Pedestrian mobility management for heterogeneous networks

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ABSTRACT

Pending the arrival of the next generation of 5G which is not yet deployed in some countries like Algeria, 4G LTE remains one of the main mobile networks to ensure adequate quality services. This paper presents a new approach called the epsilon Kalman filter with normalized least-mean-square (ϵ KFNLMS) to ensure and improve the mobility management of pedestrian UEs in two-tier 4G LTE networks. ϵ KFNLMS uses a two-step process: i) Tracking process, performed by Kalman filter, known for its very low estimation error. ii) Prediction process, performed by the variable step-size least mean squares (NLMS) algorithm (VSS-NLMS), known for its prediction of the future state at "t+p", where "p" is the prediction footstep. Through different numerical simulations in several indoor/outdoor environments, the results show that the effectiveness of the proposed approach provides: a precise setting of the handover trigger, a lower mean square error (MSE), a faster convergence with a steady-state compared to the classical normalized LMS (NLMS) and Li-NLMS adaptive filters.

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1. INTRODUCTION

The demand for radio spectrum is expected to increase by several orders of magnitude due to the rapid proliferation of wireless technologies. To address this issue, significant improvements in the spectral efficiency, robustness, and performance of wireless devices have been achieved through technological and regulatory innovations. Many regulatory agencies around the world have investigated the problems of spectrum scarcity [1]-[5], showing that the demand for spectrum will increase significantly, and pointing out that the major problem is not an insufficient spectrum, but inefficient use of spectrum. On the other hand, to ensure seamless connectivity and access to ubiquitous mobile services, switching from one network to another, is done through an efficient handover mechanism [6]-[13]. In a heterogeneous environment [4], [8], [10], [13]-[18] involving several static and dynamic parameters, the network selection decision is a critical component and represents a difficult task to make the handover decision-for any mobile user. However, A robust solution to the problem of inefficient spectrum use and handover decision-making is cognitive radio technology [1]-[5]. Since cognitive radio can coexist with existing licensed primary users, effective protocols are needed to perform spectrum detection and allocation of an unused spectrum between secondary users.

Generally, the environment around a UE during his displacement affects the RSS by the fluctuations frequently and rapidly [19], mostly, when the number of obstacles increases (NLOS communication). However, small cells have been widely deployed by 4G LTE network operators alongside the conventional base station structure to provide customers with better service and coverage capacity [20]-[22]. Unfortunately, the traditional technique in the 4G LTE network initiates handoff by adjusting values of handover margin (HOM) and time to trigger (TTT) which can cause significant data loss during the session due to limited 3GPP group settings like, false handoff triggering or unnecessary handoff [9], [11] due to limited 3GPP group settings [23]-[26]. Knowing that, our previous works [23] and [24], have proven by using variable step-size normalized least mean square (VSS-NLMS) adaptive filter family, more especially, a VSS-NLMS combined with spectrum sensing (SS) probability method, can predict the detection of handoff triggering spectrum in 4G LTE heterogeneous networks (HetNets) with a rather long convergence time, mainly due to the estimation error in VSS-NLMS process.

To ameliorate this algorithm, we propose an upgrade to ensure both, the continuity of communications to UE and QoS. This solution uses the energy detection spectrum sensing (EDSS) method used in cognitive radio (CR). Specifically, the local model of spectrum sensing (SS), with a variable step-size NLMS prediction process (VSS-NLMS) combined with a Kalman filter (KF) to predict the impact of the link-down serving cell to initialize the handoff process by a probability and then, select the spectrum detected. KF presents a very good accuracy with a very low error on the estimation of positions and powers while the VSS-NLMS algorithm performs the prediction on the future state. The proposed approach was simulated in the Matlab platform with other published scientific approaches.

The rest of this paper is organized as follows: section 2 provides a detailed description of the system model. Section 3 presents a comparison of the results with the six indoor path loss models. Finally, section 4 concludes the paper.

2. SYSTEM MODEL

2.1. Path loss model

Studying the environment in which RSS is propagating, more specifically, the RSRP model in 4G LTE HetNets, provides thereafter, a sensing probability. To this end, it allows seeing the availability of one or more spectrums to help make the right decision to trigger handoff functionality. In general, when we transmit a signal via a BS, it deteriorates due to the presence of obstacles such as the number of floors/walls. At the reception (at UE's level), RSS is less than the signal power transmitted. This loss is known as path loss, and can be calculated as [27].

$$PL = P_{tx} - P_{rx} \tag{1}$$

Where P_{tx} and P_{rx} represent the transmitted and received power levels, respectively.

Many indoor and outdoor path loss models were proposed in the literature. They are a good instrument for testing various algorithms and estimating the overall capacity of a network. Thus, by minimizing path loss, better signaling can be delivered to the receiver [27]. The indoor regions are characterized by the deployment of FBS', their role is to bring a better QoS and quality of experience (QoE) for users [11], [17], [18], [28], [29]. As a result, the QoS degrades to multiple environmental factors, such as floors and walls. Therefore, we took the advice of Deb *et al.* [27], who's explains: "*it's not recommended to take a single path loss model for all the scenarios*". Six indoor path loss models were taken: i) 3GPP's Femto Model [30], with the localization setting of *UE* inside the same house as FBS; ii) ITU-R P with the configuration of the residential building [31], [27]; iii) WINNER II LOS [32]; iv) WINNER II NLOS with light/heavy walls [32]; v) multi-wall-and-Floor [33] and vi) El Chall Model [34]. All of these path loss models support a 4G LTE network. In the same technical release of 3GPP Group [30], the outdoor path loss model of MBS deployment is a suburban environment with UE inside a house.

2.2. SINR intensity

The transition from propagation models to *EDSS* approach consists in establishing the *SINR* equation. Two cases are presented by Ibrahim *et al.* [35]. In our study, we're interested at their first case, where the effect of *MBS* is ignored compared to UE_{indoor} . Thus giving to [35].

$$SINR = \frac{RSRP_{UE_{indoor}}^{PBS_{seving}}}{\sum RSRP_{UE_{indoor}}^{PBS_{NOServing}} + N_0}$$
(2)

Where $RSRP_{UE_{indoor}}^{FBS_{serving}}$ is the received power from *FBS* serving to UE_{indoor} (in dBm); $\sum RSRP_{UE_{indoor}}^{FBS_{NoServing}}$ is the sum of received powers from non-serving *FBS* to UE_{indoor} (in dBm) and N_0 is the background noise (in dBm). It's can be deduced by the following form [36].

$$N_0 = n_0 + n f_{eq} \tag{3}$$

 n_0 is a noise (exactly, the thermal noise power), defined as (4).

$$n_0 = -174 \frac{dBm}{Hz} .10 \log \left(F_{sam} \frac{SC_{used}}{SC_{total}} \right)$$
(4)

Where, F_{sam} , SC_{used} , SC_{total} , and nf_{eq} are sampling frequency, number of used sub-carriers, number of total sub-carriers and noise figure of the UE respectively. As we have only one FBS, resulting in that.

$$SINR = RSRP_{UE_{indoor}}^{FBS_{Serving}} / N_0$$
(5)

2.3. Non-cooperative spectrum sensing

We are interested to *NCSS* model. More specifically, we are addressing to *EDSS* process [37]. This process is widely less computation and implementation complexity [38]. The result of this method gives an energy value with respect to rho, which represents the predefined threshold value of an energy decision. If the energy of the received signal is higher or equal/less than a threshold value, then the detection of primary user (PU) is present or absent, respectively. Therefore, the computation and selection of threshold are a very obvious aspect [38]. Indeed, there are two binary hypotheses: $H_{0,i}$ the null hypothesis which indicates the absence of PU compared to UE_i and $H_{1,i}$ which designates the hypothesis of the presence of PU signal as a function of UE_i . To decide between them, we translate the received signal energy *E* into sensing probability metrics by applying the probability theory (the chi-squared law [23], [24], [38]. Giving thus, two metrics, the false-alarm probability P_{fa} and the probability of detection P_d .

$$\begin{cases} Prob(E > \rho | H_0) : P_{fa} = \Gamma(\tau, \rho/2) / \Gamma(\tau) \\ Prob(E > \rho | H_1) : P_d = Q_r(\sqrt{2\gamma}, \sqrt{\rho}) \end{cases}$$
(6)

Where, $Q_r(.,.)$, $\Gamma(.,.)$, $\Gamma(\tau)$ and τ are Marcum's Q function, incomplete gamma function, gamma function and the temporal product of the bandwidth respectively.

2.4. A new estimation process configuration

2.4.1. Proposed approach

The proposed concept are based respectively on: i) Kalman filter error (KFE): which is provided by KF, a better process that reduces the error rate between the real and estimated distances; ii) KFE administered in VSS-NLMS: this step estimates the next distance as presented in the Table 1 and Figure 1 by substituting the prediction error of VSS-NLMS ($e_{VSS-NLMS}(n)$) by KFE ($e_{KFE}(n)$) to predict a small error on the future state of an estimated distance; and iii) convergence step: to ensure the faster convergence with steady-state, we add the ϵ value by multiplying the difference between the estimated distances VSS-NLMS and KF in absolute value. The equations of the proposed algorithm that we call " ϵ KFNLMS" are listed (7) to (12).

$$\mathbf{D}(n) = [d(n) \ d(n-1) \ \dots \ d(n-p+1)]^T$$
(7)

$$\mathbf{W}_{n} = [w_{n}(0) \ w_{n}(1) \ \dots \ w_{n}(p-1)]$$
(8)

$$\mathbf{W}_{n+1} = \mathbf{W}_n + 2\mu(n).e_{KFE}(n).\mathbf{D}(n)$$
(9)

with,
$$\begin{cases} \mu(n) = \alpha / \|\mathbf{D}(n)\|^2 \end{cases}$$
(10)

$$\begin{cases} \text{with}, \\ e_{KFE}(n) = d(n) - \hat{d}_{KF}(n) \end{cases}$$
(10)

$$\hat{d}_{KFNLMS}(n+p) = \sum_{l=0}^{p-1} w_n(l) d(n-l) = \mathbf{W}_{n+1}^T * \mathbf{D}(n)$$
(11)

$$\hat{d}_{\epsilon KFNLMS}(n+1) = \hat{d}_{KFNLMS}(n+1) + \epsilon \times |\hat{d}_{\epsilon KFNLMS}(n+1) - \hat{d}_{KF}(n)|$$
(12)

From (7) to (12) and taking inspiration from the standard VSS-NLMS scheme, we have come to draw Figure 1.



Figure 1. Proposed algorithm scheme

2.4.2. VSS-NLMS used

VSS-NLMS algorithms and their variants are based on the principle of updating a variable step size used subsequently in the update of a weight multiplied by an error and this comes down to Table 1 [24], where $||.||^2$ is the Euclidean norm square.

Table 1. Parameters of VSS: NLMS and Li-NLMS

Algo.	Variable step size (VSS)	Weight
NLMS	$\mu(n)=lpha/\ \mathbf{X}(n)\ ^2$	$\mathbf{W}_{n+1} = \mathbf{W}_n + 2\mu(n)e(n)\mathbf{X}(n)$
Li-NLMS	$g(n+1) = \beta g(n) + (1-\beta) \frac{e(n)\mathbf{X}(n)}{\gamma + \alpha \ \mathbf{X}(n)\ ^2}; \ \mu_g(n) = p \ g(n)\ ^2$	$\mathbf{W}_{n+1} = \mathbf{W}_n + 2\mu_g(n) \frac{e(n)\mathbf{X}(n)}{\gamma + \mu_g(n) \ \mathbf{X}(n)\ ^2}$

3. SIMULATION RESULTS

To verify the effectiveness of the proposed scheme under the MATLAB platform, we analyzed and compared it with some of the existing VSS-NLMS methods such as NLMS and Li-NLMS. Let's also note that, simulation parameters have been set in the following Tables 2 to 4.

Table 2. Common simulation parameters				
Parameter	Femtocell	Macrocell		
Simulation area	1000m x 1000m			
UE's numbers	1			
Cell radius	7 m	500 m		
Number of BS	1	1		

Cartesian position

Transmit power

Thermal noise Noise figure

(281, 150)

23 dBm

(0, 0)

46 dBm

-174 (dBm/Hz) [24], [39]

9 dB

Table 3. Simulation parameters of : NLMS, Li-NLMS and ϵ KFNLMS				
VSS algorithm	Parameter	P th order predictor		
NLMS	$\alpha = 0.1$ [40]			
Li-NLMS	From [41] $\alpha = \frac{1}{2^2}$; $\beta = 0.999$; $\gamma = 0.02$; $u(0) = 0.01$; $p_{Li} = 1$; and $g(0) = 0$	2		
ϵ KFNLMS (proposed)	$\alpha=0.99~[42]$; and $~\epsilon=1.05$			

Table 4. Indoor/outdoor path loss settings						
Path loss Env.	Model	Description	Symbol	Value	Commo	n parameter
	3GPP's Femto [30]	Indoor walls thickness [43]	$d_{2Dindoor}$	0.3 m	Nun	nber of
	ITLI P. P. (Pasi buil)[31]	Power loss coefficient [27]	n	28 dB	floo	r
	110-K P (Kesi, bull.)[51]	Floor penetration loss	L_f	4 dB	$n_{f} = 1$	
Indoor	WINNER II LOS [32]	-	-	-	-	Freq.(f)
	WINNER II NLOS (LW) [32]	Lightwalls penetration loss	$x_{lightwall}$	5 dB	Number of wall	= 2 GHz [27]
	WINNER II NLOS (HW) [32]	Heavywalls penetration loss	$x_{heavywall}$	12 dB	$n_w = 2$	
	Multi Wall and Floor [33]	Power loss coefficient [44]	n	1.96	-	-
		Wavelength [23], [24]	λ	0.124 m	-	-
		Path loss at 1 meter dis- tance [23], [44]	PL_0	40 dB	-	-
		Attenuation linked of light wall	L_{w11}	3 dB	-	-
		Attenuation linked of heavy wall [27]	L_{w12}	10 dB	-	-
	El Chall [34]	Attenuation linked of one floor	L_{f11}	19 dB	-	-
El Chall [34]		Path loss at 1 meter dis- tance	PL_0	120.4 dB	-	-
	Power loss coefficient	n	2.85	-	-	
		Constant	b	0.47	-	-
		Number of walls	n_w	2	-	-
		Number of floors	n_f	1	-	-
		Wall penetration loss	L_w	1.41 dB	-	-
		Floor penetration loss	L_f	10 dB	-	-
Outdoor	3GPP's Macro [30]	Outdoor wall penetration loss [23], [24], [43], [45]	L_{ow}	20 dB	-	-

Table 4. Indoor/outdoor path loss settings

3.1. Analysis metrics

The performance of all EDSS approaches with NLMS, Li-NLMS, and the proposed process can be assessed using the following metrics:

- Predicted energy sensing: the EDSS combined with NLMS, Li-NLMS, or the proposed approach, predicts the presence of FBS link-down spectrum, to keep the link as long as possible to UE; initialize the handoff at the right time; reduce the number of the unnecessary handovers and avoid ping-pong effect [9], [11]. The purpose of this metric is to evaluate: the physique aspect of prediction (the steady-state convergence) and speed of convergence.
- Mean square error (MSE): the second metric is well-known to evaluate the estimation error between the estimated and original probability of detection in order to assess the quality of the prediction accuracy of each approach. Mathematically, the formula of MSE can be obtained easily as (13).

$$MSE = E\{(P_d - \hat{P}_d)^2\}$$
(13)

Where E denotes the expectation symbol and presents the statistical average [46]; P_d and \hat{P}_d denote respectively real and estimated probability of detection.

3.2. Evaluation of predicted energy sensing and mean square error

As shown in Figure 2, the proposed general topology is composed of a two-tier heterogeneous 4G LTE network, one UE localized inside a house, on the 1^{st} floor; one FBS is centered on the ground floor with two walls that separate them and also, one MBS to cover most parts of the suburban area. Both, FBS and MBS are assumed to operate in the same, frequency band and OFDMA technology [43], [47], [48]. We assume the UE's mobility is heading outward (balcony or terrace). UE's pedestrian mobility was taken from the METIS-2020 group [49]. However, Figure 3 represents the topology zoomed only on the Femtocell that shows the UE traces, moving outwards.

The ϵ KFNLMS handoff prediction process is incorporated into the ITU-R P Model with two other adaptative filters, NLMS and Li-NLMS as illustrated in Figure 4. The results show that the handoff decision of

the proposed approach is trigged at the right time (at 5 sec) compared to NLMS and Li-NLMS models.

The graphical results of the detection probability of the spectrum link-down for the three approaches in the WINNER II LOS environment are presented in Figure 5, where the proposed work is compared and achieves an efficient convergence speed with a steady-state leading to an optimal handoff process.

The graphical plots of the WINNER II NLOS model for light and heavy walls are depicted in Figures 6 and 7 respectively. The results show that there is not a big major difference between NLMS, Li-NLMS, and ϵ KFNLMS. This is due to the wall type parameter. But, the proposed work always gives better results.

Figure 8 displays the handover decision based on Multi-Wall and Floor model. Many parameters are raised for this environment. The figure shows that the NLMS and Li-NLMS processes present a less good convergence time than ϵ KFNLMS. Therefore, a delay is recorded to initialize the handoff process.

Figure 9 shows that the proposed approach ϵ KFNLMS adapts better even in adverse conditions as in the case of the EL Chall model, unlike other approaches that cause a significant disturbance compared to the real link-down. This leaves plenty of time to handoff to MBS.

In Figure 10, ϵ KFNLMS widely exceeds the other approach proposed in terms of accuracy, even in the most aggressive of multi-path cases users. Since the MSE of our approach is not readable on Figure 10 for some models proposed. Table 5 provides more details. The proposed algorithm is considered the best in all cases and works well on all used path loss models.

Figure 11 provides the damage on the link (outage period). Li-NLMS and NLMS suffer from convergence problems, they need some moments. Thereby causing a data loss, contrary to the ϵ KFNLMS is more rapid and stable which initializes the handoff triggering at the right instant towards MBS with zero interruption and zero failures. Li-NLMS starts the handoff triggering at the instant 7 sec to MBS, 2 sec of damage on the link. However, NLMS initiates the handover process at the time of 8 sec to MBS, 3 sec of data loss.



Figure 2. General topology proposed

Figure 3. Zoomed topology only on the Femtocell



Figure 4. Link-down and Handoff prediction-ITU-R P model

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Figure 5. Link-down and Handoff prediction-WINNER II LOS model



Figure 6. Link-down and Handoff prediction-WINNER II NLOS model (light wall)



Figure 7. Link-down and Handoff prediction-WINNER II NLOS model (heavy wall)



Figure 8. Link-down and Handoff prediction-MWF model



Figure 9. Link-down and Handoff prediction-EL Chall model



Figure 10. Mean square error



Figure 11. Damage on the link-outage

4. CONCLUSION

Enhance mobility management of pedestrian UE in a two-tier heterogeneous 4G LTE network is presented in this work, by analyzing and comparing in-depth, six different indoor environment models under three VSS-NLMS to evaluate the problem of false/late triggering of the handover process, caused by the presence of obstacles such as different types of walls (light or heavy) and several walls/floors. The proposed solution is extensible from previous works, which permits us to improve the fast convergence with excellent accuracy and steady-state. Simulation results show in terms of probability, a good put performance of prediction of the serving cell link-down to initialize the handoff at the right time with low mean squared error with zero interruption and zero failures.

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