (i.e., the preference) that a user would give to an information item (e.g. music file, book or any other product) or social element (e.g. people or groups) she has not yet considered. RSs recommend those items predicted to better match user preferences, thereby reducing the user's cognitive and information overload. Recommendation are made either implicitly (e.g. through ordering a list of information items or displaying a 'those you bought this product, also bought that' bar) or explicitly (when the user requests a recommendation). Nowadays, RSs are classified in several types, based on their target applications, the knowledge used, the way they formulate recommendations and the algorithms they implement. Below, we describe six (6) categories of RSs (Adomavicius and Tuzhilin, 2005; Ricci et al., 2010).

Collaborative filtering (Breese et al., 1998): This type is the most widely used in e-commerce and social media, among others. Target users are recommended items similar to those chosen by other users with similar preferences, therefore users are correlated with each other. A pair of users is correlated on the basis of how common are their individual past selections/ratings.

Content-based filtering (Pazzani, 1999): The recommendations of those systems depend on content items that the target user has opted for in previous interactions. In particular, various candidate items are compared with items previously rated by the user and the best-matching items are recommended.

Knowledge-based filtering (Trewin, 2000): Those systems pursue a knowledge-based approach to generate a recommendation, by reasoning about what items meet the user's requirements (e.g., a recommendation for a car will depend on whether fuel economy or comfort is more important for the target user). Knowledge is built through recording user preferences/choices or through asking users to provide information as to the relevance of the choices. The similarity function represents an estimate of the extent that user needs correlate with available content item options; the similarity function's value is typically shown to illustrate the usefulness of each recommendation.

Demographic filtering (Pazzani, 1999): Those systems are primarily used in marketing, recommending items based on the user's demographic profile. User profile is formed based on demographics, such as the number of times a user views a particular content item's information according to her country, language, age or gender.

Matrix factorization (Koren, 2008): This type essentially comprises a variation of collaborative filtering, using 'baseline' parameters for each user and item. Baselines are additional model parameters introduced for each user and item. They indicate the general deviation of the rating of a user or an item from the global average. For instance, the user baseline for a user that tends to rate higher than the average of users' population will be a positive number.

Hybrid RSs (Burke, 2002): Those systems use a combination of the abovementioned methods, exploiting the advantages of one technique to compensate the shortcomings of another, thereby improving the overall performance. Hybridization may be implemented in several ways: for instance, by making content-based and collaborative-based predictions separately and then combining them; by adding content-based capabilities to a collaborative-based approach (and vice versa); or by unifying the approaches into one model.

3. Recommender systems in tourism

Existing recommendation systems in e-tourism acquire the user needs and wants, either explicitly (by asking) or implicitly (by mining the user online activity), and suggest destinations to visit, points of interest, events/activities or complete tourist packages. The main objective of travel RSs is to ease the information search process for the traveler and to convince (persuade) her of the appropriateness of the proposed services.

In recent years, a number of travel RSs has emerged and some of them are now operational in major tourism portals. Ricci (2002) illustrates several examples whereby a matching engine derives recommendations according to the user input, providing an excellent introduction to the field. Below, we briefly present a representative list of popular web e-tourism systems:

- TripAdvisor (2012) is a tourism website that advises trips, locations and activities for each user and also contains a social component, which allows for lots of elements to be reviewed, commented and rated by others users to assist in the complex decision-making process that pertains to the tourism domain.
- DieToRecs (2012) supports the selection of travel products (e.g. a hotel or a visit to a museum or a climbing school) and building a 'travel bag', i.e. a coherent bundling of products. DieToRecs also supports multiple decision styles by letting the user 'enter' the system through three main 'doors': iterative single-item selection (efficient navigation over the whole content), complete personalized trip selection and inspiration-driven selection (personalization of travel templates shown by means of a user interface).
- Heracles (2012) employs content-based filtering over tourist information mined throughout various online data sources and search engines.
- TripSay (2012) uses a collaborative filtering-based approach to match destinations, places, sights, content and activities, leveraging the user's network of friends as well as those with similar preferences.

4. Services offered by mobile recommender systems in tourism

With the rapid development of mobile computing technologies, various kinds of mobile applications have become very popular (Gavalas and Economou, 2011). As a revolutionary technology, mobile computing enables the access to information anytime, anywhere, even in environments with scarce physical network connections. Among others, the effective use of mobile technology in the field of mobile tourism has been actively studied. Along this line, mobile RSs (i.e. RSs tailored to the needs of mobile device users) represent a relatively recent thread of research with numerous potential application fields (e.g., mobile shopping, advertising/marketing and content provisioning) (Ricci, 2011). For instance, Yang et al. proposed a location-aware recommender system that accommodates customers' shopping needs with location-dependent vendor offers and promotions (Yang et al., 2008). Yuan and Tsao introduced a framework which enables the creation of tailor-made campaigns targeting users according to their location, needs and devices' profile (i.e. contextualized mobile advertising) (Yuan and Tsao, 2003).

Notably, mobile tourism is a privileged application field for mobile RSs, which leverages massive opportunities to provide highly accurate and effective tourist recommendations that respect personal preferences and capture usage, personal and environmental contextual parameters. Below, we focus on typical recommendation tasks and the corresponding support functions commonly offered by existing mobile tourism RSs. The tasks presented herein are not intended to be exhaustive, but provide a reasonable coverage of recent research in the field.

4.1. Attractions (POIs) recommendations

Most prototyped tourism-relevant mobile RSs are utilized to recommend city attractions (e.g., museums, archeological sites, monuments, churches, etc.). The recommendations are typically visualized either in a traditional hierarchical list-based interface (Kenteris et al., 2009) or by superimposing attraction icons on a map interface (Baus et al., 2005).

Recommended attractions are computed based on session-specific and long-term preferences stored in the user profile, often using current user location to filter the results (e.g. Horozov et al., 2006; Noguera et al., 2012). However, mobile recommendation engines increasingly take into account additional contextual parameters, including time (e.g. (Amendola et al., 2004; Cheverst et al., 2000; Pashtan et al., 2003)), attractions already visited (e.g. (Cheverst et al., 2000; Gavalas and Kenteris, 2011; van Setten et al., 2004)), user mobility pattern (e.g. (Amendola et al., 2004; Barranco et al., 2012; Cheverst et al., 2000), weather (e.g. (Gavalas and Kenteris, 2011)), transportation mode in use (e.g. (Savage et al., 2011)), user's mood (e.g. (Savage et al., 2011)), social environment (e.g. (Brown et al., 2005; Gavalas and Kenteris, 2011)), etc.

As regards the type of informative content, this varies from text and images (e.g. (Cheverst et al., 2000)) to sound/video (e.g. Kenteris et al., 2009), 2D maps (e.g. (Averjanova et al., 2008; van Setten et al., 2004)) 3D maps (e.g. (Noguera et al., 2012)), VRML models (Malaka and Zipf, 2000) and augmented reality views (e.g. (mtrip Travel Guides, 2012)). Some map-based systems incorporate GIS servers (e.g. (Malaka and Zipf, 2000; Noguera et al., 2012; Poslad et al., 2001)) to improve interactivity with geo-references attractions.

4.2. Tourist services recommendations

This refers to functionality rather similar to that described above. The user typically receives information relevant to travel services such as restaurant, hotel, transportation services, information offices, etc. (Horozov et al., 2006; Pashtan et al., 2003; Ricci and Nguyen, 2007; Savage et al., 2011). Most systems use constraint-based filtering approaches to control which services are suggested. The user specifies constraints and the system retrieves and ranks services which satisfy those constraints (e.g., (Dunlop et al., 2004)). For instance, hotel recommendations may be based on offered facilities, customers' reviews, room availability, check-in/checkout times, distance from POIs and price, while restaurant recommendations on cuisine, location, opening hours, customer rating score, menu and price range (Yu and Chang, 2009).

More advanced systems (e.g., (Park et al., 2007)) offer personalized recommendations through modeling the probabilistic influences of input parameters (i.e., the user's personal information and contextual information) on tourist services attribute values. For instance, restaurant attributes may be the class (e.g., Greek or Italian restaurant), price (e.g., low or medium) and mood (e.g., romantic or tidy). User's contextual information may include season (e.g., spring), time in day (e.g., breakfast), position, weather (e.g., sunny), and temperature (e.g., warm). Having collected contextual information, a restaurant's recommendation score may be a weighted sum of the conditional probabilities of the restaurant's attribute values.

4.3. Collaborative user-generated content and social networking services for tourists

A number of systems enable recommendations aiming at discovering, even unexpected, attractions or services. Those systems are largely inspired by features often offered by popular social networking platforms, providing access to repositories of user-generated content (Strobbe et al., 2010); as such, they are designed to support visitors to explore a city as well as share their visit experiences (Brown et al., 2005; García-Crespo et al., 2009; Gavalas and Kenteris, 2011; Savage et al., 2011; Zheng and Xie, 2011). User activity (e.g., movement pattern, visited attractions, pages browsed, etc.) is automatically logged, while tourist-relevant content (e.g., comments, attractions ranking, photographs/videos) may be collaboratively managed and shared. Moreover, some systems visualize the positions of nearby visitors (e.g., for personalized friend recommendations (Zheng and Xie, 2011)) and support their leisure collaboration or direct VoIP communication (e.g., in Brown et al. (2005)).

Social networking services are either supported as integral part of the RS (Brown et al., 2005; Gavalas and Kenteris, 2011) or based on third-party social networks to extract user profile information (e.g., the I'm feeling Loco system (Savage et al., 2011) is based on the foursquare platform (foursquare, 2012), while the SPETA system (García-Crespo et al., 2009) is based in the OpenSocial API (OpenSocial API, 2012)).

4.4. Routes and tours recommendations

A number of transportation and navigation tools offer routing services based in the geographical location of mobile users. Location information is typically extracted from GPS receivers, but also through using alternative location tracking techniques (Wi-Fi, cell-id, RFID, etc.). Apart from the widely used navigator systems, route (i.e., point-to-point) recommendation services are integrated in many prototyped mobile guide applications to assist users finding their way from their current location to a recommended attraction.

Early projects offered shortest-path route guidance from the user's current location to the next (typically, nearest) recommended POI (e.g., (Cheverst et al., 2000)). Some projects also exploited information retrieved from social networks (through collaborative rating/tagging) to provide personalized route recommendations (e.g., (Rey-López et al., 2011)).

Further to point-to-point routing guidance, several mobile RSs focused on deriving personalized tourist tours, i.e. ordered lists of intermediate locations (visits to attractions) along an origin-destination path, subject to several user's preferences and constraints such as current location, available time and travel interests (Di Bitonto et al., 2010). Several tour planning mobile RS implementations incorporate optimization algorithms, in effect, solving variations of the well-known traveling salesman problem (TSP) (e.g., (Maruyama et al., 2004; Shiraishi et al., 2005)). Furthermore, some projects offer personalized walking tours, wherein paths presumably problematic with respect to environmental burden (e.g., routes along streets with high traffic) are substituted by more appropriate paths (e.g., by routes through pedestrian zones, parks and forests) (Fink and Kobsa, 2002; Malaka and Zipf, 2000).

Another popular line of research involves mobile tourism RSs that incorporate city transport advisory services, considering all available transportation modes (e.g. walking, cycling, bus, tram, metro, etc.). Those systems either derive point-to-point multi-modal routes via a set of POIs (suitably located along the multi-modal route) (Tumas and Ricci, 2009) or first derive a tourist tour and subsequently provide multi-modal route generation among successive recommended POIs (Zenker and Ludwig, 2009).

4.5. Personalized multiple-days tour planning

In a typical scenario, a tourist visits a destination for one or more days with a multitude of interesting attractions. Due to time and/or budget restrictions, visiting all these attractions is usually infeasible. Hence, a selection of the most important POIs to visit, without violating user restrictions, is in need. A significant body of mobile RS prototypes addresses this requirement through generating multiple-day personalized tours via a subset of available POIs (each tour corresponds to each day of stay); In addition to user-defined restrictions and preferences, several constraints may be considered, such as the opening hours of POIs, the number and duration of desirable breaks (e.g. for lunch or rest), etc. In the relevant literature, this problem is known as the tourist trip design problem (TTDP).

TTDP is a far more algorithmically challenging task compared to generating single tourist tours. As it cannot be solved in polynomial time (Vansteenwegen et al., 2011), efficient heuristic algorithms are typically implemented to deal with TTDP in online applications. High quality TTDP solutions should feature POI recommendations that match user preferences (thereby maximizing user satisfaction) and near-optimal feasible route scheduling. The algorithmic and operational research literature include many route planning problem modeling approaches, effectively simplified versions of the TTDP. One of the simplest problems that may serve as a basic model for TTDP is the orienteering problem (OP) (Tsiligirides, 1984). The OP is based on the orienteering game, in which several locations with an associated score have to be visited within a given time limit. Each location may be visited only once, while the aim is to maximize the overall score collected on a single tour. The OP clearly relates to the TTDP: the OP locations are POIs associated with a score (i.e., user satisfaction) and the goal is to maximize the overall score collected within a given time budget (i.e., time allowed for sightseeing per day).

Extensions of the OP have been successfully applied to model the TTDP. The team orienteering problem (TOP) (Chao et al., 1996) extends the OP considering multiple routes (i.e., daily tourist itineraries). The (T)OP with time windows (TOPTW) (Vansteenwegen et al., 2009) considers visits to locations within a predefined time window (this allows modeling opening hours of POIs). The time-dependent TOPTW (TDTOPTW) (Garcia et al., 2013) considers time dependency in the estimation of time required to move from one location to another (this is suitable for modeling multi-modal public transportation among POIs). Several further generalizations exist that allow even more refined modeling of the TTDP, e.g. taking into account multiple user constraints (MCTOPTW) (Sylejmani et al., 2012) such as the overall budget that may be spent for POI entrance fees.

Several research prototypes and commercial tours incorporate sophisticated algorithms addressing the TTDP. In effect, most are TOPTW solvers (e.g. (Gavalas et al., 2012; mtrip Travel Guides, 2012; Vansteenwegen et al., 2011)) taking into account several user-defined parameters within their recommendation logic (days of visit, preferences upon POI categories, start/end location, visiting pace/intensity), while also allowing the user to manually edit the derived routes, e.g. add/remove POIs. Recommended tours are visualized on maps (Gavalas et al., 2012; mtrip Travel Guides, 2012; Vansteenwegen et al., 2011), allowing users to browse informative content on selected POIs. Some tools also offer

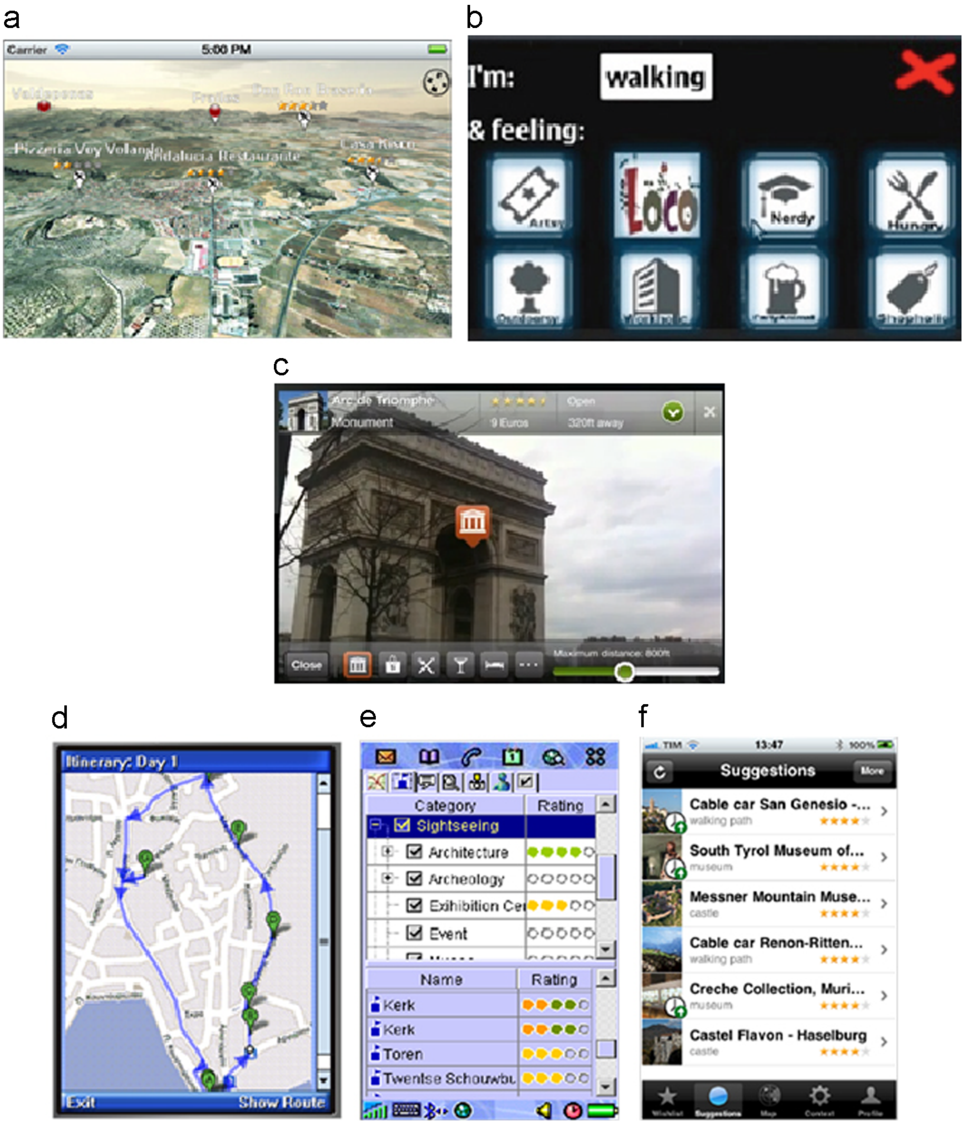

Fig. 1. Screenshots of representative mobile tourism RSs: (a) POI recommendations superimposed on a 3D virtual representation, shown on iPhone display (Noguera et al., 2012), (b) screen displaying captured user transportation mode in I'm feeling LoCo (Savage et al., 2011), (c) augmented reality-based POI recommendation in the mtrip iPhone application (mtrip Travel Guides, 2012), (d) map-based tourist itinerary visualization in DailyTRIP (Gavalas et al., 2012), (e) list of nearby 'objects' with relevance scores in COMPASS (van Setten et al., 2004) and (f) POIs recommendation list in ReRex (Baltrunas et al., 2012).

augmented reality views of recommended attractions (e.g., (mtrip Travel Guides, 2012)).

Recently, the work of Garcia et al. (2013) was the first to address algorithmically the TDTOPTW (namely, they consider the option of public transportation transfers in addition to walking), presenting two different approaches to solve the problem, both applied on real urban test instances. The authors argue that their approach is suitable for real-time applications, requiring slightly longer computational time than fast TOPTW algorithms to derive sufficiently qualitative solutions.

Figure 1 presents screenshots of representative mobile tourism RSs.

5. Classification of mobile recommender systems in tourism

The landscape of mobile RSs employed in tourism is extremely diverse in terms of their architectural, technological and functional aspects. Certainly, a concrete classification of those systems is essential to understand their characteristics and contrast their respective advantages and restrictions. We argue that a taxonomy scheme solely relying on a single classification criterion carries the risk of being fragmentary and deficient while hiding the complexity, diversity and multidimensionality of mobile RSs. On the other hand, a single taxonomy scheme combining multiple uncorrelated criteria may prove ambiguous and confusing. Rather, we propose a multi-faceted scheme to classify existing mobile tourism RSs with respect to the following aspects: (a) their chosen architecture, (b) the degree of user involvement in the delivery of recommendations, and (c) the criteria taken into account for deriving recommendations. The first two aspects are examined in less detail as their respective taxonomy is common to the majority of mobile information systems. On the contrary, the last aspect (i.e. recommendation criteria) is tailored to the systems reviewed herein; hence, it is investigated in more depth.

Figure 2 illustrates a generic architecture for mobile tourism RSs. It is noted that the focus of this article is not on the technical aspects of the employed RS engines, explained in detail in previous works (Adomavicius and Tuzhilin, 2005; Breese et al., 1998; Burke, 2002; Koren, 2008; Pazzani, 1999; Ricci et al., 2010; Trewin, 2000). Rather, our focus is on the methods used to consume information from tourism-relevant content repositories, elicit user requirements and capture situational context to deliver personalized tourist recommendations to mobile clients.

5.1. Classification based on architectural style

As regards their architectural style and the approach taken for the provision of tourist recommendations, existing mobile tourism RSs fall into one of the following categories:

- *Web-based RSs* (e.g., (Amendola et al., 2004; Cheverst et al., 2000; Gavalas and Kenteris, 2011; Gavalas et al., 2012)): These are typical client–server systems, wherein a mobile application

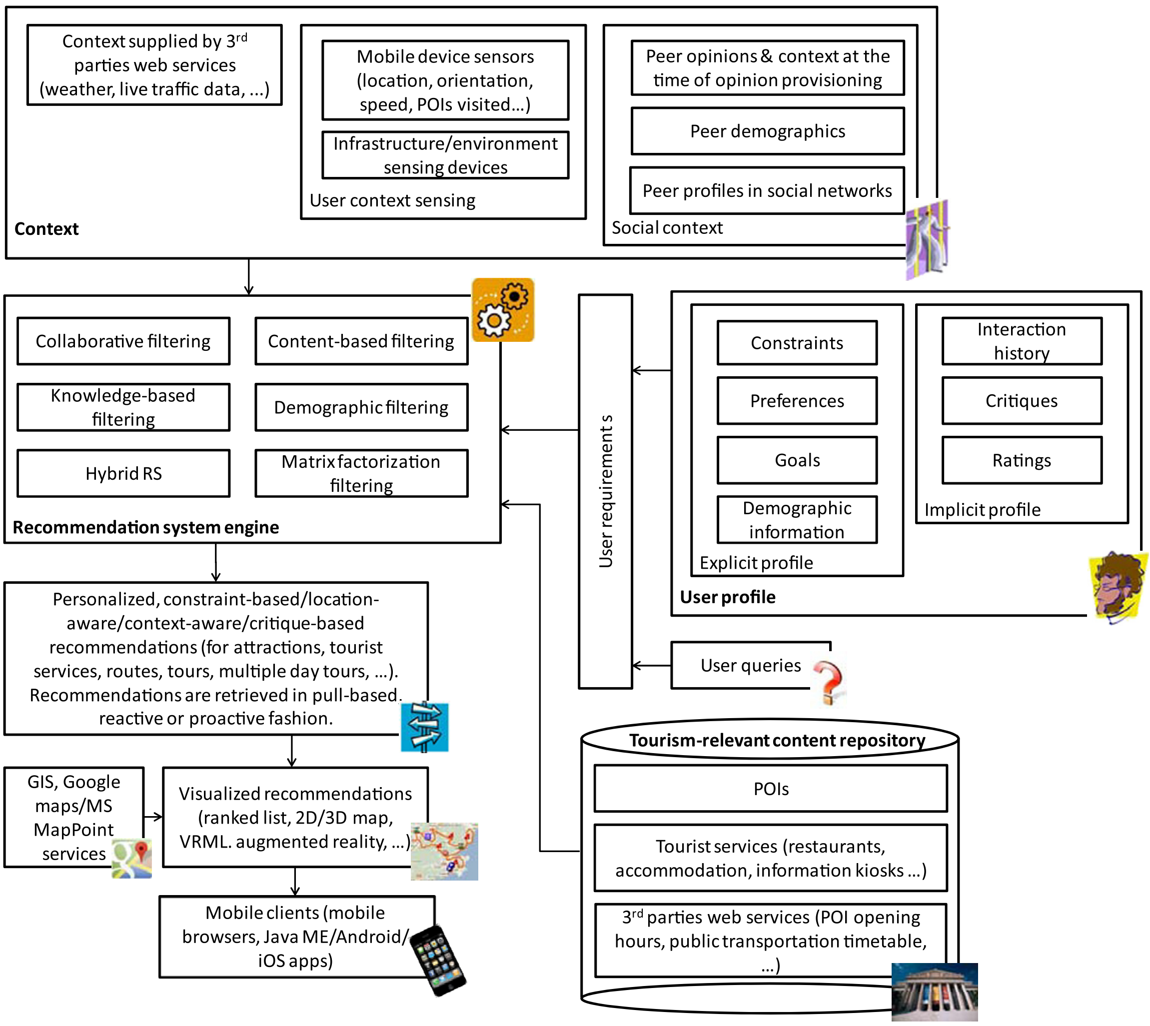

Fig. 2. A generic architecture of a mobile tourism RS.

(client) corresponds to the presentation tier and the recommendation logic is maintained on the server (hence, continued network connectivity is required). Web-based RSs may exploit the sufficient computational resources of the RS server to execute sophisticated recommendation algorithms. As regards the client-side of web-based RSs, that may either be based on mobile browsers (potentially enhanced by JavaScript/Ajax code for asynchronous browser-server information exchange) or implemented as Java ME, .NET Compact Framework, Android or iOS applications (Gavalas and Economou, 2011), which offer basic offline functionality, rich UI widgets and persistent storage.

- *Standalone systems* (e.g., (mtrip Travel Guides, 2012)): These refer to full-fledged mobile applications that incorporate the recommendation logic and the tourist content. They are typically downloaded and installed on mobile devices thereafter functioning in disconnected mode. As a result, recommendation techniques based on matching different user profiles (e.g. collaborative filtering-based approaches) are out of scope in those systems.
- Web-to-mobile (e.g., Kenteris et al., 2009; MyCityMate 2012): These systems provide a typical web interface for the pre-visit stage, whereby users initially select content and then build a customized tourist application, incorporating the recommendation logic. Similarly to standalone systems, the application is subsequently downloaded and installed on a mobile device thereafter executing offline and achieving cost savings (e.g. 3G roaming charges). On-demand connections to a remote server may be used, for instance, to update POI information or public transportation data. Similarly to standalone systems, collaborative filtering-based recommendations are unsuitable for web-to-mobile RSs.

5.2. Classification based on the degree of user involvement in the delivery of recommendations

Mobile tourism RSs differ on the way they capture the situational context to rank recommended items and the degree of user involvement in the delivery of recommendations, categorized as

- *Pull-based* (Barranco et al., 2012; Di Bitonto et al., 2010; Gavalas et al., 2012; Kenteris et al., 2009; van Setten et al., 2004): The delivery of recommended content is driven by queries, i.e., by users requests. Since users maintain control on information delivery, pull-based systems are considered as less intrusive (Kabassi, 2010) (users commonly regard as intrusive the presentation of any information items not explicitly requested).
- *Reactive* (Bellotti et al., 2008; Poslad et al., 2001; van Setten et al., 2004): These systems react to the changing situational context to generate content recommendations without requiring any explicit user intervention. System settings dictating the adaptation on the changing context may either be 'hardcoded' or explicitly defined by the user.
- *Proactive* (McCarthy et al., 2006; O'Hare and O'Grady, 2003): While pull-based and reactive systems make use of current and historic contexts, proactive systems are capable of proactively pre-caching appropriate content (downloaded from a content server) on the user's mobile device through extrapolating future context (using specialized prediction models). This enables high responsiveness in the case that recommended items include large multimedia files (e.g. audio, video) and prevents functionality disruptions in environments with fluctuating network connections.

Proactive systems become less meaningful nowadays, in the face of high-speed wireless technologies supported by modern smartphone devices. However, the push model employed in proactive RSs may be an effective option in scenarios where potentially recommended items change often and rapidly (Bedi and Agarwal, 2012) or the users cannot focus their full attention on the system and should not be distracted from other activities (e.g., while driving) (Bader et al., 2011). Certainly, reactive and proactive systems require intelligent inference techniques to handle uncertainty inherent in situation assessment so as to yield relevant items and improve users' acceptance.

5.3. Classification based on the criteria taken into account for deriving recommendations

Last, mobile tourism RSs may be approached on the basis of the criteria taken into account for deriving recommendations, as detailed in the following subsections.

5.3.1. User constraints-based recommender systems (UCRS)

A considerable number of mobile RSs rely on user constraints and preferences, either explicitly stated or implicitly inferred, to derive content recommendations (Felfernig and Burke, 2008). The explicit user profile is typically created through a short survey, in the application startup, denoting demographic information, 'hard' constraints, preferences and user goals. The implicit users profile is fed as the user interacts with the system, thereby implicitly denoting preference upon certain items (through interaction behavior/history, ratings and critiques upon recommended items) (see Fig. 2).

Tourism-relevant UCRSs typically exploit contextual information to determine the appropriateness of POIs. Strictly speaking though, they lack an actual recommendation engine (Noguera et al., 2012). Although resembling knowledge-based filtering systems (Felfernig and Burke, 2008), UCRSs lack similarity assessment techniques and domain-specific knowledge, to be characterized as such. Hence, those systems imply a broader definition of RSs (i.e., a RS is defined as "any system that guides a user in a personalized way to interesting or useful objects in a large space of possible options or that produces such objects as output" (Felfernig and Burke, 2008)). Herein, we take this relaxed definition of RSs and briefly survey representative UCRSs for sake of completeness. Notably, all UCRSs reviewed below are location-aware, while the majority among them takes additional contextual parameters into account; however, they are not classified as location-aware or context-aware RSs (see the following two subsections) as they lack a recommendation engine.

GUIDE (Cheverst et al., 2000) is a milestone tourist guide project deployed in the city of Lancaster. Its supporting infrastructure was based on a number of wireless access points to locate a user and present information for a POI via a browser-based interface. Apart from user location, recommended POIs information was based on the user's walking speed, the places already visited, the time of the day, the language and interests of the user. GUIDE was also the first system known to create personalized tours. Factors taken into account for tour creation were the opening and closing times of POIs, the best time to visit an attraction (e.g. avoiding peak hours), the distance between attractions and the most esthetic route between them. The system offered the user navigation instructions from one POI to the next and dynamic reordering of POIs initially included the tour (e.g. at the event of a visitor staying longer than anticipated at a location).

UbiquiTO (Amendola et al., 2004) is an adaptive 'journey companion' for mobile users in Turin. Its recommendation engine exploits personalization rules to suggest items (hotels, restaurants, information about events or POIs) tailored to the user preferences and location. Moreover, a 'presentation adapter' adapts the presentation (e.g., descriptions) to the user features (age, possible vision impairments, etc.), the device characteristics (screen size) and the context (e.g., time of day, movement speed).

CATIS (Pashtan et al., 2003) is a context-aware tourist information system with a web service-based architecture. The context elements considered to this project are location, time of day, speed, direction of travel and personal preferences. This system provides the user with context-aware information, retrieved from web services. For example, if the user is traveling at noon, a simple integration of the time context, the location and respective user preferences for restaurants, will result on a list with restaurants to lunch.

COMPASS (van Setten et al., 2004) (see Fig. 1e) is a system that offers map-based information services to tourists based on their specific context and preferences. The objects displayed on a map are updated when the user moves (context changes) or when her profile or goal changes. The systems discovers search services, used to retrieve objects matching the context's 'hard' criteria (e.g. objects located within a certain radius from the user's position); those objects are fed into the recommendation engine, which scores each object using 'soft' criteria, such as the users interests and other contextual factors like the last time an object was visited.

CRUMPET (Poslad et al., 2001) provides tips, tour suggestions, maps and other information on a range of tourist-related venues (restaurants, movies, shows, etc.). The system relies on implicit feedback (mainly through logging places visited by users) to infer user preferences. CRUMPET incorporates a sophisticated middleware layer enabled by a FIPA-compliant multi-agent system (agents are used for UI adaptation, monitoring the communication layer, wrapping and publishing/subscribing to e-tourism services).

MyMytilene (Kenteris et al., 2009) is a web-to-mobile system delivering rich multimedia content for categorized tourist locations of Mytilene, Greece, based on user profile information. In the pre-visit stage, users select content incorporated into a dynamically built mobile guide application, downloaded and installed on a mobile phone. The mobile application may function on offline mode. Mycitymate (MyCityMate, 2012) takes a similar approach providing information for tourist services like venues, café, pubs, bars, accommodation, etc., while also offering personalized social features like 'where are my friends' and 'make new friends'.

Deep Map (Malaka and Zipf, 2000) is an early research framework for generating personalized guided walks for tourists. The core of Deep Map is an agent-based GIS module (along with a content repository storing 3D information of selected landmarks) which handles spatial queries and offers navigational assistance and route finding. The tour planning algorithm takes into account 'hard' physical restrictions (e.g., road steepness, turn rules, legal rules, etc.) along with 'soft' user-defined parameters (e.g. route esthetic aspects, dislike of motorized traffic, etc.). The interface layer supports the natural language modality and interactive 3D VRML models.

DailyTRIP (Gavalas et al., 2012) (see Fig. 1d) is a mobile web-based multiple-days tour planner, which derives near-optimal itineraries for the traveler (one itinerary for each day of visit). DailyTRIP takes into account the current user location, user preferences (such as the time available for visiting sights in daily basis), opening days and anticipated visiting times for the POIs considered. The objective of DailyTRIP is to maximize the overall profit associated with suggested POIs (where individual profits are calculated as a function of the POIs' 'objective' importance and the user's potential interest for the POI) while not violating the traveler's daily time budget for sightseeing. Along the same line, mtrip (mtrip Travel Guides, 2012) (see Fig. 1c) represents a recent development, known to work as standalone Android, iPhone and iPad application. The mobile application generates location-aware personalized itineraries for selected travel destinations and uses augmented reality to offer enhanced views of physical spots.

5.3.2. Pure location-aware recommender systems (LARS)

In effect, mobile LARSs represent a special case and early versions of context-aware RSs (reviewed in the following subsection), as their recommendation logic solely relies on location among the many potentially measurable contextual parameters. LARSs constituted a major breakthrough over traditional RSs, utilizing the ability of modern (including early) mobile devices to capture their geographical position and seamlessly convey it to the recommendation engine. Most LARSs have been prototyped on early cellular phones, lacking sensors other than GPS.

GeoWhiz (Horozov et al., 2006) employs a collaborative filtering-based solution that uses location as a key criterion for generating restaurant recommendations. GeoWhiz utilizes a 'convenience' metric in making recommendations, i.e. recommended restaurants should be conveniently-situated nearby the user's current location, unless there is an overriding criterion (e.g., restaurant suitable for a special occasion or offering discount coupons) that warrants the recommendation.

Biuk-Aghai et al. (2008) presented a LARS (built on the top of the earlier MacauMap system (Biuk-Aghai, 2004)), which takes into account user preferences and feedback information (ratings) for delivering recommendations (using a collaborative filtering-based engine). The proposed system employs a genetic algorithm for generating travel itineraries and a fuzzy-logic based module for calculating visit/stay times for each stop of the entire trip. Itineraries are calculated on the basis of the user's stated preferences, the user's visit history, official spot ratings and peer users' feedback ratings.

The PECITAS system (Tumas and Ricci, 2009) offers location-aware recommendations for personalized point-to-point paths in the city of Bolzano, Italy. The paths are illustrated by listing the various connections that the user must take to reach the destination using public transportation and walking. An interesting aspect of PECITAS is that, although an optimal shortest-path facility is incorporated, users may be recommended alternative (longer) routes that pass through several attractions, given that their specified constraints (e.g. latest arrival time) and travel-related preferences (maximum walking time, maximal number of transport transfers, sightseeing preferences, etc.) are satisfied. The recommendations (in effect, a vector of route features, e.g. transport modalities, length, number of POIs touched) are selected in a personalized way, using a knowledge-based recommendation technology.

Yu and Chang proposed a LARS system architecture (Yu and Chang, 2009) which supports personalized tour planning using a rule-based recommendation process. An interesting aspect of this system is that it packages 'where to stay' and 'where to eat' features together with 'typical' tourist recommendations for sightseeing spots and activities. For instance, recommended restaurants (selected based on their location, menu, prices, opening hours, customer rating score, etc.) are integral part of the tour and the time spent for lunch/dinner is taken into account to schedule visits to attractions or to plan other activities.

Noguera et al. (2012) proposed a 3D-GIS mobile LARS (the recommendation engine is based on REJA (Martinez et al., 2009), a hybrid collaborative/knowledge-based filtering RS) (see Fig. 1a). Content item recommendations are restricted to an 'influence area' around the user's location. The system visualizes (on mobile displays) 3D virtual representations of the world where the users are physically located (based on a custom 3D GIS architecture). The prototype was tested on iPhone smartphones.

5.3.3. Context-aware recommender systems (CARS)

Pure LARSs employ unidimensional logic in recommending items as they only consider a single dimension (i.e. location) of the multi-dimensional contextual and situational space. The notion of unidimensionality also applies to RSs that require some short of user feedback such as ratings in order to make personalized propositions of items: typically, ratings are unidimensional in the sense of consisting of a scalar value that represents the user's appreciation for the rated item. Multi-criteria ratings allow users to express more differentiated opinions by allowing separate ratings for different aspects or dimensions of an item (Fuchs and Zanker, 2012).

Several lines of research have successfully exploited multi-criteria ratings to improve the accuracy of recommendations. Adomavicius et al. (2005) proposed a contextualized view on ratings, giving rise to CARS. Although the users still provide unidimensional ratings, the situational context of users (e.g., age, time or weekday) introduces additional dimensionality to the ratings.

The concept of context-awareness agrees with the ubiquitous nature of mobile devices. Mobility adds several contextual dimensions, either implicitly fed (e.g. change of location) or inferred (e.g. multiple visits or spending more time than average in a POI may be regarded as a positive 'vote'). A recent survey revealed that recommendations offered by CARS may significantly improve the appreciativeness of tourists in comparison to the recommendations provided by 'plain' RSs (Baltrunas et al., 2012). For instance, museum visits are more highly appreciated in less crowded days, walking paths are rated worse at night time and open archeological sites are rated higher in sunny days. Likewise, the recommendation of a music club to young, male users that visit a city in August is presumably more accurate if the system exploits ratings submitted by young, male users, who rated the club in the summertime.

Context values may be captured by mobile devices' built-in sensors (e.g. GPS unit, accelerometer, timer, compass, gyroscope and camera) (Campbell and Choudhury, 2012), web services (e.g. weather report or public transportation information service), supporting infrastructure (e.g. obtain temperature information from sensors deployed in a specified area or crowdeness from presence sensors) or peer users (through WPAN adhoc connections).

Examples of potentially useful context parameters are location, distance from POI, budget, time, weak day, season, time available for sightseeing, means of transport, weather conditions, mobility history (e.g. POIs already visited by the user), social environment, etc. Notably, all CARS reviewed herein take into account location, in addition to other context elements.

One of the early mobile CARS examples employed in tourism is the Cyberguide project (Abowd et al., 1997), which encompassed several tour guide prototypes for different handheld platforms. Cyberguide provided tour guide services to mobile users, exploiting the contextual knowledge of the user's current and past locations in the recommendation process.

Barranco et al. (2012) proposed a context-aware system for mobile devices that incorporates the user's location, trajectory and speed (while driving) to personalize POIs recommendations. POIs are chosen among those located within a radius around the user's location; the radius is calculated based on the user's trajectory and speed. The contextually-filtered POIs are then fed into a hybrid RS (REJA (Martinez et al., 2009)) as an input, which selects the most appropriate ones according to the user's preferences.

Gavalas and Kenteris (2011) introduced the concept of 'context-aware rating' to denote the higher credibility of users that upload reviews, ratings and comments while onsite (via their mobile devices) in comparison with others that perform similar actions through standard web interfaces. In this context, MTRS assigns increased weights to ratings/content provided by tourists actually visiting a POI compared to ratings submitted by web users. Hence, MTRS captures context-aware user evaluations and ratings and uses such data to provide recommendations to other users with similar interests, using a collaborative filtering-based RS engine. Furthermore, MTRS delivers several personalized recommendation services to mobile users, taking into account contextual information such as the user's location, the current time, weather conditions and user's mobility history (e.g. POIs already visited by the user). An interesting aspect of MTRS is the support offered to tourists to upload ratings or multimedia content, through wireless sensor network (WSN) installations, deployed around important POIs; this suggests a cost-effective networking solution either when high 3G roaming charges apply or in areas lacking WLAN coverage. A similar approach in taken in the iTravel system (Yang and Hwang, 2013), which adopts a peer-to-peer (P2P) communication model (powered by WiFi or Bluetooth) to enable detection of nearby tourists and direct cost-effective information exchange among them.

I'm feeling Loco (Savage et al., 2011) (see Fig. 1b) is a ubiquitous location-based RS which considers automatically inferred user preferences and spatiotemporal constraints for sites recommendation. The system learns user preferences by mining a person's profile in the foursquare location-based social network (foursquare, 2012). The physical constraints are delimited by the user's location and mode of transportation (walking, bicycle or car), which is automatically detected (based on measurements taken by a smartphone's accelerometer sensor) through the use of a decision tree followed by a discrete Hidden Markov Model. The individual only has to explicitly define how she is currently feeling, to determine the type of places she is currently interested in visiting.

Magitti (Bellotti et al., 2008) is a mobile leisure guide system that detects current user context, infers current and likely future leisure activities and recommends content about suitable venues (e.g., stores, restaurants, parks and movies). Magitti supports three key features: context-awareness (current time, location, weather, venues opening hours and user patterns); activity-awareness (it filters items not matching the user's inferred or explicitly specified activity modes); serendipitous, relaxing experience (users do not need to enter profile, preferences or queries).

ReRex (Baltrunas et al., 2012) (see Fig. 1f) is a CARS that takes a new approach for assessing and modeling the relationship between contextual factors and item ratings, whereby users are asked to judge whether a contextual factor actually influences the rating given under a certain contextual condition (e.g., whether escorting children influences the decision to visit a museum). The application presents the recommendations generated by a predictive model (based on matrix factorization) and shortly justifies the recommendations. In addition to context-dependent recommendations of touristic POIs, ReRex offers assistance in the preparation of a complete itinerary and the modification of the itinerary according to circumstances and eventualities that occur during the itinerary.

5.3.4. Critique-based recommender systems (CBRS)

Critiquing is a form of minimal feedback which helps conversational RSs to narrow the search space and help the user find the product they are looking for more efficiently (McCarthy et al., 2006). A critique is a directional preference feature indicated by the user (typically on a 1–5 rating scale) with respect to a presented recommendation. For example, a user receiving a holiday package recommendation may specify that she is looking for a similar cheaper holiday by critiquing the price feature.

CBRSs represent a separate thread of CARS, as they take into account user critiques in addition to 'typical' contextual factors to further improve recommendations accuracy and effectiveness.

Table 1
Main features of mobile tourism RSs recommending attractions and tourist services.

Mobile RS	Release date	Recommendation technique	RS category	Items recommended	Additional services offered/unique features	Criteria used for recommendation	Architecture/client application implementation platform
GUIDE (Cheverst et al., 2000)	2000	User constraints-based	UCRS	POIs	Accommodation booking	User location, walking speed, places already visited, time, user preferences	Web-based (mobile browser client)
UbiquiTO (Amendola et al., 2004)	2004	User constraints-based	UCRS	Hotels, restaurants, events, POIs	Presentation adaptation based on device profile	User location and movement, time of day	Web-based (mobile browser client)
CATIS (Pashtan et al., 2003)	2003	User constraints-based	UCRS	Restaurants, hotels	Tourist content fetched from web services; content adaptation based on the screen size and supported by the user's device markup (WML or HTML)	User location, time of day, speed, direction of travel and personal preferences	Web-based (mobile browser client)
COMPASS (van Setten et al., 2004)	2004	User constraints-based	UCRS	POIs	Open architecture enabling effortless integration of services provided by third parties (services are described in OWL)	Distance, last time visited, user goal	Web-based (mobile browser client)
CRUMPET (Poslad et al., 2001)	2001	User constraints-based	UCRS	Travel tips, tour suggestions, tourist-relevant venues	Component-based FIPA-compliant multi-agent system used for wrapping, publishing and subscribing to e-tourism services	User location, visited POIs	Web-based (mobile browser client)
MyMytilene (Kenteris et al., 2009)	2009	User constraints-based	UCRS	POIs	Dynamic generation of a mobile guide application through a web interface; ability to function offline and download content updates on demand	User location	Web-to-mobile (Java ME client application)
GeoWhiz (Horozov et al., 2006)	2006	Collaborative filtering	LARS	Restaurants	Use of a 'convenience' metric for deriving recommendations	User location	Web-based (Java ME client application)
Noguera et al. Noguera et al. (2012)	2012	Hybrid (collaborative/ knowledge-based filtering)	LARS	Attractions, venues, restaurants, bars, accommodation	3D-GIS virtual representation of the physical world	User location	Web-based (iOS client application)
Barranco et al. (2012)	2012	Hybrid RS (collaborative/ knowledge-based filtering)	CARS	POIs	Support for on-the-move users traveling aboard automobiles in interurban environments	User location, trajectory and speed	Web-based (iOS client application)
MTRS (Gavalas and Kenteris, 2011)	2011	Collaborative filtering	CARS	POIs	Sharing ratings, comments and multimedia content with peers; use of WSN installations to enable cost-effective interaction of user devices with remote server	User location, time, weather, user's mobility history, peer users ratings	Web-based (Java ME clients)
I'm feeling LoCo (Savage et al., 2011)	2011	Content-based filtering	CARS	Restaurants, hotels, bars, walking trails	Use of social media (foursquare) profile data for personalized recommendations	User location, user preferences, transportation mode, user's mood	Web-based (client implemented as a Nokia N900 app)
Magitti (Bellotti et al., 2008)	2008	Collaborative filtering	CARS	Leisure activities (e.g. restaurants, museum events)	Prediction of future activities; activity-awareness (items not matching the user's activity mode are filtered out); users do not enter profile, preferences or queries	Current time, location, weather, venues opening hours, user patterns, user's activity	Web-based (mobile browser client)
ReRex (Baltrunas et al., 2012)	2012	Matrix factorization	CARS	POIs, tourist itineraries	Short explanation of recommendations, asynchronous notifications of changes on contextual conditions (along with revisions of recommendations)	Criteria influencing context-aware recommendations are configured by the user (e.g. distance from POI, weather, season, time of day, crowdeness, companion)	Web-based (iPhone client application)
MobyRek (Ricci and Nguyen, 2007)	2007	Hybrid (content-based/ collaborative filtering)	CBRS	Restaurants	Support for three types of critiques: 'no preference', 'must' and 'wish'	User location, critiques, restaurant data (location, average cost, opening days)	Web-based (Java ME client application)

Table 2
Main features of mobile tourism RSs providing route, tour and multiple-days tour planning services.

Mobile RS	Release date	Recommendation technique	RS category	Main recommendation functionality	Additional services offered/unique features	Criteria used for recommendation	Architecture/client application implementation platform
GUIDE (Cheverst et al., 2000)	2000	User constraints-based	UCRS	Routes among pairs of POIs and tours	Accommodation booking	User location, walking speed, places already visited, time, peak hours, user preferences	Web-based (mobile browser client)
Deep Map (Malaka and Zipf, 2000)	2002	User constraints-based	UCRS	Tour planning	Recommendation of routes via pedestrian zones, bypassing high-traffic streets; VRML models; natural language-based interface	User location, travel preferences, steepness and esthetic aspects of routes, transportation mode	Web-based
DailyTRIP (Gavalas et al., 2012)	2012	User constraints-based	UCRS	Multiple-days tour planning	Implementation of a TOPTW heuristic optimization algorithm to derive tourist itineraries	User location, travel preferences, time available for sightseeing, opening days of POIs and anticipated visiting times	Web-based (Java ME client application)
mtrip (mtrip Travel Guides, 2012)	2012	User constraints-based	UCRS	Multiple-days tour planning	Augmented reality views of physical spots	User location, travel preferences, time available for sightseeing, opening hours of POIs, anticipated visiting times, visiting pace/intensity	Standalone (released as Android and iOS apps)
Biuk-Aghai et al. (2008)	2008	Collaborative filtering	LARS	Tour planning	Offline re-arrangement of recommended itineraries	User preferences, user visit history, official spot ratings, peer users ratings	Web-based
PECITAS (Tumas and Ricci, 2009)	2009	Knowledge-based	LARS	Public transportation routes via suitably located POIs	Point-to-point shortest-path multimodal route planning	User location, user constraints, travel preferences	Web-based (Java ME client)
Yu and Chang (2009)	2009	User constraints and rules-based	LARS	Tour planning	Recommendations for restaurants and hotels are integrated within the tour plan	User location, travel preferences, restaurants/hotels data	Web-based (mobile browser client)

User critiques are interpreted and incorporated in the user's preferences model managed by the system. Eliciting user preferences through critiques may be advantageous and particularly suited to the mobile scenario. Firstly, the preferences are explicitly stated by the user, and hence, are more reliable than those implicitly collected, for instance, by mining the user's interaction behavior, or those expressed on the whole item (as in collaborative filtering ratings). Secondly, the user effort to make a critique is low, as compared to methods utilizing standard survey pages.

A critique-based approach has been adopted in MobyRek (Ricci and Nguyen 2007), which aims at supporting on-the-move travelers in the selection of an appropriate restaurant using a hybrid (content-based/collaborative filtering) RS. The user makes a critique when one feature of a recommended product is somewhat unsatisfactory or very important. MobyRek has been designed to run on Java ME-compatible mobile phones and requires limited user input. The system search functionality lets the user formulate both 'must' and 'wish' conditions and returns a ranked list of products. MapMobyRek (Averjanova et al., 2008) extended MobyRek using maps as the main interface for accessing items and displaying information, providing new decision-support functions based on the map.

Table 1 provides an overview of the main features offered by several mobile tourism RSs. Listed projects offer a balanced view of surveyed RSs, with respect to their release date, recommendation technique used, RS category, provided services, recommendation criteria, architecture and client implementation platform. Table 2 summarizes similar information, focusing on mobile tourism RSs providing route/tour planning services.

6. Research challenges and future prospects

It should have become clear by now that mobile RSs represent a highly evolving domain of research with dozens of prototypes reported in the recent scientific literature. Although mobile RSs have been applied in various application fields (e.g. mobile shopping, advertising and content provisioning), tourism is undoubtedly the most crowded field among them (Ricci, 2011). Interestingly, several early mobile tourism RSs focused in treating the limitations of mobile devices (limited processing power and display resolution, restricted bandwidth, lack of support for certain markup standards, etc.). Recent developments in mobile computing, though, tend to make these research efforts obsolete or at least less relevant. At the same time, the emergence of mobile devices with increased sensing, computational and visualization capabilities raises new challenges and opens unprecedented research opportunities. This section closes our article highlighting challenges, open issues and promising research directions in the field of tourism-relevant mobile RSs.

6.1. Intelligent user interfaces approaches

The use of appropriate user interface techniques to visualize recommended items on mobile displays represents a major design challenge for mobile RSs. To this end, a number of HCI techniques have been proposed for general-purpose RSs but still represent an open research area in tourism-relevant mobile RSs (Ricci, 2011)

- *Displaying similar searches:* Instead of recommending information explicitly requested by the user, the system presents information searched by other users in similar contexts; this allows users to browse through community search experiences and learn from them (Marchionini and White, 2009).
- *Critique-based interfaces*: The user is required to express her preferences by criticizing items that the system recommended (Chen and Pu, 2009) (in contrast with standard preference

elicitation techniques that ask upfront for user preferences). User critiques are used to improve recommendations in future interactions.

- *Query rewriting*: In the event that a user query is over-constrained and no item in the database satisfies the query conditions, then one or more relaxed queries may be offered to the user (the relaxed version of the user query can be computed automatically to simplify the user-system interaction) (Ricci and Nguyen, 2005).
- *Visualizing query results*: Content items recommended by mobile RSs are typically displayed as a ranked list of information items, similarly to the format used by a search engine to display suggested hyperlinks. To address the limitations of limited screen size, several techniques have been proposed to convey as much information as possible, including the use of snippet texts (i.e., short descriptions of the hyperlink content), the display of a subset of the item features considered as more important (Ricci and Nguyen, 2005) and the display of key phrases to enable a more economic use of screen space (Jones et al., 2004).
- *Support for alternative means of user interaction*: The advanced video and imaging capabilities of modern mobile devices may be utilized to develop novel user-device interaction techniques. For instance, the recognition of gesturing (Lei and Coulton, 2009) or pointing (Khosravy and Lev, 2009) may serve as alternative means of interaction with the surrounding space (e.g., providing recommendations for POIs located along the direction the user points to) and can overcome some of the limitations of more classical interactions (keyboard).

6.2. Non-disruptive use of reactive and proactive recommendations

Most reviewed mobile RSs exploit contextual information to reactively or proactively personalize the interaction experience on mobile devices. These systems typically provide some short of visualization of recommended content or services not-driven by user queries. Yet, information delivered and visualized without having been explicitly requested may be disruptive and, therefore, cause user frustration. This may be even more true in cases that recommendations are performed though the audio modality. Hence, intelligent multi-modal recommendation output methods are needed so as to opt for the most appropriate output mode which will convey recommendations in an a non-disruptive manner, through evaluating the current user context (e.g. visualization of a discreet recommendation sign if the user currently posts an email or switch from audio to visual mode when the user is on a public transit service).

6.3. Improved context inference mechanisms and elicitation of user preferences

Many mobile RSs exclusively collect contextual data to refine user profiles in order to avoid the cognitive load connected with filling long surveys/questionnaires or the feedback required by critique-based RSs. However, context-aware recommendations often fall short as user context may be incorrectly interpreted (e.g. spending more time than anticipated while visiting a POI does not necessarily connote user satisfaction), hence, leading to inappropriate recommendations (Sae-Ueng et al., 2008). Therefore, sophisticated context inference mechanisms are required to remove uncertainty and improve the accuracy of recommendations. Those mechanisms may combine hand-crafted knowledge bases, advanced machine-learning techniques, elicitation of user feedback and interpretative user models.

Along the same line, methods that enable efficient and accurate elicitation of user preferences are still an open research subject (Ricci and Nguyen, 2007). Inferring (implicit) preferences from user's behavior sounds as the most obvious solution, but new interfaces, e.g., based on speech recognition, could provide a more effective channel (Ricci, 2011).

6.4. Metrics and formal evaluation methods for assessing the effectiveness of recommendations

User evaluations assessing the experience of users are of critical importance to measure the success and perceived usefulness of web and mobile RSs. Yet, although some works have dealt with the automated evaluation of web RSs (Herlocker et al., 2004), very little has been done in executing formal field studies and evaluation tests on mobile RSs. Although some first evaluation reports have already appeared (e.g., (Baltrunas et al., 2012; Gavalas and Kenteris, 2012; Modsching et al., 2007; Noguera et al., 2012; Ono et al., 2009; Tintarev et al., 2010)), there is still a long way to go.

Certainly, the exercise of user trials in realistic environments calls for the participation of large groups of evaluators and is known to comprise a lengthy process, which engages a considerable amount of human resources in the orchestration of trials and compilation of evaluation reports. To this end, the 'simulation' of contextual situations has been proposed as a reference model to easily capture data regarding how the context-aware recommendations are perceived by users (e.g., in Ono et al. (2009)) participant users were asked to imagine that a given contextual condition holds and then assess the derived context-aware recommendation). However, Baltrunas et al. (2012) argued that this method must be used with care as users tend to act differently in real and supposed contexts.

Future research should aim at gaining deeper understanding in questions concerning methods, theories and techniques that assess the scrutability, trust, efficiency, effectiveness, accuracy, satisfaction and perception of mobile tourism RS recommendations (Ricci et al., 2010; Tintarev and Masthoff, 2011). The question of how the above parameters can be defined, evaluated and measured needs to be answered. Having resolved this, the formalization of usability trials and evaluation methods could help to gain insights into factors affecting the perceived usefulness of mobile RSs and possibly extract design guidelines for developers.

6.5. User effort-accuracy tradeoff

Psychological studies (Payne et al., 1993) have revealed that customers find it difficult to assess their exact preferences until dealing with the actual set of item options in offer. In order to successfully deploy commercial mobile RSs, we have to understand the limiting factors tourists are subject to when interacting with a recommender application. On the one hand the 'need for cognition' (Martin et al., 2005) is a property which engages users' time and cognitive efforts in order to yield accurate recommendations for products and services. The estimation of the actual impact of this effort-accuracy tradeoff in mobile tourism RSs requires the investigation of psychological theories and synergies with the scientific areas of decision theory and cognitive psychology (Felfernig and Burke, 2008).

6.6. Privacy protection in mobile RSs

RSs exercise recommendation rules upon massive data repositories. Recommended items largely depend on stored user profiles which hold privacy-sensitive information (e.g. demographic data, explicitly specified preferences, user interaction history and behavior, etc.). To make things worse, several RSs (e.g. collaborative filtering-based systems) commonly merge RS databases that belong to separate stakeholders (to expand the data pool and enable more intelligent recommendations) raising further privacy disclosure hazards (Zhan et al., 2010). Privacy concerns are more serious in mobile RS environments wherein a multitude of changing contextual parameters may by transparently measured and uploaded to remote recommender engines. In fact, user awareness of threats against location and identity (among others) privacy aspects has been recognized as one of the greatest barriers to the adoption of context-aware services (Barkhuus and Dey, 2003).

As a result, concrete mobile RS-tailored methodologies for protecting user anonymity and privacy are required. Those methodologies should guarantee the effectiveness and accuracy of recommendations without compromising the privacy of user profiles and sensitive contextual information.

6.7. Unified attractions/tourist services recommendations

Hotel selection is often a cumbersome task for tourists unfamiliar with hotels and POI locations or with the structure of the public transportation network in the tourist destination area. This is even more true when planning long road trips across large geographic areas (in such scenarios, changing accommodation in daily basis is common) (Vansteenwegen et al., 2012). Several criteria could apply in hotel recommendations, including cost, amenities and cost-for-tourist profit (e.g. recommend an affordable hotel suitably located nearby must-visit POIs). Restaurants selection is equally important as meal/dinner breaks are mandatory, while constrained by several—often contradictory—user preferences (e.g. budget, diet preferences and favorite cuisine) and restaurant characteristics (e.g. menu, price list and opening hours).

Notably, the majority of mobile RS prototypes focuses either in recommending tourist attractions (see Section 4.1) or on tourist services (e.g. restaurants and accommodation) (see Section 4.2). We argue the two abovementioned recommendation service types should not by approached separately, as the selection of restaurants or accommodation largely affects tourist decisions with regards to POI visits (due to time or budget constraints). Hence, RS prototypes offering a unified perspective (i.e. bundling attractions and tourist facilities recommendations) are in need.

6.8. New prospects in tourist route/tour planning services

The state-of-the-art presented in Sections 4.4 and 4.5 reveals that not much has been done with respect to problems that closely match realistic TTDP requirements, e.g. allowing modeling multiple user/physical constraints and transfers through public transportation. This highlights a promising field of research which calls for modeling and solving extensions of TOPTW and TDTOPTW problems that take into account TTDP issues or constraints like the following:

- Weather conditions: Museums may be more appropriate to visit than open-air sites in rainy or relatively cold days, while the contrary may be true in sunny days; hence, route planning could take into account weather forecast information in recommending daily itineraries.
- Accessibility features of sites should be taken into account when recommending visits to individuals with motor disabilities.
- Tourists are commonly under inflexible budget restrictions when considering accommodation, meals, means of transport or visits to POIs with entrance fees. Hence, next to the time budget, money budget further constrains the selection of POI visits.
- Recommended tourist routes that exclusively comprise POI visits and last longer than a few hours are unlikely to be followed closely. Tourists typically enjoy relaxing and having breaks as much as they enjoy visits to POIs. A realistic route/tour should therefore provide for breaks either for resting (e.g. at a nearby park) or for a coffee and meal. Coffee and meal breaks are typically specific in number, while respective recommendations may be subject to strict time window (e.g. meal should be scheduled around noon) and budget constraints.
- Max-n Type (Souffriau and Vansteenwegen, 2010) restrictions constrain the selection of POIs by allowing users to state a maximum number of certain types of POIs, per day or for the whole trip (e.g., maximum two museum visits on the first day). Likewise, mandatory visits (i.e. tours including at least one visit to a POI of certain type, such as a visit to a church) could also be asked for.
- Tourists commonly prefer strolling downtown rather than visiting museums. In such cases, tourists may prefer to walk along routes featuring buildings and squares with historical value or routes with scenic beauty. Such routes are likely to be preferred also when moving among POIs, e.g. a detour through a car-free street along a medieval castle walls would be more appreciated than following a shortest path though streets with car traffic.
- The use of public transportation services is common among individuals touring a tourist area. Tourist route/tour planners should, therefore, incorporate online multimodal public transportation route planning facilities, tailored to tourist needs (e.g. walking routes through pedestrian zones may be preferable than taking a shorter subway ride, while the use of 1/3-day tourist passes may be recommended to save transportation expenses). The design of efficient algorithms that address this issue is still an open research topic.

7. Summary

RSs represent a fascinating and fast evolving field of software systems that have find particular success in web environments. New developments in mobile computing, wireless networking, web technologies and social networking create vital space for the development of innovative mobile RSs which capture personal, social and environmental contextual parameters to deliver highly accurate and effective situation-aware recommendations. As a result, mobile RSs have been a subject of intense research in the recent years, as evidenced by the proliferation of the relevant research prototypes. Among their many application fields, mobile tourism has been the most popular field of research for mobile RSs.

This article explored the landscape of mobile RSs, providing details on their supported services and discussing open research issues in the field. Our review followed a systematic approach, based on a classification scheme that takes into account three different view angles in the examination of existing mobile tourism RSs: their chosen architecture, the degree of user involvement in the delivery of recommendations and the criteria taken into account for deriving recommendations.

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