Mobile Positioning by Combination of RSSI using Artificial Neural Network and TOA Local Search Algorithms

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***Abstract*— This paper presents the combination of two methods of localization: RSSI (Received Signal Strength Indicator) and TOA (Time of Arrival). Artificial neural networks will be used for location by RSSI and the resulting estimated position will be consolidated by the TOA method in order to increase the accuracy. A simulation study is presented.**

Keywords*— *Positioning; RSSI; TOA; neural network; local search; least squares; likelihood

I. INTRODUCTION

There are several methods for determining positioning of mobile from the fixed nodes whose positions are known.

These techniques uses the measures of TOA, TDOA (Time Difference of Arrival), DOA (Direction of Arrival) and RSSI. The corresponding accuracy depends on the noise includes during the measurements.

In order to obtain a better estimation of the position of the mobile, we propose in this paper a combination of the RSSI method using artificial neural network and the TOA technique to refine the resulting estimated position.

For this purpose, we will present firstly the fundamentals of RSSI and the TOA location, as well as the main parameters relevant to the measures. Secondly, we will describe all the process's steps to achieve the position refining: from the collect of needed data to the output position estimation. At last, through simulation, we will apply the method to a chosen part of Antananarivo city located in

II. TOA POSITIONING

Let, the position of the mobile which is unknown and $\mathbf{x}_l = [x_l\ y_l]^T$ the position of the lth base station, where $l = 1,2,\dots,L$ and $L \geq 3$ the number of the base station.

The distance d_l between the mobile and the lth base station is:

$$d_l = \| \mathbf{x} - \mathbf{x}_l \|_2 \qquad (1)$$

$$= \sqrt{(x - x_l)^2 + (y - y_l)^2},$$

$$l = 1,2,3,\dots,L$$

We suppose that the target output a signal at $t = 0$, and the lth base station get the signal at $t = t_l$, meaning that $\{t_l\}$ are the TOAs and the relation between the distance d_l and t_l is:

$$t_l = \frac{d_l}{c}, \qquad l = 1,2,3,\dots,L \qquad (2)$$

Where c is the propagation speed [1]

III. RSSI POSITIONING

Another way to estimate the position is to use the radio channel physical characteristics: the RSSI.

The RSS model is formulated as follow. Assuming that the transmitted power is P_t, and in noiseless environment, the mean received power on the lth receiver, noted by $P_{r,l}$, is

$$P_{r,l} = K_l P_t d_l^{-\alpha}$$
$$= K_l P_t \|\mathbf{x} - \mathbf{x}_l\|_2^{-\alpha}, \qquad l = 1,2,\dots,L \qquad (3)$$

Where K_l includes all the parameters affecting the received power, such as the antenna height and gain. α is the path loss constant. [1]

IV. MEASURE MODEL

The measure model from the TOA and the RSSI can be generalized by:

$$r = f(x) + n \qquad (4)$$

Where r is the vector measure, x the source position to be determined, $f(x)$ a nonlinear function of x and n the vector of zero mean additive noise. [1].

V. MAIN PARAMETERS RELEVANT TO THE MEASURES

The RSSI is the received power on the wideband, including the thermal noise and noise generated by the receiver. The reference point of this measure is the antenna connector of the mobile.

To determine which receiving cells communicate with the mobile, it is necessary to match with their CID (Cell Identity). The RSSI and the CID are, therefore in our case, the important measurements parameters used to locate the mobile position.

VI. DATA COLLECTION

The input data contains the transmitted power of the mobile stations with respect to each sector of the base station.

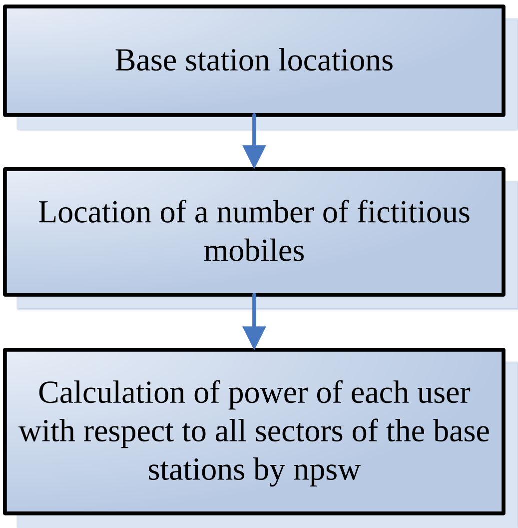

Fig. 1. Data collection steps

If one user is not served by a given sector, the corresponding power will have -936 dBm for not being considered. The positions of the base stations, as well as the mobile stations, are all geographically known.

VII. POSITIONING OF THE MOBILE BY ARTIFICIAL NEURAL NETWORK (ANN)

The Multilayer Perceptron (MLP) artificial neural network is a multiple layer feedforward model which contains hidden layers with sigmoid activation function, followed by linear output layer.

It can approximate a nonlinear function using the following model:

$$\hat{y}(k+1) = f[\,y(k), y(k-1), \ldots, y(k-n+1), u(k), u(k-1), \ldots, u(k-m+1)] \quad (5)$$

Where u are the inputs, y the outputs, $\hat{y}$ are the approximations, m input rank, n the output rank, f the nonlinear function and k represents the iterations.

This model is used to estimate the function in the measurement model of the relation (4) in order to get the mobile positioning by ANN [2][3][1].

The number of base stations correspond to the input layer of the ANN.

There will be two hidden layers. The output layer will give us the estimated coordinates of localization x and y.

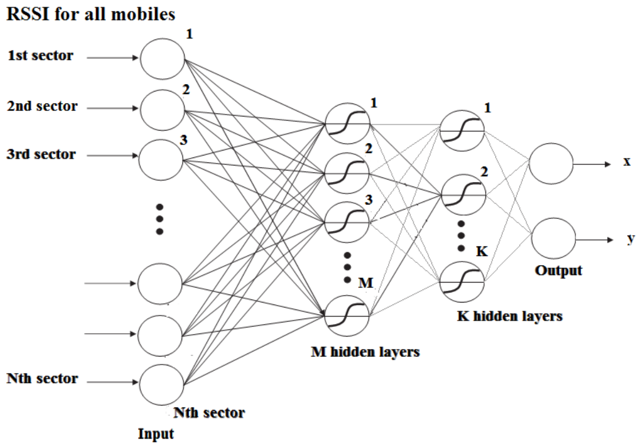

Fig. 2. Schematic representation of ANN used

VIII. REFINEMENT OF POSITIONING BY TOA ESTIMATOR TECHNIQUE

The estimation of the TOA is the second step in the combined technique of estimating the position of the mobile.

After getting estimated TOA by using estimated position given by the ANN, these measures pass through estimator in order to refine the mobile positioning. [4][5]

A. TOA estimation

We assume that the TOA and the mobile position are constant (ie the mobile do not move during measurements). The ML ((Maximum Likelihood) of TOA τ_b is given by :

$$\hat{\tau}_b = \arg\min_{\tau} a_0^2(\tau) E_s - 2a_b(\tau) \int_0^{T_0} \mathcal{R}(r_b^*(t) s(t-\tau)) dt \quad (6)$$

Where $a_b(\tau) = \sqrt{\kappa}(d_0/c\tau)^{\frac{1}{2}\gamma_b}$ is the gain of the path as function of TOA. $\mathcal{R}(.)$ is the real part of . and T_0 is the observation period in which the TOA and the mobile position are constant.

B. Least square

The LS (Least Square) estimator by of mobile positioning, can be calculated by the following relation

$$\hat{\mathbf{p}}_{LS} = \arg\min_{x,y} \sum_{b=M+1}^{B} \left(\hat{\tau}_b - \frac{1}{c}\sqrt{(x_b - x)^2 + (y_b - y)^2} \right)^2 \quad (7)$$

C. Weighted Least Square

The WLS (Weighted Least Square) estimation of $\mathbf{p}$ is given by:

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$$\hat{\mathbf{p}}_{WLS} = \arg\min_{p} \|\hat{\tau} - \tau\|_{\mathbf{W}}^{2}$$

$$= \arg\min_{x,y} \sum_{b=M+1}^{B} \frac{1}{\sigma_b^2(x,y)} \left(\hat{\tau}_b - \frac{1}{c}\sqrt{(x_b - x)^2 + (y_b - y)^2}\right)^2 \quad (8)$$

Where $\|v\|_{\mathbf{W}}^2 = v^H \mathbf{W} v$ is the weighted Euclidian norm with a defined positive unknown having Hermitian weighting matrix $\mathbf{W} \in \mathbb{C}^{B \times B}$and $(.)^H$ denote the Hermitian transpose, M is the number of base station which receive non line of sight signal, B are the total number of all BSs, $\sigma_b^2(x,y)$ is the error value and $\hat{\tau}_b$ is defined in relation (6).

D. Maximum likelihood

The ML estimation of $\mathbf{p}$ is given by:

$$\hat{\mathbf{p}}_{ML} = \arg\min_{x,y} \sum_{b=M+1}^{B} \ln(\sigma_b^2(x,y)) + \frac{1}{\sigma_b^2(x,y)} (\hat{\tau}_b - \tau_b(x,y))^2 \quad (9)$$

The detailed derivation of equation (09) is straightforward from the probability density function of the estimated TOA, which is assumed to be Gaussian.

IX. SIMULATION

In this simulation case, we will apply the method to a chosen part of Antananarivo city located in Madagascar.

We will use 51 sectors of base stations, where each position is known in a 6km*6km map, and 2000 users placed fictitiously in the network.

The geographical positions of these 2000 users are also known.

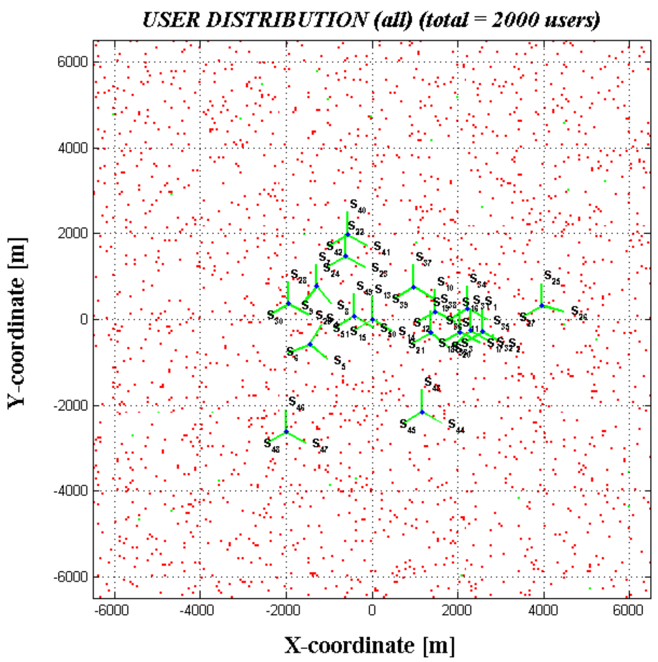

Fig. 3. Graphical representation of base stations and mobile stations

A. Input data collection

The power data of 2000 users will be used as input to the ANN

	M1	....	M4	...	M10	...	M2000
BS1	-936	...	-83,3209048	...	-65,5417899		-936
BS2	-936	...	-95,1873723	...	-100,14455		-936
...	...	...	...	...	...	...	...
BS50	-936	...	-98,5603488	...	-106,146514		-936
BS51	-936	...	-74,0312058	...	-106,750256		-936

Fig. 4. Sample power input data

	M1	....	M4	...	M10	...	M2000
x	6450,75386	...	-5630,81762	...	-348,493501		-3405,96232
y	5,436174	...	2047,2352	...	4293,587		4053,85552

Fig. 5. Sample coordinates of mobile station
Fig. 6.

B. Positioning using ANN

The MLP neural network is used to find the mobile positioning. We use Matlab *feedforwardnet* function to simulate the MLP.

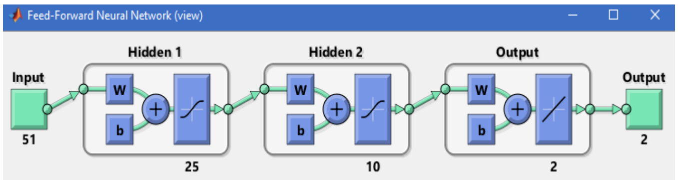

Fig. 7. MLP used with two hidden layers

As shown in fig.6, the MLP has two hidden layers. The first of is 25 and the second one is 10. The input layer has 51 inputs which correspond to the number of sectors of base stations.

The output layer has two output and represents the coordinates x and y of estimated position of mobile.

The network training is done by Levenberg-Marquardt algorithm. The data ratio repartitions are: 80% for the training, 10% for validation and 10% for tests.

After 34 epochs, the weights of the ANN are adjusted and the best validation performance that minimize the Mean Square Error (MSE) is 11,1416 at epoch 28.

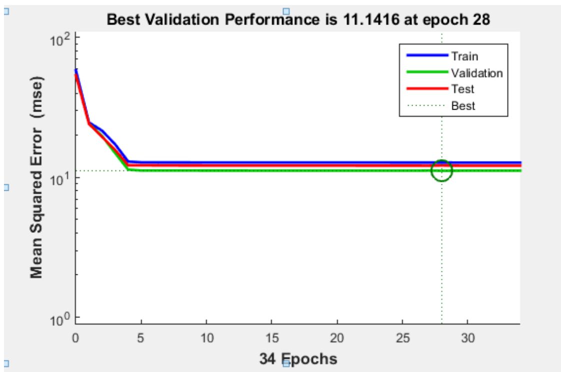

Fig. 8. MSE evolutions graph

The error histogram in Fig. 08 shows a maximum accuracy of about 300 m. The highest error values is due to the fact that some mobiles are served by none of the base stations.

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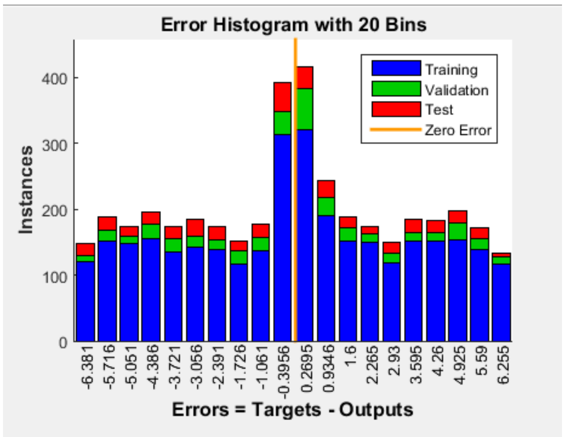

Fig. 9. Error histogram of positioning

In Fig. 9 we present some examples of localization. The red represent the real positions, while the blues represent the estimated positions.

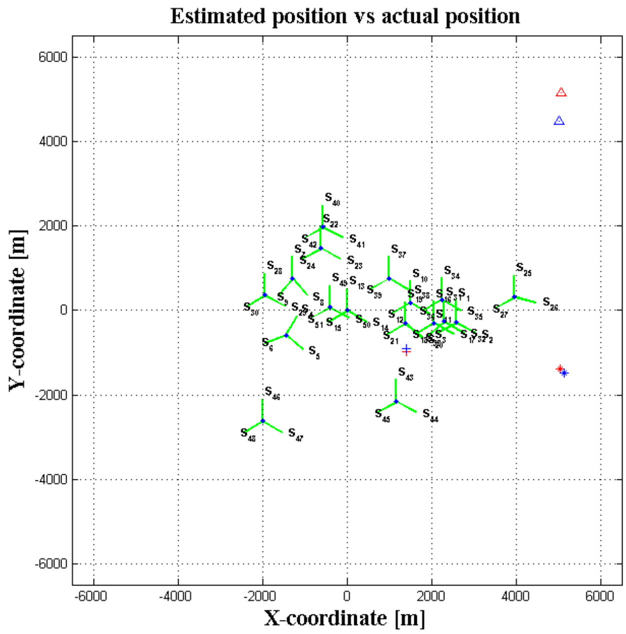

Fig. 10. Graph comparison between real and estimated positions

C. *Position refinement by TOA*

As we can see in to fig. 9, almost all the estimated positions are closer to the actual position of the target, except a case where the triangular target mobile is located away from the base stations.

To improve the accuracy of this location, we will apply the refinement of mobile positioning by TOA.

On the one hand, the estimated position is provided by the RSSI method as seen previously. And on the other hand, we know the locations of the base stations interacting with the mobile to locate. It is thus possible to apply the TOA local search algorithms in order to approach the real position.

We particularly use the following local search methods: the steepest descent, the Newton-Raphson and the Gauss-Newton method.

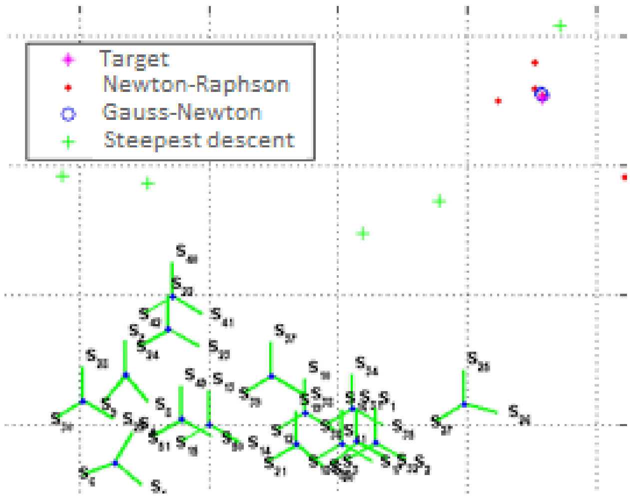

Fig. 11. Application of correction iterations for position refinement by TOA

We can see in the fig.10 that the Gauss-Newton method which approaches much more closely the target mobile.

In the fig 11, we will present the mean square error of positioning as function of the signal to noise ratio of transmission from -10 dB to 60 dB by linear approach.

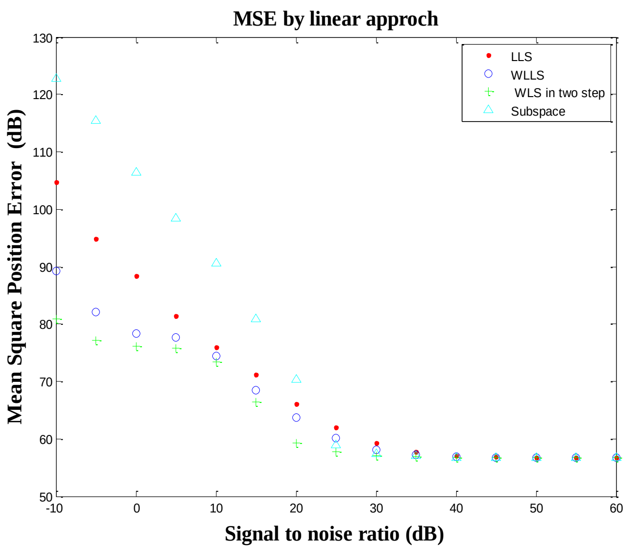

Fig. 12. Mean square error as function of signal to noise ratio

We can see that all the estimators are in their optimal value when SNR>30dB, although the WLS in two steps presents a bit more performance.

X. CONCLUSION AND PERSPECTIVES

The accuracy of mobile postioning can be improved applying the estimation algorithm of TOA on the estimated position obtained by power information of RSSI.

The MLP artificial neural network allow us to estimate the mobile postion through the RSSI, but the accuracy depend on the number of base stations sectors which serve the target mobile.The higher the number of sectors, the more accurate the precision.

From these estimated positions, local search methods of TOA can then be applied in order to further improve the accuracy.

Our main objective was not to compete with GPS positioning, but to present a method independent of user equipment to locate.

We used a planning tool to provide the RSSI values. The prospects envisaged for an upcoming work will be to take real values from drive-test and also to take into account the temporal mobile position in order to better predict the positions and know the cases where there would be a lot of measurement errors due to the environment conditions.

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