Mobility Prediction for Mobile Agent-based Service Continuity in the Wireless Internet

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Abstract. New challenging deployment scenarios are integrating mobile devices with limited and heterogeneous capabilities that roam among wireless access localities during service provisioning. This calls for novel middleware solutions not only to support different forms of mobility and connectivity in wired-wireless integrated networks, but also to perform personalized service reconfiguration/adaptation depending on client characteristics and in response to changes of wireless access locality. The paper proposes the adoption of Mobile Agent (MA) proxies working at the wired-wireless network edges to support the personalized access of limited wireless clients to their needed resources on the fixed network. In particular, the paper focuses on how to predict device mobility between IEEE 802.11 cells in a portable lightweight way, with no need of external global positioning systems. In fact, we claim that mobility prediction is crucial to maintain service continuity: MA-based proxies can migrate in advance to the wireless cells where mobile clients are going to reconnect to, in order to anticipate the local rearrangement of personalized sessions. The paper proposes and evaluates different mobility prediction solutions based on either client-side received signal strength or Ekahau positioning, all integrated in the SOMA platform. Both simulation and experimental results show that SOMA can predict the next visited cell with a very limited overhead and enough in advance to maintain service continuity for a large class of wireless Internet services.

1 Introduction

The increasing availability of public wireless access points to the Internet and the widespread popularity of wireless-enabled portable devices stimulate the provisioning of distributed services to a wide variety of mobile client terminals, with very heterogeneous and often limited resources. Even though devices and networking capabilities are increasing and increasing, the design of mobile applications will continue to be constrained by several factors, from limited display size to high connectivity costs, from bandwidth fluctuations to local resource availability, also abruptly changing due to client mobility among wireless cells during service provisioning.

Let us focus on the common deployment scenario where wireless solutions extend accessibility to the traditional Internet via access points working as bridges between fixed hosts and wireless devices [1]. An exemplar case is the usage of IEEE 802.11

access points to support connectivity of WiFi-equipped terminals to a wired local area network [2]. In the following, we will indicate these integrated networks with fixed Internet hosts, wireless terminals, and wireless access points in between, as the wireless Internet.

Service provisioning over the wireless Internet must consider the specific characteristics of client portable devices, primarily their limits on local resources and their high heterogeneity. Limited processing power, memory and file system make portable devices unsuitable for traditional services designed for fixed networks and require both assisting wireless terminals in the service access and downscaling contents to obey resource constraints. In addition, portable devices exhibit extreme heterogeneity of hardware capabilities, operating systems, installed software, and network technologies. This heterogeneity makes hard to provide all needed service versions with statically tailored contents and calls for on-the-fly adaptation of service provisioning.

We claim the need of middleware solutions to dynamically adapt service results to the specific properties of client devices and to the runtime resource availability of the provisioning environment [3-6]. Middleware components should follow client roaming in different wireless localities and assist them locally during their service sessions. Moreover, client limited memory suggests deploying middleware components over the fixed network, where and when needed, while portable devices should host only thin clients, loaded by need and automatically discarded after service.

By following the above solution guidelines, we have recently designed and implemented application-level middlewares, based on Secure and Open Mobile Agent (SOMA) proxies, to support the distribution of context-dependent news and video on demand to wireless devices with strict limits on on-board resources [5, 7, 8]. The primary design idea is to dynamically deploy SOMA proxies acting on the behalf of wireless clients over the fixed hosts in the network localities that currently offer client connectivity. In particular, this paper focuses on a crucial challenge for MA-based middlewares for the wireless Internet: how to predict the client movements among wireless cells, making unnecessary any external Global Positioning System (GPS). Mobility prediction permits to migrate personalized SOMA proxies in advance with regards to the client roaming. Thus, SOMA proxies have the time to proactively reorganize user sessions in the newly visited network localities, by rebinding to needed resources and local middleware components for service adaptation, with the ultimate goal of supporting session maintenance and continuous service provisioning [5].

We propose three different mobility prediction solutions, all exploiting a first-order Grey Model (GM) [9]. The first approach uses only the client-side monitoring data about Received Signal Strength Indication (RSSI) in a decentralized, lightweight, and portable way (we call it RSSI-GM for shortly). The other two solutions take advantage of the positioning data provided by the commercial Ekahau Positioning Engine (EPE) [10]. Ekahau Cell Probability (ECP) exploits the EPE-provided probabilities of being located in a cell, both currently and in the recent past, as the input for GM-based mobility prediction. Ekahau Distance (ED)-GM bases its prediction on the current/recent distances of client nodes from the borders of IEEE 802.11 cells of base stations in their visibility.

We have evaluated the performance of the three mobility prediction solutions both via a simulator, which can model nodes randomly roaming among IEEE 802.11 localities, and by exploiting a system prototype deployed over WiFi-enabled PDAs with

MS Windows CE.NET. Both experimental results show that the simplest and completely decentralized RSSI-GM approach outperforms the others. In addition, notwithstanding the portable and application-level approach, RSSI-GM has demonstrated to be capable of predicting the next cell location enough time in advance to permit SOMA middleware to rearrange personalized sessions before the client connects to the new wireless locality. This permits to provide adapted services to limited wireless devices without any interruption in the case of client roaming.

2 Motivating Mobility Prediction in MA-based Middlewares

Service provisioning in the wireless Internet usually calls for downscaling service contents to suit the specific limits of client devices. For instance, dynamic content negotiation and tailoring are crucial for multimodal services providing resource-consuming multimedia in Web pages. In addition, device mobility requires other support operations that are too expensive to be performed by severely limited devices, e.g., context-aware local/global resource retrieval and binding. On the one hand, local discovery operations may consume non-negligible client resources to explore the execution environment and to negotiate with available services. On the other hand, the global identification and retrieval of user-related properties, such as user/terminal profiles and security certificates stored in directories, may require long continuous connectivity, difficult to be handled directly by portable devices.

We claim that wireless Internet service provisioning can significantly benefit from distributed and active infrastructures of mobile middleware proxies working in the fixed network on behalf of portable devices [6]. Proxies can decide the best adaptation operations to perform on service results and can be in charge of any additional management operation, such as supporting connectivity and discovering the needed resources/service components. Moreover, proxies can act, locally to the client, as distributed cache repositories for successive service requests. In addition, if proxies are mobile, they can follow device movements during service provisioning by supporting session migration between the different network localities visited, and install automatically only where and when needed [6].

For all above reasons, the primary design choice in SOMA-based middlewares for the wireless Internet is to provide any wireless device with one SOMA-based companion entity, called *shadow proxy*, which run in a wired node (place) in the same wireless network locality that currently provides connectivity to the device [5, 8]. Wired/wireless terminals in a locality can be grouped into logical domains, as depicted in Figure 1; domains are disjointed, even if they include wireless access points with coverage areas that partially overlap.

Shadow proxies are in charge of determining the applicable context for their clients and of consequently retrieving and binding to the needed local/global resources. Proxies solve the issues related to receiving, caching, and coordinating the tailoring of service contents by taking context-dependent decisions based on profile metadata that describe device characteristics and user preferences [6].

In the following, the paper concentrates on the crucial issue of how to predict the client movements between SOMA localities in order to migrate in advance the proxies to the next domain of attachment of their associated clients. A detailed description of the implementation of the different SOMA middleware components that support the distribution of context-dependent news and video on demand to wireless devices is out of the scope of the paper, and can be found elsewhere [5, 8].

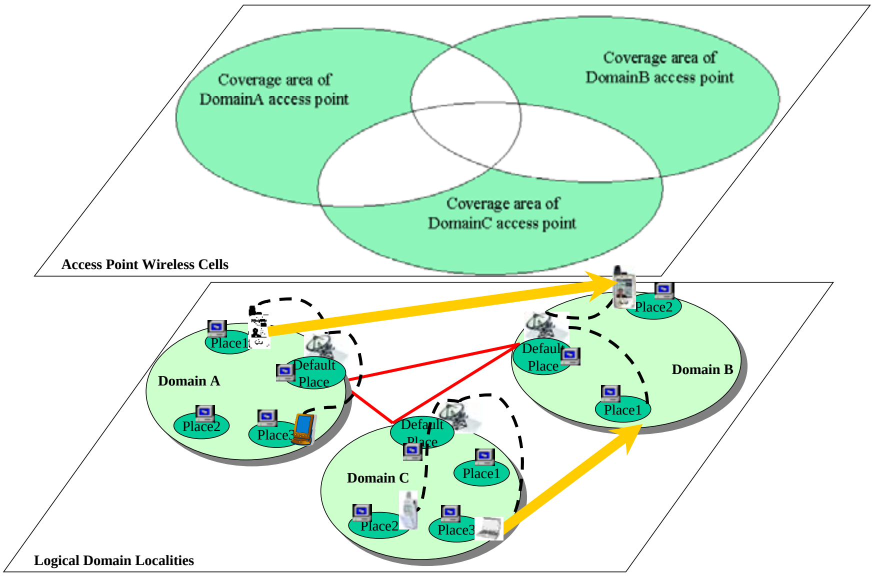

Figure 1. Portable devices roaming among SOMA wireless access localities.

To better understand the need for mobility prediction, let us describe the service management operations that the SOMA-based middleware performs in response to a client change of locality. Let us suppose a user roams from DomainA to DomainB in Figure 1 while she is receiving her personalized location-aware service contents. Note that user movements also produce the user change of access point coverage area, since in location-aware services clients should typically associate with their closest base station. Depending on the (usually configurable) handoff strategy of the underlying communication layer, the user device is transparently de-associated from the origin wireless cell and associated to the destination one i) when the client no more receives the origin signal, ii) when the destination RSSI overcomes the origin RSSI (handoff hysteresis = 0), iii) or, more generally, when the destination RSSI overcomes the origin RSSI of a specified threshold t (handoff hysteresis = t), also to reduce bouncing effects.

Once notified of the communication handoff, the middleware should migrate the shadow proxy to the destination domain. There, the proxy should instantiate and configure the needed local middleware components and reconnect to the server (or to an equivalent local replica of it) before being capable of serving its client again. This can cause a temporary suspension of the service typically experienced by the client as a provisioning block or delay [8]. The goal of mobility prediction is to effectively perform the migration of a shadow proxy clone before the client communication handoff, so to establish the cloned proxy in the new destination domain, ready for the service session of its incoming client.

Let us notice that the addressed wireless Internet provisioning environment considers medium/short-range wireless technologies (IEEE 802.11b or Bluetooth) in open and extremely dynamic scenarios where the user mobility behaviors change very frequently and irregularly. Thus, the relevant results of research activities about hand-over prediction based on user movement patterns/history cannot apply [11].

3 The Proposed Mobility Prediction Solutions

In this paper, we propose and compare three alternative solutions for mobility prediction: RSSI-GM, ECP-GM, and ED-GM. The proposed solutions do not need any additional specific hardware; in particular, they do not require external GPSs, which are still rather expensive, battery-consuming, and therefore unsuitable for very resource-constrained wireless devices. Moreover, the mobility prediction solutions, which we have evaluated and implemented for IEEE 802.11 connectivity, are easily applicable also to wireless clients that exploit other forms of access point connectivity, e.g., Bluetooth clients towards Bluetooth infotainment points [12]. The only constraint is to have client-side awareness of RSSI, either directly exploited in RSSI-GM or indirectly used (via the EPE mediation) in both ECP-GM and ED-GM.

3.1 Received Signal Strength Indication-Grey Model

The RSSI-GM prediction solution requires a lightweight client stub running on any client device. It is the client stub that autonomously predicts the next cell visited by the hosting wireless device and that communicates the prediction to the shadow proxy place, thus triggering the clone migration. To this purpose, the client stub needs to access the monitoring data about the RSSI values of the IEEE 802.11 base stations in its visibility. The RSSI data is used as input for a simple Grey-based discrete model GM(1,1) for the prediction of future RSSI values [9]. Client stubs achieve platform- and vendor-independent visibility of RSSI data by integrating with portable and dynamically installable monitoring mechanisms, as extensively described in [13].

Given one reachable access point and the set of its actual RSSI values measured at the client side $R_0 = \{r_0(1), \ldots, r_0(n)\}$, where $r_0(i)$ is the RSSI value at the discrete time i, it is possible to calculate $R_1 = \{r_1(1), \ldots, r_1(n)\}$, where:

$$r_1(i) = \sum_{j=1}^{i} r_0(j)$$

Then, from the GM(1,1) discrete differential equation of the first order:

$$\frac{dr_1(i)}{di} + ar_1(i) = u$$

the client stub determines a and u, which are exploited to obtain the predicted RSSI value $pr(i)$ at discrete time i according to the GM(1,1) prediction function:

$$pr(i) = \left(r_1(1) - \frac{u}{a} \right) e^{-ak} + \frac{u}{a}$$

When the $pr(i)$ for a base station x overcomes the $pr(i)$ for the currently associated base station y, then the client stub communicates the mobility prediction to the shadow proxy place, thus triggering the proxy clone migration.

The above solution for client mobility prediction is completely local and lightweight; any client stub can estimate its future RSSI values simply by maintaining a finite series of previous RSSI data. In particular, the client stub catches the needed monitoring information and predicts the next cell in a completely autonomous way, with a very limited overhead. The client stub exploits the limited bandwidth wireless channel only occasionally to inform the shadow proxy place in the case of predicted change of logical domain.

3.2 Ekahau Cell Probability-Grey Model and Ekahau Distance-Grey Model

Similarly to RSSI-GM, both ECP-GM and ED-GM prediction solutions use GM(1,1) discrete models. However, they do not exploit RSSI data as the input values for the prediction models but, respectively, the estimated probability that a client device is located in a cell and the estimated device distances from the borders of IEEE 802.11 cells of access points in visibility. In these two solutions, it is directly the SOMA place hosting the shadow proxy execution that performs mobility prediction by communicating with EPE to obtain the needed information about cell probabilities and distances.

EPE is a widespread commercial solution for non-GPS-based positioning in IEEE 802.11 infrastructure-mode networks [10]. For any target device, EPE provides the probabilities that the device is located in a set of pre-defined logical areas, i.e., configurable disjointed portions of the wireless deployment scenario. Bayes-based probability estimation is performed by observing the current and recent RSSI values at the target device, by comparing them with a database of RSSI samples for the provisioning environment, and by considering a set of specified admitted mobility paths in that environment. This implies that system administrators must provide EPE with a map of the environment and the admitted paths of client movements in any specific deployment scenario. In addition, an initial "learning" phase is necessary for EPE to acquire the database of RSSI samples for the different points of the provisioning environment. The EPE system consists of a centralized server responsible for the whole processing to obtain the position estimations, and of lightweight clients that run on wireless clients and regularly send the observed RSSI values to the EPE server.

Given a target device, ECP-GM considers the finite set of probabilities provided by EPE and applies GM(1,1) to these probabilities. The proxy clone migration is triggered when the predicted probability of the current shadow proxy cell becomes minor than the predicted probability of another logical area. ED-GM, instead, exploits the position estimation provided by EPE to calculate the distances between the target device and the cell borders of visible base stations, and applies GM(1,1) to these distances. In this case, the proxy clone migration is triggered when the predicted distance from the borders of the current cell exceeds the predicted distance from the borders of another logical area.

Let us note that, differently from RSSI-GM, both ECP-GM and ED-GM are not completely decentralized prediction solutions. It is the Ekahau client running on the target device that monitors RSSI data and regularly sends them to EPE. In addition, the shadow proxy in charge of mobility prediction has to interwork with the centralized EPE, which feeds the proxy with current estimations about either cell probabilities or distances from the cell borders of visible base stations. In addition, since the Ekahau client is available only for MS Windows, ECP-GM and ED-GM are not portable on different operating systems, differently from RSSI-GM.

4 Simulation and In-the-Field Experimental Results

To evaluate the effectiveness and performance of the proposed prediction solutions, we have developed three alternative implementations of the mobility prediction module: all the solutions are integrated with the SOMA platform and present the same API. SOMA* is a Java-based mobile agent system intended to support service provisioning in pervasive and ubiquitous environments [5, 7]. We have extended SOMA with the mobility prediction module by adding a shadow proxy which is a new MA subclass that exploits the usual one. The SOMA platform (by either the client stub in RSSI-GM or the SOMA place in ECP-GM and ED-GM) automatically notifies the shadow proxy in the case of handoff prediction for the associated client devices. The prediction notification triggers the transparent cloning of the shadow proxy and the clone migration to the predicted cell. The original proxy executes at its previous place until the associated device eventually exits its wireless access locality and completes its handoff. Application developers can concentrate only on the service-specific application logic that implements this part of shadow proxy while SOMA automatically handles cloning, anticipated migration, and lifecycle management of shadow proxy instances.

We have measured some performance indicators for all three mobility prediction solutions in both a simulated environment (with a large number of mobile clients roaming among a large number of wireless localities) and our campus deployment scenario. Considered performance indicators are:

- effectiveness $E1_{\%} = \left(1 - \frac{NFSP}{NR}\right) * 100$

where *NFSP* measures times the wireless devices do not find their shadow proxies already running at their destination domains at their arrivals, while *NR* is the total number of client handoffs;

- efficiency $E2_{\%} = \left(\frac{USP}{NM}\right) * 100$

where *USP* is the number of shadow proxies eventually used by the wireless clients and *NM* is the total number of migrated proxies;

- advance time *AT*, i.e., the time interval between the shadow proxy arrival at the destination domain and the eventual client reconnection to that domain.

Effectiveness and efficiency are both significant performance indicators. In general, high effectiveness may be tied to low efficiency: an excessive migration of proxy clones to visible localities generates useless network traffic (migrated clones are automatically discarded if the associated clients do not reach them within a timeout).

We have measured the three indicators above in a challenging simulated environ-

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* Additional information about the SOMA platform and its downloadable code are available at: `http://lia.deis.unibo.it/Research/SOMA/`

ment where 16 access points are regularly placed in a 64m x 64m square. We have developed a simple lightweight simulator to analyze wireless device movement and to monitor RSSI. Already existing but more complex simulators cannot supply so easily and efficiently these feature. We have simulated two extreme trajectories: *trajectory1*, a straight path with constant random velocity between two random points, and *trajectory2,* with random variable velocity and with random direction with a Gaussian component of 30 degree standard deviation. In both trajectories the velocity is always between 0.2 and 2.5 m/s to mimic the behavior of walking mobile users. Typically, wireless device performs a cell roaming when the destination cell RSSI rises above actual cell RSSI of a fixed hysteresis threshold. In our simulated environment the hysteresis threshold value ranges from 0 to 2 db. On the average, each mobile client has the contemporaneous visibility of 6 access points, that represents a worst case scenario significantly more complex than the actually deployed wireless networks (where usually no more than 3 access points are visible from any point). We have evaluated scenarios with fewer access points for each wireless client device; in all the scenarios $E1_{\%}$, $E2_{\%}$, and *AT* have proven to be better than in the simulation case.

Table 1 shows the average performance for a set of about 600 experiments where wireless devices roam by following *trajectory1*. When handoffs are rarely predicted, that is when $E1_{\%}$ is really low, *AT* is not shown because it does not present a significant positive value, due to poor performance. RSSI-GM outperforms the other solutions for all three performance indicators. EPE performs positioning quite well, but it is less prompt in ascertaining device movements that affects negatively ECP-GM and ED-GM performance. When the hysteresis threshold increases, roaming is delayed and there is more time to predict wireless device roaming: consequently both $E1_{\%}$ and *AT* increase. In this case, RSSI-GM $E2_{\%}$ lowers because delayed roaming triggers more predictions, most of them unnecessary. In summary, RSSI-GM $E1_{\%}$ is good also with a null hysteresis, and a higher hysteresis does not make $E1_{\%}$ much better. As a consequence, $E2_{\%}$ decreases since NM increases and USP is almost constant. On the contrary ECP-GM and ECP-GM $E2_{\%}$ often rises, in particular when $E1_{\%}$ increases, because the number of useful predictions significantly increases, proportionally more than total number of predictions. In fact, NM increases but USP increases further.

Table 2 shows the average performance measured with client devices moving according to *trajectory2*. As expected, the Gaussian trajectory component makes handoff prediction more difficult; however, the performance exhibits only a slight occasional deterioration. Let us stress that simulated scenarios are worst case scenarios. In simulation we assume the visibility of several nearby access points and more unnecessary predictions occur than in a real scenario with fewer visible access points, where wireless devices rarely come close to several access points. Moreover, we have tested our system also with irregular access point dispositions, with negligible performance deterioration.

	$E1_{\%}$			$E2_{\%}$			AT (s)		
Threshold (db)	0	1	2	0	1	2	0	1	2
RSSI-GM	79.01	91.69	94.67	80.53	74.27	74.19	2.99	4.34	5.30
ECP-GM	9.67	14.89	19.61	30.07	33.24	37.32	---	---	---
ED-GM	21.93	34.99	43.01	40.63	43.79	47.21	---	0.79	2.56

Table 1. RSSI-GM, ED-GM, and ECP-GM performance results in the case of trajectory1.

	E1$_{\%}$			E2$_{\%}$			AT (s)		
Threshold (db)	0	1	2	0	1	2	0	1	2
RSSI-GM	75.35	91.00	93.01	78.61	76.31	72.86	2.88	4.12	4.80
ECP-GM	10.37	13.50	20.18	34.10	34.62	38.97	---	---	---
ED-GM	22.12	33.00	37.94	40.34	44.15	43.78	---	0.84	1.91

Table 2. RSSI-GM, ED-GM, and ECP-GM performance results in the case of trajectory2.

Apart from simulation, we have tested the three different mobility prediction modules over an actual deployment scenarios with 5 partially overlapping IEEE 802.11b wireless cells and 10 client devices (Compaq iPAQ h3850 with Windows CE.NET) randomly roaming in the campus environment. The deployed CISCO Aironet 1100 access points use a null signal strength hysteresis threshold for cell handoff triggering. The client-performed scan for visible access points requires only a very limited packet exchange, with negligible bandwidth occupation. The experimental results outperform the simulation-based, by also verifying the assumption that the simulated environment represents a worst case scenario. RSSI-GM shows better performance despite the strong signal fluctuations observed in the real environment because access points are not as close as in simulations. For the same reasons, also ECP-GM and ED-GM show better performance, even if still worse than RSSI-GM.

In summary, the RSSI-GM mobility prediction solution has proven to offer the best performance, both in the simulated environment and the actual deployment, at least when the goal is handoff prediction and not fine-grained positioning prediction. In particular, RSSI-GM achieves AT values that permit SOMA to move and re-organize the middleware support in the next visited locality for a wide set of Internet services. In addition, if compared with ECP-GM and ED-GM, RSSI-GM has also significant advantages in terms of simplicity since it does not need additional components as EPE. For a more detailed presentation of the RSSI-GM, ECP-GM and ED-GM experimental results in different simulated environments, please refer to `http://lia.deis.unibo.it/Research/SOMA/MobilityPrediction/`

5 Related Work

Several relevant research activities have recently investigated the issues involved in achieving full visibility of mobile device position, most of them with the goal of supporting the provisioning of location-dependent services, some of them to provide the basis for mobility prediction solutions.

A rough estimate of mobile device position can be obtained via different positioning techniques, which are based on RSSI, angle of arrival, time of arrival, or time difference of arrival [14]. It is possible to achieve higher accuracy in position estimation by exploiting either positioning-specific hardware or additional information about the deployment environment. On the one hand, Medusa and the widespread GPS require clients with additional receivers and typically impose larger energy consumption at the clients [15]. On the other hand, some positioning solutions exploit the knowledge of RSSI distribution and/or the movement history (and usual habits) of the target mobile devices, such as in RADAR [16] and Ekahau [10].

By focusing on mobility prediction, most proposals in the literature require the knowledge of both the current position and the speed of target devices. [17] predicts future location/speed by exploiting a dynamic Gauss-Markov model applied to the current and historical movement data. [18] bases its trajectory prediction on the spatial knowledge of the deployment environment, e.g., by considering road network databases, and on past trajectories followed. [19] focuses on mobile ad hoc networks and is aimed at predicting the dis/connection time of mobile devices by monitoring device position and speed; it exploits RSSI data only to identify when the devices are located in overlapping areas with multiple base stations in direct visibility.

Few research activities have addressed mobility prediction with no need of monitoring the location and speed of mobile devices, similarly to what proposed in SOMA. [20] predicts future RSSI values by using a retroactive adaptive filter to mitigate RSSI fluctuations; the device handoff is commanded when the difference between current and predicted RSSI values is greater than a specified threshold. [21] exploits a Grey model to decide when actually forcing the communication handoff by comparing RSSI predictions with average and current RSSI values. However, both [20] and [21] apply RSSI prediction to improve the communication handoff process, e.g., to reduce unnecessary bouncing handoffs due to signal fluctuations, and not to predict the movements of wireless clients with the goal of anticipating the support re-organization in the access locality to be visited.

A very few proposals have recently started to investigate the possibility to integrate mobility prediction with MA anticipated migration over the fixed Internet, with the goal of pre-setting up the next visited wireless access locality. Their main idea is to exploit the history of the past movements of target devices, by assuming a high probability of recurrent mobility patterns. In [22] the MA state is used to maintain the information about the cell paths covered by the MA-associated mobile devices; MAs entirely base their predictions on these historical data. [23] represents an evolution of this kind of approach, by exploiting a machine learning automaton applied to path historical data. To the best of our knowledge, SOMA (extended with RSSI-GM) is the first MA platform that integrates a lightweight and completely decentralized mobility prediction solution, which is exclusively based on the simple RSSI information and implemented in a completely portable way.

6 Conclusions and Ongoing Work

The wireless Internet deployment scenario strongly suggests dynamic middlewares to support the provisioning of personalized services that are reconfigured and tailored at the wireless access locality, to fit the specific characteristics of roaming client devices. The design guideline of exploiting MA-based middleware proxies that work over the fixed network on behalf of their resource-constrained clients is showing its suitability and effectiveness, especially when associated with mobility prediction solutions. These solutions can enable the proactive migration of middleware components to the access localities that are going to be visited by the roaming users.

Our work of design, implementation, and evaluation of different prediction solutions has achieved two main objectives. On the one hand, it has shown that predicting the next visited cell is possible with a limited overhead and enough time advance to preserve service continuity in a large class of wireless Internet services. On the other hand, it has pointed out that simple lightweight solutions such as the completely decentralized RSSI-GM can even outperform more complex approaches such as ECP-GM and ED-GM. As a consequence, we have decided to integrate the RSSI-GM prediction module in the next release of the SOMA platform.

The promising results obtained by the RSSI-GM integration in SOMA are stimulating further related research activity. We are working on achieving service continuity in our MA-based middleware for the dynamic tailoring of Video-on-Demand streams to mobile wireless devices [7, 8]. In particular, this requires combining mobility prediction with the identification, design, and implementation of optimal strategies to dimension client-side buffers for multimedia streams. Buffer size should depend not only on the device profiles that describe the memory characteristics of access terminals, but also on the estimation of service resume time after client handoff. A too small buffer endangers streaming continuity, thus thwarting the anticipated migration of MA-based proxies; otherwise, a too large buffer uselessly wastes the typically limited memory of client devices.

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