Optimization of radio measurements exploitation in wireless mobile networks

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***Abstract*— Radio measurements play a crucial role in mobile wireless networks as they are input of Radio Resource Management (RRM) mechanisms, needed to assess mobile network reliability and to supervise the planned coverage area. Nevertheless, these measurements are used in their crude state without any additional intelligent treatment whereas they are a rich and unexploited source of information for the network. In this paper, we propose a new approach for the manipulation of existing radio measurements in wireless mobile networks. The goal is to optimize the use of these measurements with new approaches of exploitation in different locations of the network, basing on advanced signal processing tools.**

This new approach is based on nonparametric regression and smoothing methods. Interesting results are inferred from this analysis, based on real measurement traces collected in different environments and situations. Main results are the elaboration of a dynamic estimator of the attenuations components (pathloss, shadowing and fast fading), a method for the determination of the mobile user situation (incar, pedestrian and unmoving) as well as ameliorations in the handover procedure.

We conclude that integrating advanced radio signal processing in RRM mechanisms is an efficient and easy-to-implement way for a better use of radio measurements.

***Index Terms*—Radio measurements, optimization, wireless mobile networks, non parametric, smoothing, regression methods**

I. INTRODUCTION

Radio measurements, realized by the mobile terminal or the base station, are crucial to assess mobile network reliability as they are needed to guarantee quality of service and to supervise the planned coverage area.

These measurements are standardized for each wireless radio technology (GSM, UMTS, EDGE, HSDPA...) and are essentially used as input for Radio Resource Management (RRM) algorithms (for example handover procedure and power control). The main types of radio measurements are quality measurements (e.g. downlink physical channel bit error rate), traffic volume measurements (e.g. uplink traffic volume) and power measurements (e.g. user equipment transmitted power).

Measurement reporting increases the amount of signaling in wireless mobile networks. Hence, this reporting needs to be limited to avoid overloading the network. Thus, each wireless technology standard specifies the periodicity of its radio measurements.

Today, radio wireless networks are in constant evolution, providing many different and complex services for an increasing number of users. We assist to the emergence of new concepts and services, involving the cooperation of different radio access technologies, seamless mobility and also cognitive radio: the intersection of wireless technology and computational intelligence [1].

Regarding this evolution, the need to reconsider the standardized radio measurements becomes a real challenge to follow the wireless radio network innovations and to ensure a better and more efficient radio resource management (RRM).

II. STUDY APPROACH

Wireless networks, providing more services and capacity, typically require frequent and accurate radio measurements. Current standardized radio measurements are used in their crude state, without much processing (other than averaging or filtering operations for handover algorithms) whereas they are a rich and unexploited source of information for the radio network.

In previous studies, we described some methods to better exploit existing radio measurements [2] [3]. The obtained results were very encouraging: using statistical tools, we extracted useful information of the state of the mobile (indoor, outdoor, incar, pedestrian, unmoving). The tested methods are: the wavelet transform with the multiresolution representation [2] and the likelihood ratio function associated with the Neyman-Pearson test [3].

These results incited us to deal with more sophisticated statistical tools to extract additional information from existing radio measurements. To reach this objective, we choose first to characterize the studied measurements using nonparametric regression and smoothing analysis

methods including local polynomial regression and smoothing splines. The second step is the exploitation of the results and a study of the possibilities of application in radio wireless networks. The analysis we undergo aims to fulfill two main goals:

- Avoid supplementary signaling with more frequent reporting or the definition of new measurements,
- Provide new inputs for RRM mechanisms to meet the new demands and evolutions of wireless networks in terms of capacity and rate.

This paper is structured as follows. Section III gives an overview on standardized radio measurements in current wireless networks, including a brief presentation of radio propagation as well as the measurement setup. Section IV presents the regression and smoothing methods and more specifically the methods applied on radio measurements. In Sections V, VI, VII, we propose new approaches of exploitation of radio measurements in different locations of the radio network. Section VIII concludes the paper.

III. OVERVIEW: RADIO MEASUREMENTS IN WIRELESS NETWORKS

In this study, we focus on power measurements. This category of measurements is characterized with a basic property: the measured signal undergoes attenuations due to signal propagation, from the transmitter antenna to the receptor antenna (such as reflexion, diffraction and diffusion). Thus, these measurements are strongly influenced by the external context: the external environment and the user situation.

A. Radio propagation

Three influencing parameters are mainly identified to give increased precision on the description of the propagated radio signal:

- Pathloss: It is the median variations of the signal. The transmitted signal power decreases proportionally to the distance between the transmitter and the receiver (Figure 1). This is due to free space wavefront spreading. The received power depends on the radiated power EIRP (Equivalent Isotropic Radiated Power), the gain of the receiver antenna Gr, the distance d and the frequency f.

$$\Pr[dBm] = EIRP[dBm] + 10\log(Gr) - \underbrace{\left[-10\log(K) + 10\alpha\log(d) + 10\beta\log(f)\right]}_{PL}$$

  Where $\Pr$ is the received power, K, α and β are constants depending on the environment of propagation and the term PL denotes the pathloss. There are mainly two empirical models to express the pathloss: Lee's model and Hata's model [4].

- Shadowing: It is the low variations of the signal around the average curve (Figure 1). The radio signal undergoes additional attenuation caused by local obstacles (or masks) between the transmitter and the receiver. It is generally modeled by a Gaussian distribution with zero mean and standard deviation σ. A typical standard deviation for rural environment is 6 dB.

- Fast Fading: It is the short-term fading and it is present in the signal in form of rapid variations (Figure 1). It is due to multipath propagation: The presence of numerous obstacles and reflectors in the wireless propagation channel implies that the transmitted signal arrives at the receiver from various directions over a multiplicity of paths. Generally, the fast fading is not considered in the deployment phase as it is taken into account in the power threshold defined in the receiver side (sensitivity of the receiver).

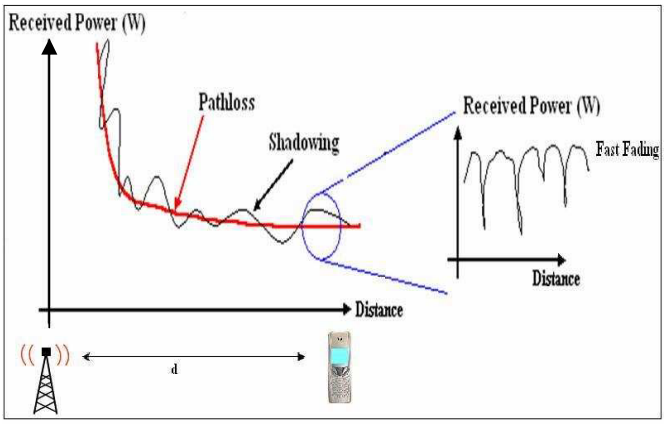

Figure 1 - Signal propagation in a wireless network

These characteristics of power measurements motivate us to undergo an advanced processing on these measurements to extract further information on the external environment.

B. Standardized radio measurements

Radio measurements are standardized in each wireless radio technology. Thus, specific standardized power measurements are defined such as:

- RXLEV: the received signal level defined in the GSM system,
- UE_Tx_Power: User Equipment Transmitted Power defined in the UMTS system

For the GSM system, the parameter RXLEV is defined as the measure of RSSI (Received Signal Strength Indicator) which is the wideband received power within the channel bandwidth [5]. This measure is obtained after an average on instantaneous measurements over a period of 480 ms and on logarithmic scale. It is available in *Measurement Report* messages (uplink).

The UE_Tx_Power denotes the User Equipment transmitted power [6]. In WCDMA, the power control is necessary, especially in the uplink, as a solution to the near far problem. Closed loop power control commands the mobile station to use a transmit power proportional to the inverse of the received power (or SIR). Thus, the

UE_Tx_Power measurements include the attenuations undergone by the propagated signal. The initial processing (done before the reporting to the access network) is different from the GSM system. The instantaneous measurements undergo a filtering, defined by:

$$F_N = (1-a)F_{N-1} + aM_N$$

Where F_N is the filtered measurement, F_{N-1} is the old filtered measurement result, M_N is the last measurement available from layer 1 and $a = \frac{1}{2}^{k/2}$ with k the filter coefficient.

Collected radio measurements form a vector of discrete observations, which could be modeled as following:

$$Y_k = F_k + P_k + S_k$$

Where F_k is the fast fading component, P_k is the pathloss component and S_k is the shadowing component.

C. Experimental setup

The study is based on real radio measurements, collected in different situations and corresponding to low, medium and high velocity of the mobile user (namely unmoving, pedestrian and incar situations).

For this goal, a database of radio measurements is elaborated for both parameters RXLEV (GSM system) and UE_Tx_Power (UMTS system). The experimental procedure is based on:

- A tracing mobile used to collect the *Measurement reports* (send by the mobile to the Access Network),
- A specific software tool to decrypt these messages (Figure 2). The software tool depends on the considered radio access technology. Thus, we used:
  - For the GSM system, the tool TEMS (Ericson) [7] with a GSM tracing mobile,
  - For the UMTS, the tool CAIT (Qualcomm) [8] with an UMTS tracing mobile.

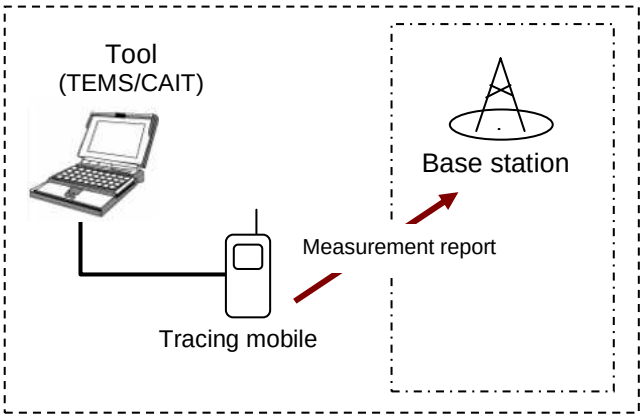

Figure 2 - Experimental setup

Figure 3 shows examples of measurements corresponding to unmoving and pedestrian situations. We can notice that they present different types of fluctuations. In fact, the fast fading is preponderant for unmoving users (short-term variation of the signal), while the effect of pathloss and shadowing clearly appears for moving users (long-term variation).

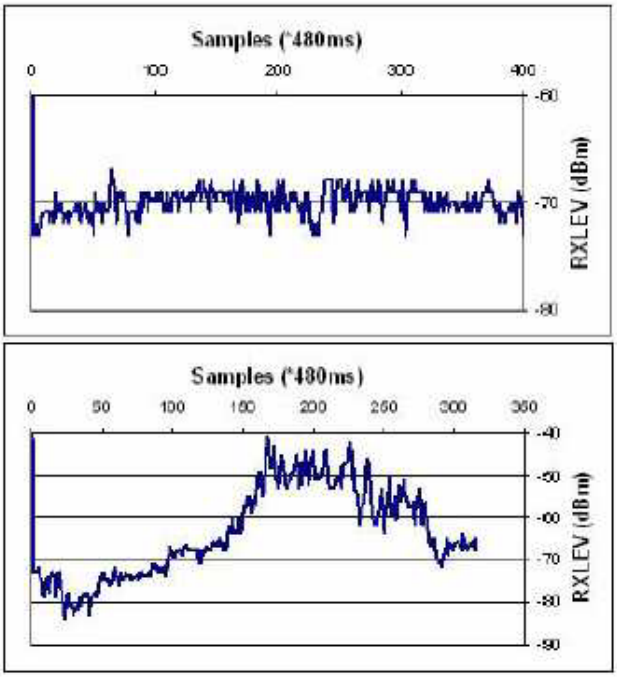

Figure 3 - RXLEV measurement for unmoving (top) and pedestrian (bottom) situations

IV. Regression and Smoothing Methods

Regression and smoothing methods are a major tool in data analysis in several domains. These techniques have been specifically developed in the last ten years with the introduction of non parametric approach, offering further flexibility in empirical analysis.

Several domains are concerned with the application of these methods such as the environmental field (for example the prediction of river flows [9]) and also the economic field (for example the study of rice patterns of demand in Thailand [10]).

A. Definitions

A regression curve [11] describes a general relationship between an explanatory variable X and a response variable Y. Given $\{(X_i, Y_i)\}_{i=1}^{n}$, the regression relationship can be expressed as:

$$Y_i = m(X_i) + \varepsilon_i \qquad (1)$$

Where $i = 1... n$, m the unknown regression function and ε_i the measurement errors.

Two main categories of regression are identified in the literature: parametric and non-parametric. In the parametric approach, the regression function depends on a finite number of unknown parameters. Whereas, in the nonparametric approach, the regression curve is assumed

to belong to a function class (for example a ball in a Sobolev space), and allows more flexible regression specification.

In this study, we choose a nonparametric approach, as it offers flexibility, extremely helpful in a preliminary and exploratory statistical analysis of radio measurements.

The smoothing of a dataset $\{(X_i, Y_i)\}_{i=1}^n$ involves the approximation of the curve *m* in the regression relationship (1). The smoothing can be expressed as a local average of the observations $\{Y_i\}$ in a small neighborhood around *x* and can be formulated as:

$$\hat{m}(x) = \sum_{i=1}^{n} W_{n,i}(x) Y_i \qquad (2)$$

Where the weight function $\{W_{n,i}(x)\}$ is a sequence of weights which may depend on the whole vector $\{X_i\}_{i=1}^n$. The amount of averaging is controlled by this sequence, which is tuned by a smoothing parameter.

B. Smoothing spline

It is a class of non parametric functions defined by Whittaker (1923) [13] and used for data interpolation and/or smoothing.

A spline $S:[a,b] \to \Re$ is a special function defined piecewise by polynomials:

$$S(t) = P_i(t),\ t_{i-1} \le t \le t_i \qquad (3)$$

With $i = 1...k$ and $a = t_0 < t_1 < ... < t_{k-2} < t_{k-1} = b$

Points t_i are called knots.

The smoothing splines are fitted with the penalized least squares regression. This method realizes a trade-off between two different aims in curve estimation: fitting the data and avoiding too much local fluctuations. The compromise is expressed in the form of a penalized sum of squares *S* [12]:

Given any twice differentiable function g defined on *[a,b]* and a smoothing parameter $\alpha > 0$:

$$J(g) = \sum_{i=1}^{n} \{Y_i - g(t_i)\}^2 + \alpha \int_a^b \{g''(x)\}^2 dx \qquad (4)$$

The penalized least squares estimator $\hat{g}$ is defined as the minimizer of *J(g)* over the class of all twice differentiable functions g. The different terms of *J(g)* are:

- The residual sum of squares $\sum_{i=1}^{n} \{Y_i - g(t_i)\}^2$ measures the fit of observations by the model,
- The roughness penalty $\int_a^b \{g''(x)\}^2 dx$ quantifies the roughness of the obtained regression function,
- The smoothing parameter α controls the trade-off between residual errors and local variation. If α is large then the main component in *J(g)* is the roughness penalty term and then the rapid variations are eliminated from the minimizer $\hat{g}$,

The solution of this problem may be expressed as:

$$\hat{g}(x) = \sum_{i=1}^{n} W_{n,i}(x) Y_i$$

C. Friedman's Super smoother

It is proposed by Friedman (1984) [14] and is based on local linear k-nearest neighbor (K-NN) fits in a variable neighborhood of the estimation point x. The (K-NN) smoother is defined as:

$$\hat{m}_k(x) = \sum_{i=1}^{n} W_{k,i}(x) Y_i$$

Where $\{W_{k,i}(x)\}_{i=1}^n$ is a weight sequence defined through the set of indexes:

$J_{k,x}$ = {i: X_i is one of the k nearest observations to x}

The (K-NN) weight sequence is constructed as:

$$W_{k,i}(x) = \frac{1}{k} \text{ if } i \in J_{k,x} \text{ and 0 otherwise.}$$

The parameter k controls the smoothness of the obtained curve.

V. ATTENUATION COMPONENTS ESTIMATION

A. Introduction

As a first approach, our goal is to study the effects of the regression and smoothing methods on the fluctuations of the radio measurements. We tested two non parametric regression and smoothing methods: the smoothing spline and Friedman's super smoother. These methods are applied with different values of smoothing parameters on a database of radio measurements.

Figure 4 illustrates the results of the application of the smoothing spline with two different smoothing parameters. A small value of the smoothing parameter α (0.2) leads to rapid fluctuations remaining in the result curve. Whereas, a high value of the smoothing parameter α (0.8) produces a much smoother prediction, but which doesn't capture some of the salient features of the measurements (for example at 10:59:37:93 in Figure 4).

The Friedman's super smoother solves this problem as it is a weighted average in a varying neighbourhood. Hence, it allows a better elimination of the rapid fluctuations. Figure 5 illustrates the application of the Friedman's super smoother on the same input data as for

the smoothing spline (with two smoothing parameters *sp=0* and *sp=7*).

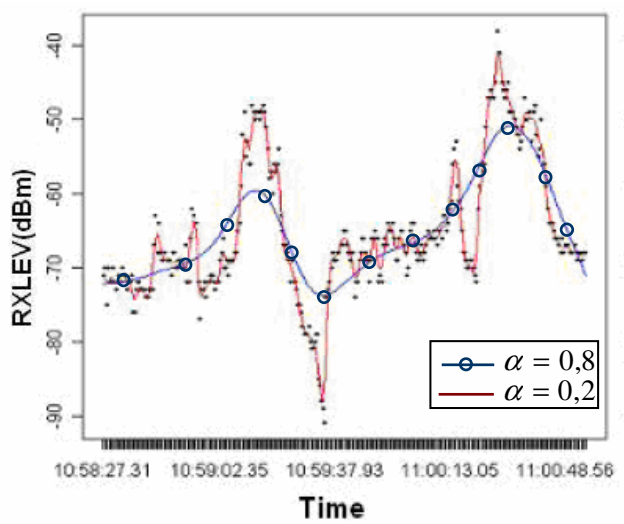

Figure 4 – Smoothing spline application on a vector of RXLEV measurement for an incar user

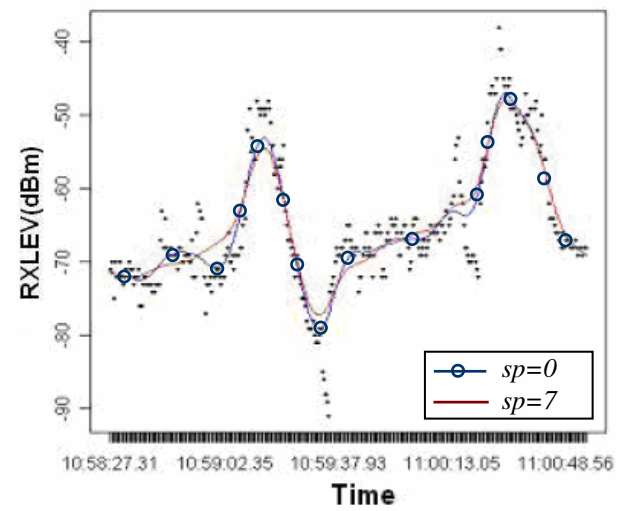

Figure 5 –Friedman's super smoother application on a vector of RXLEV measurement for an incar user

A. *Estimation method*

The regression and smoothing methods with adequate parameters allow the estimation of the attenuation components of the radio signal. In other terms, these methods behave as adaptive filters to extract different scales of variations from the input data (rapid, medium and slow variations). Exploiting the properties of each regression method, we estimate the attenuations components of the radio signal: the pathloss (the median curve), the shadowing (slow variations) and the fast fading (rapid variations).

The smoothing splines (SS) with a high smoothing parameter (Figure 6 and Figure 7) is adequate to estimate the median variations of radio signal, which corresponds to the pathloss component P_k (typically $\alpha = 2$ in (4))

$$P_k = SS(Y_k)$$

The Friedman's super smoother (FSS) is a weighted average in a varying neighbourhood. Hence, this method with a small smoothing parameter allows an efficient elimination of the rapid fluctuations in radio signal, remaining the pathloss and shadowing components (Figure 6 and Figure 7).

As we evaluate previously the pathloss with the smoothing spline method, the shadwoing component S_k is thus obtained by subtraction:

$$Z_k = FSS(Y_k) = P_k + S_k \quad \Rightarrow \quad S_k = Z_k - P_k$$

The fast fading component F_k is then estimated directly by the following formula:

$$F_k = Y_k - (P_k + S_k) = Y_k - FSS(Y_k)$$

Basing on the previous results, we have elaborated a dynamic estimator (Figure 9) allowing the estimation of the attenuation components of the radio signal (pathloss, shadowing and fast fading) after a period of observation τ of the reported power measurement (in Figure 6, $\tau = 144s$). Figure 8 illustrates the estimated attenuation components for a vector of 300 samples of RXLEV measurement.

The attenuation components (pathloss, shadowing and fast fading) are used to be estimated from predefined empirical models, elaborated in given conditions and environments. No direct method is available in the literature to estimate these components from radio measurements in real time. The main originality of our estimator is its validity in all environments and for all mobile user situations, with results obtained in real time (about 5.10^{-3} seconds for the processing of 400 samples with Intel Pentium 4 CPU 3.40 GHz). The dynamic and flexibility properties allow the exploitation of this estimator in RRM mechanisms or any other real time application in wireless networks.

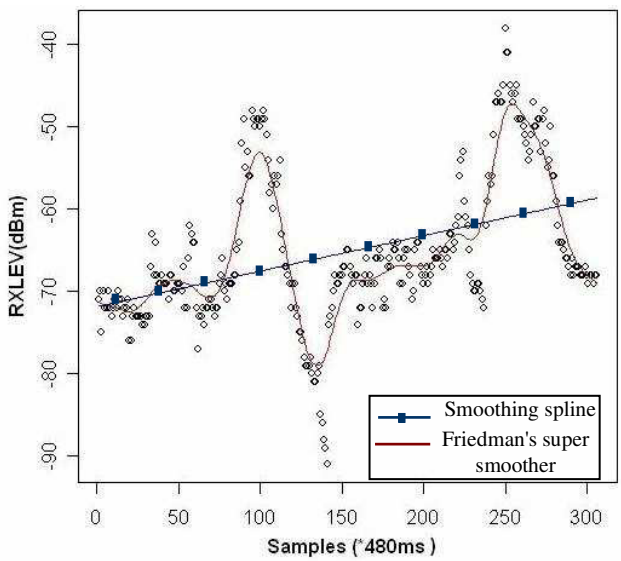

Figure 6 – Smoothing and regression methods application on RXLEV measurement

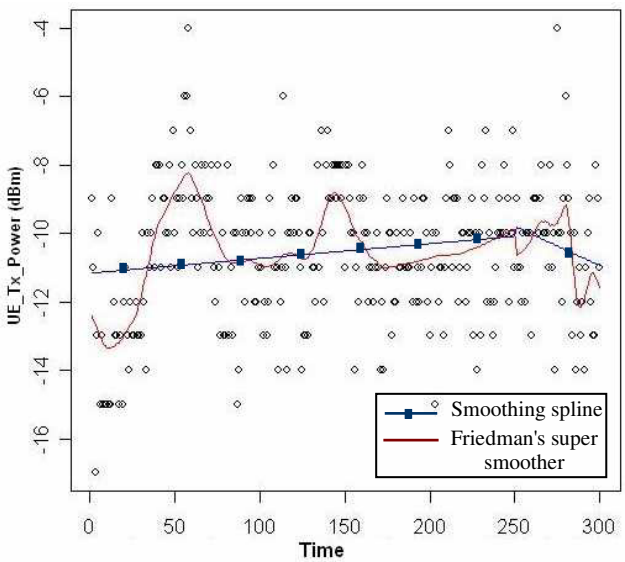

Figure 7 – Smoothing and regression methods application on UE_Tx_Power measurement

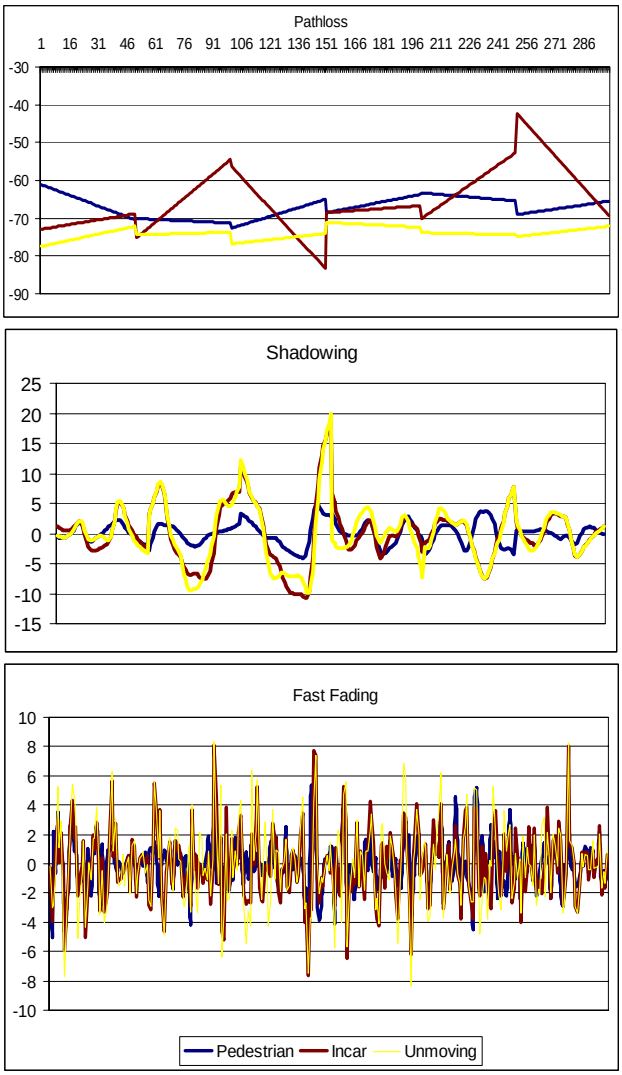

Figure 8 – Estimated attenuation components

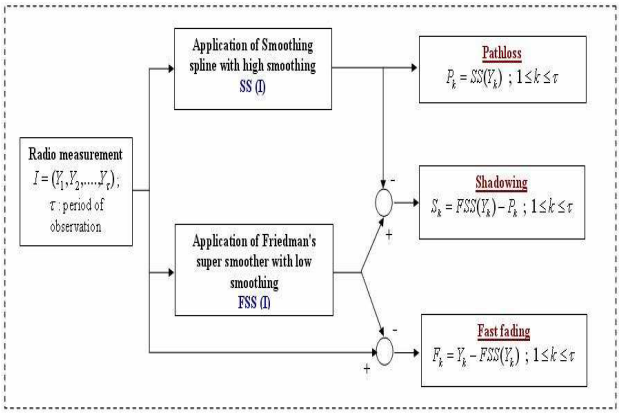

Figure 9 - Dynamic estimator of attenuation components of radio signal

VI. MOBILE USER CLASSIFICATION

The attenuations undergone by the radio signal are strongly related to the mobile user velocity. If the mobile user is unmoving then the measured power signal doesn't present too much variation contrary to the incar or pedestrian cases. Hence, the attenuations undergone by the propagated signal are more important in the mobile case than the unmoving one. This suggests proportionality between the velocity of the mobile user and the attenuations undergone by the radio signal. For example, in the unmoving case, the pathloss is almost constant; the user doesn't move and so he doesn't meet new obstacles. In the other hand, in the incar case, the pathloss is varying.

To illustrate this difference, we use the histogram representation on each attenuation component (Figure 8), estimated using our method (Figure 9) in three cases: unmoving, pedestrian and incar users. Figure 10 presents the results of this representation, with connecting points in the middle of the bars (for clearness raison). To formulate the difference between the three cases, we calculate the standard deviation σ on the previous representation (TABLE I.) to measure the spread of the data. We can verify that the incar case is characterized with the highest value of σ for the three attenuations components. More generally, we verify for the three attenuation components that:

$$\sigma_{unmoving} < \sigma_{pedestrian} < \sigma_{incar}$$

Hence, we can use this method to deduce thresholds on the standard deviations in order to identify the mobile user situation.

As a future work, we aim to exploit these results to build an advanced statistical classifier for more efficient mobile user identification.

As our classification method is based on dynamic and real-time estimator (Figure 9), we can include our dynamic classification of the mobile user in RRM decisions. For example, choosing macro cells instead of micro cells for incar users, in order to avoid frequent handovers.

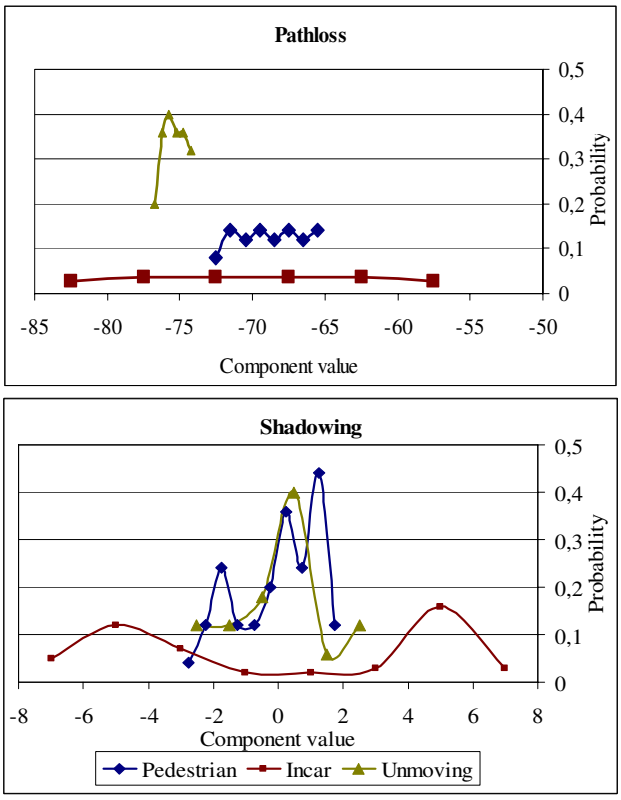

Figure 10 - Shadowing and pathloss histogram representations for unmoving, pedestrian and incar situations

TABLE I.
STANDARD DEVIATION OF THE ATTENUATIONS COMPONENTS

Case	Pathloss	Shadowing	Fast Fading
Incar	5.56	4.98	3.67
Pedestrian	1.71	1.85	2.75
Unmoving	0.93	1.34	2.07

VII. APPLICATION IN HANDOVER PROCEDURE

A. *Handover process description*

Handover process is based on radio indicators traducing the level of received signal and quality of service (for example in GSM, RXLEV and RXQUAL for serving and neighborhood cells).

The handover algorithm implemented in current wireless networks consists of two phases [15]:

1. Phase 1: It is the radio measurement collection and evaluation process, in parallel to the target cell determination algorithm,
2. Phase 2: It is the handover triggering and execution process.

A standardized algorithm allows the determination of target cells: It is the list of neighborhood cells candidate for the next handover. The Choice of the target cells is made first on the criterion of received power and then on power budget criterion [5] [16]. This is traduced by the following equations:

$$RXLEV\_NCELL(n) > RXLEV\_MIN(n) + Max(0, Pa)$$

$$PGBT(n) - HO\_MARGIN(n) > 0$$

With:

- $RXLEV\_NCELL$: the received signal level for the adjacent cell "n" (available for 16 cells),
- $RXLEV\_MIN$: the trigger threshold parameter,
- $Pa = MS\_TXPWR\_MAX(n) - P$,
- $MS\_TXPWR\_MAX(n)$: Maximum TX power a MS is authorized to use in the adjacent cell "n",
- P : Maximum TX power of a MS,
- $PGBT$: the power budget,
- HO_MARGIN : A parameter used in order to prevent repetitive handover between adjacent cells.

Basing on the decreasing value of $PGBT - HO\_MARGIN$ of each adjacent cell, the network elaborates an ordinate list of target cells. The handover then occurs with the first cell in the previous list.

B. *Proposed ameliorations*

We focus on the first phase of the handover process and more specifically on the target cell determination algorithm. We propose to apply a pre-treatment on radio measurements for more efficient determination of target cells list.

We tested our smoothing and regression methods on RXLEV parameter for both serving and neighborhood cells. The goal is to conclude on possible improvement in handover algorithm. In GSM system, a cell is identified by the parameters ARFCN (Absolute Radio Frequency Channel Number) and BSIC (Base Station Identity Code). Figure 11 shows an example of RXLEV during a handover occurring between the serving cell and the neighborhood target cell (559,31). This figure shows the evolution of the signal level for all present cells.

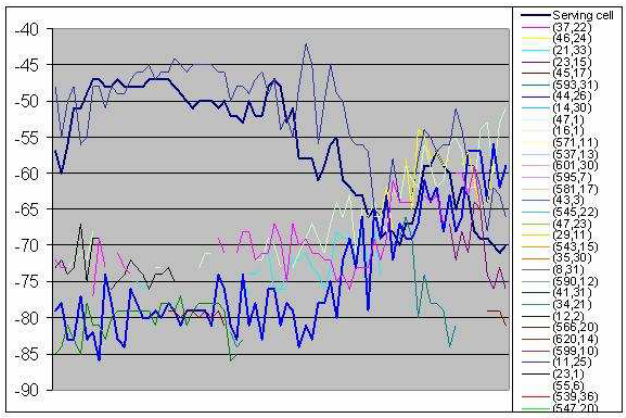

Figure 11 - RXLEV for serving and neighborhood cells during handover for incar user

Figure 12 represents the RXLEV for only the serving cell and the destination cell. We can notice that, at the beginning, the RXLEV of the serving cell is decreasing whereas the RXLEV of the destination cell (559,31) is increasing during the same time interval. After duration, the handover occurs and the destination cell becomes the serving cell (when the red curve disappears).

From this observation, we had concluded that we can use the smoothing method on the cell levels to improve the handover algorithm, by deducing the target cells to become the next serving cell. In fact, the application of the smoothing spline method (with high smoothing parameter for example $\alpha = 1$) on RXLEV of all present cells (serving and neighbourhood) allows studying the evolution of each cell separately (Figure 13). In other terms, the smoothed curve obtained for each cell is studied to decide if the cell could become the serving cell or not. For this aim, the slope of smoothed curve is calculated (table I).

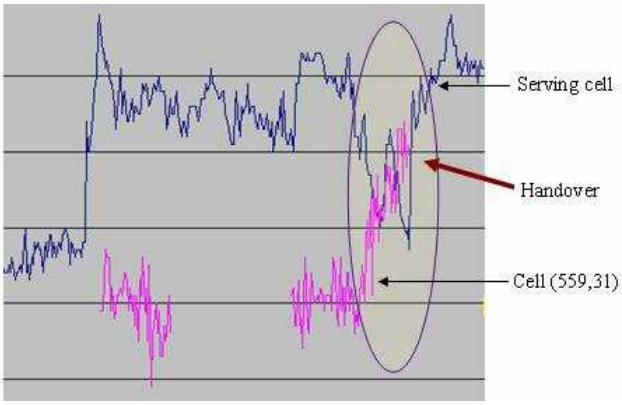

Figure 12 - Handover procedure

The serving cell is decreasing before the handover. Thus, the slope of its curve is negative (-0.38). The target cell will be a cell with a higher level. Nevertheless, the cell (11,25) could not become the serving cell even if its level is higher. In fact, the level of (11,25) cell is decreasing and the handover will not occur with this cell.
Thus, the target cell is characterized with a positive slope (an increasing level) and could be differentiated from other neighbourhood cells by the higher slope.
In Figure 13, the target cell is (559,31) cell and its slope is 0.53.

Basing on the previous observations, we can conclude that the smoothing and regression methods can ameliorate the handover process with an enhanced target cell determination algorithm. In fact, adding to the power budget parameter, we propose to determine the list of the target cells more precisely, basing on their variations (slope of the smoothed curve). This could be considered as an anticipated action in the handover process, which aims to improve the radio resource management algorithms.

The other advantage of such methods is that they conserve in memory previous measurements and include them when calculating the smoothed curve.

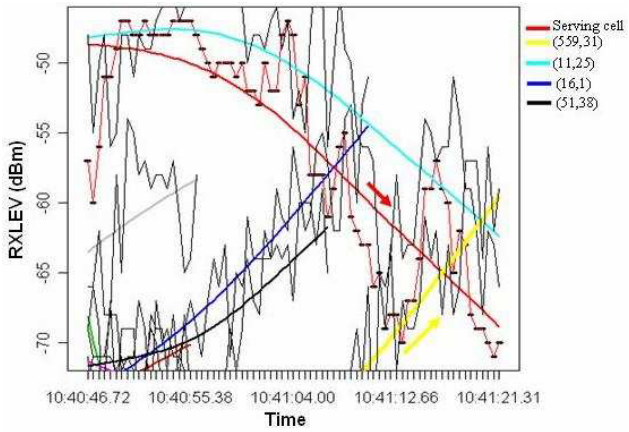

Figure 13 - Smoothing spline application for serving and neighborhood cells in GSM system

TABLE II.
CURVE SLOPES AFTER SMOOTHING SPLINE APPLICATION ON RXLEV OF SERVING AND NEIGHBORHOOD CELLS

Case	Serving cell	(21,33)	(529,31)	(16,11)
Slope	-0,38	0,21	-1,7	0,48

Case	(559,31)	(58,35)	(51,12)	(15,26)
Slope	0,53	0,25	0,38	-0,11

Case	(11,25)	(23,1)	(616,33)	
Slope	-0,35	-0,16	0,03	

VIII. CONCLUSION

In this work, we propose to apply intelligent treatments on radio measurements in wireless mobile networks. The purpose of these treatments is inferring external context and ameliorating radio resource management, which is a crucial and necessary tool for future wireless technologies such as cognitive radio.
For this goal, we use a statistical analysis based on advanced tools that have been introduced recently in non parametric statistics. We focus on nonparametric regression and smoothing methods. We choose two specific methods with optimal smoothing parameter settings: the smoothing splines and the Friedman's super smoother.

These methods allowed reaching interesting results. In fact, we elaborated a dynamic and real time estimator of the attenuation components of radio signal (namely pathloss, shadowing and fast fading), basing on reported radio measurements. Then, we used this estimator to develop a method of classification of mobile user, basing on the velocity criterion. The main classes are incar, pedestrian and unmoving. We also proposed improvements in the handover procedure with enhanced target cell determination algorithm (using the smoothing spline method).

To conclude, we provide in this study flexible and dynamic methods to explore efficiently radio measurements, providing real time results. These methods can thereby be implemented in future wireless networks for an efficient and optimal use of radio measurements.

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