Mobile Decision Support for Time-Critical Decision Making

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INTRODUCTION

The wide availability of advanced information and communication technology has made it possible for users to expect a much wider access to decision support. Since the context of decision making is not necessarily restricted to the office desktop, decision support facilities have to be provided through access to technology anywhere, anytime, and through a variety of mediums. The spread of e-services and wireless devices has increased accessibility to data, and in turn, influenced the way in which users make decisions while on the move, especially in time-critical situations. For example, on site decision support for fire weather forecasting during bushfires can include real-time evaluation of quality of local fire weather forecast in terms of accuracy and reliability. Such decision support can include simulated scenarios indicating the probability of fire spreading over nearby areas that rely on data collected locally at the scene and broader data from the regional and national offices. Decision Support Systems (DSS) available on mobile devices, which triage nurses can rely on for immediate, expert advice based on available information, can minimise delay in actions and errors in triage at emergency departments (Cowie & Godley, 2006).

Time-critical decision making problems require context-dependent metrics for representing expected cost of delaying an action (Greenwald & Dean, 1995), expected value of revealed information, expected value of displayed information (Horvitz, 1995) or expected quality of service (Krishnaswamy, Loke, & Zaslavsky, 2002). Predicting utility or value of information or services is aimed at efficient use of limited decision making time or processing time and limited resources to allow the system to respond to the time-critical situation within the required time frame. Sensitivity analysis (SA) pertains to analysis of changes in output due to changes in inputs (Churilov et al., 1996). In the context of decision support, traditionally SA includes the analysis of changes in output when some aspect of one or more of the decision model's attributes change, and how these affect the final DSS recommendations (Triantaphyllou & Sanchez, 1997). In time-critical decision making monitoring, the relationship between the changes in the current input data and how these changes will impact on the expected decision outcome can be an important feature of the decision support (Hodgkin, San Pedro, & Burstein, 2004; San Pedro, Burstein, Zaslavsky, & Hodgkin, 2004). Thus, in a time-critical decision making environment, the decision maker requires information pertaining to both the robustness of the current model and ranking of feasible alternatives, and how sensitivity this information is to time; for example, whether in 2, 5, or 10 minutes, a different ranking of proposed solutions may be more relevant. The use of graphical displays to relay the sensitivity of a decision to changes in parameters and the model's sensitivity to time has been shown to be a useful way of inviting the decision maker to fully investigate their decision model and evaluate the risk associated with making a decision now (whilst connectivity is possible), rather than at a later point in time (when perhaps a connection has been lost) (Cowie & Burstein, 2006).

In this article, we present an overview of the available approaches to mobile decision support and specifically highlight the advantages such systems bring to the user in time-critical decision situations. We also identify the challenges that the developers of such systems have to face and resolve to ensure efficient decision support under uncertainty is provided.

MOBILE DECISION SUPPORT

Recent work on mobile decision support focuses on the implementation of knowledge-based services on hand-held computers. Work on mobile clinical support systems, for example, addresses different forms of intelligent decision support such as knowledge delivery on demand, medication consultant, therapy reminder (Spreckelsen et al., 2000), preliminary clinical assessment for classifying treatment categories (Michalowski, Rubin, Slowinski, & Wilk, 2003; San Pedro, Burstein, Cao, Churilov, Zaslavsky, & Wassertheil, 2004), and providing alerts of potential drugs interactions and active linking to relevant medical conditions (Chan, 2000). These systems also address mobility by providing intelligent assistance on demand, at the patient's bedside or on-site.

Research on location-based mobile support systems uses search, matching, and retrieval algorithms to identify resources that are in proximity to the location of the mobile users and that satisfy multi-attribute preferences of the users and the e-service providers. Examples of such location-based systems are those that recommend best dining options to mobile users (Tewari et al., 2001), locate automatic teller machines nearby (Roto, 2003), and locate nearest speed cameras and intersections using GPS-enabled mobile devices. Most of these mobile decision support systems use intelligent technologies and soft computing methodologies (e.g., rule-based reasoning, rough sets theory, fuzzy sets theory, multiattribute utility theory) as background frameworks for intelligent decision support. However, none of these systems address the issue of quality of data or quality of decision support while connected or disconnected from the network or consider a comprehensive measure of reliability of data as part of supporting time-critical decision-making.

It should be noted that not all real-time decision situations, which could benefit from mobile DSS, are also constringed by the period of time, in which this decision support should be provided. For example, if a decision problem is more of a strategic, rather than operation nature, the time factor could be less critical, hence, more time can be devoted to improve the quality of data before the final decision has to be accepted by the user. In this article, we mainly address the needs of operational decision making, when time before the final choice is made is limited. In such situations an aggregate measure of quality of data (QoD) is particularly important when aiming to enhance a level of user's confidence and trust.

In recent papers (Hodgkin et al., 2004; San Pedro, Burstein, & Sharp, 2003) the issue of QoD has been addressed. A framework has been proposed for assessing QoD as an indicator of the impact of mobility in decision-making (Burstein, Cowie, Zaslavsky, & San Pedro, 2007; Cowie & Burstein, 2006; Hodgkin et al., 2004; San Pedro et al., 2003). QoD is based on multiple parameters which measure user-specific factors, current technology-related factors, and some factors which can be learned based on past experiences with similar problem situations. By providing a QoD alerting service from the mobile device, the mobile decision maker can be warned against making decisions when QoD falls below a predetermined threshold or when QoD becomes critically low. The assumption made is that a decision maker should feel more confident with a decision when QoD is high, or be alerted when QoD becomes lower than acceptable.

In mobile DSS, QoD can be calculated incrementally at every stage of the decision making process, as the mechanism for alerting the user when more data and/or resources are needed before the best option can be selected. For example, following Simon's classical decision making principal phases (Simon, 1960), when describing a decision situation, QoD can be used to judge how accurate the set of data collected is at the Intelligence phase; when designing alternative actions, QoD can assist in making sure the user is satisfied with the range of possibilities the user is presented with for a choice; when a model is applied for selecting the best alternative, the final output includes a full and explicit representation of the QoD, which is derived as an aggregate of the ones used in the previous stages (Burstein et al., 2007).

Providing the user with a measure of QoD is extremely important in a mobile decision making environment as the focus of decision support moves from strategic long term decision analysis to just-in-time operational decision support (Hodgkin et al., 2004; Malah, 2000). In addition, in a mobile environment, data timeliness, completeness, reliability, and relevance have to be considered as contributing factors of QoD metrics. For example, in the area of contingency management a "good enough" feasible decision achievable "on the spot," anytime, anywhere is often preferable to a perfect solution that may require extensive additional computational resources as well as time. 5 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: www.igi-

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