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An Approach to Self-Locate Patients in a Psychiatric Center based on Received Signal Strength Indicator and Sensor Information History

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ABSTRACT
In recent years, research around sensor networks has made significant progress. Increasingly, sensor networks are more present at almost every level of daily life. An interesting application of these, is their use for the localization of mobile entities such as animals, vehicles, humans, etc. In this work, the interest is focused on the localization of patients in a psychiatric center. Most of the work around the location of mobile entities is based on models for planning or predicting the trajectory of the mobile entity. However, for humans, even more psychiatric patients, it is difficult if not almost impossible to predict or plan their displacement successfully. It is in this context that the present workoffers this simple and effective indoor localization approach, which is based on the received signal strength indicator and the history of the mobile sensor's journey, to determine its position. In this technique, patients wear sensors without GPS on their arm. It is these sensors that will locate patients in the center in real time. The implementation and simulation of this approach made it possible to validate its effectiveness in terms of accuracy and localization time.

General Terms
Indoor Localization, Accuracy

Keywords
Indoor localization, Mobile sensor networks, Received signal strength indicator, Information history, Accuracy

1. INTRODUCTION
Nowadays, Wireless Sensor Networks (WSNs) are increasingly used in tracking applications, requiring knowledge of the real-time location of a system entity. The literature contains some examples of positioning systems already designed and used at present. One of these most widespread and used systems is the Global Positioning System (GPS). But although it is widely accessible, it faces problems such as: poor reception of signals inside certain environments (dense forest, buildings, etc.), security problems due to radio interference, high costs and high energy consumption making it difficult to install in each sensor where service life is crucial [15], [6], [3]. Because of this, many works have been interested in a new localization technique, called indoor localization to obtain the position of the active agents of a system.

Indoor localization has been the subject of in-depth studies in recent years. Most of these studies rely on the condition that only a small proportion of WSNs nodes, called anchors, know their exact positions using GPS devices or through manual configuration. The other so-called blind nodes obtain their position information through an indoor localization method. These methods provide a satisfactory level of precision with a low proportion of anchors.

This workseeks to locate the sensors carried by mobile entities in order to have the location of these mobile entities. The work looked more specifically at the location of patients in a psychiatric center through sensors worn on their arms, for example. To do this, the center has fixed sensors called anchorsknowing their locations. The work is therefore in the category of localization techniques using fixed anchors and mobile sensors. The methods in this category usually use algorithms based on historical information from mobile sensors [2], [10]. Most of these algorithms are based on models for planning or predicting the trajectory of the mobile to determine its position.

However, this way of proceeding is not always realistic when one finds oneself in reality where the movement of the mobile does not always follow a precise model. For example, in the work environment, it is not easy to successfully predict a patient’s behavior; even more of a psychiatric patient. This is why, this work proposes an approach for locating patients in a psychiatric center, through sensors worn on their wrist, not using a planning or trajectory prediction model. In this approach, the sensors will base on the received signal strength indicator (RSSI) and on the history of information from their journeys to determine their position.This approach is called HI-RSSI.

The rest of the work is organized into three (3) sections. Section 2 present the elements that motivated this work. Section 3 is intended for the presentation of HI-RSSItechnique for locating patients in a psychiatric center. And finally, Section 4 presents the results obtained after simulation of this localization protocol. This work ends with a conclusion and perspectives.

2. MOTIVATIONS
2.1 Patient location
The choice was made on patient localization because this work actually wanted to locate moving sensors in a network that have fixed anchors in the environment. However, one way to obtain moving sensors is to have them carried by

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mobile entities. In this way work will situate in a more realistic application of sensor networks. In addition, being able to locate patients in a hospital in real time is very important for better monitoring of the latter.

2.2 Psychiatric center

The choice of the psychiatric center supports the hypothesis according to which it is difficult in reality to always predict the behavior of the mobile entities of a system. Indeed, their displacement does not always follow a known or predictive law.

Psychiatric centerinterns patients with mental disorders. How to predict with certainty the behavior of such patients, especially in terms of movement? It is clear that this is not always feasible. So, the trajectory planning or next position prediction models cannot be reliable in such a case.

2.3 No use of GPS

The GPS is certainly very widespread and used but it is not always the best choice to make especially in indoor environment. Indeed, equipping all the sensors with a GPS will demand a lot in terms of finances and will cost a lot in terms of energy, especially in large-scale networks [6], [3]. In addition, the interior of buildings and dense environments in forests, for example, remain poorly covered by GPS, [7], [15]. In addition, mobile nodes equipped with GPS will suffer from a serious problem of power consumption because they will call on the GPS module continuously to locate each time [16].

Therefore, the context of this work requires the useof sensors not equipped with GPS. This is why the workis in a context of indoor location. We also opted for the use of fixed anchors not equipped with GPS to limit the cost of the network in terms of finances, especially in a large center which would certainly require a lot of anchors.

2.4 Limitations of previous approaches

In the literature, many works propose solutions for indoor localization of mobile sensors, in particular techniques based on Monte Carlo algorithms sometimes coupled with optimization algorithms for particle swarms.

However, the Monte Carlo methods use processes that are not always very applicable in reality. A very obvious example is the definition of a maximum speed of movement of the sensors [16], [9]. However, in reality, it is not always easy to define the speed of movement of a mobile entity. It is this speed of movement with other parameters that allow these methods to predict the trajectory or the position of the mobile. But this remains difficult to achieve in real cases.

The methods using particle swarms provide good results when the model is well parameterized. Indeed, a bad parameterization of the model will lead to very approximate solutions. In addition, these methods are very often subject to local optima because of the premature convergence of the optimization model, thus leading to poor exploration of solutions in the search area.

3. HI-RSSI: LOCATION BASED ON RECEIVED SIGNAL STRENGTH AND SENSOR INFORMATION HISTORY

This section presents the hypotheses and the principle of HI-RSSI approach. HI-RSSIuses fixed anchors and mobile sensors.

3.1 Assumptions

3.1.1 Regarding anchors

HI-RSSIassumes that the anchors are arranged correctly and optimally in the environment which is the hospital center. HI-RSSIalso assumes that the anchors do not have GPS equipment. Theirposition coordinates were configured manually after a preliminary coordinate survey in the environment. This is to limit the cost of the network linked to the massive use of GPS. Finally, HI-RSSIuses identical anchors in terms of properties.

3.1.2 Regarding sensors

The sensors do not have any movement or obstacle avoidance module because, they are carried by mobile entities which are the patients. HI-RSSIassumes that the sensors know their movement speed, distance of movement and angle of movement measured.

3.2 Principle of HI-RSSI approach

Network is made up of two types of components: anchors and sensors. Anchors are fixed sensors in the environment deployed with their position coordinates manually configured. The sensors are deployed on the wrist of each patient, without position coordinates. They must self-calculate their position in order to allow the localization of their host.

3.2.1 Anchors behavior

The anchors are responsible for periodically broadcasting their position coordinates in the network. The sensors will use its information to calculate their location.

3.2.2 Sensors behavior

The sensors receive the messages broadcast by the anchors in the network. After receiving the first message from an anchor, the sensor over time and its movements, will save its speed and angle of movement. When it receives a second message from an anchor, it can start its locate process. The saved speed makes it possible to evaluate the distance covered during this quantum of time.

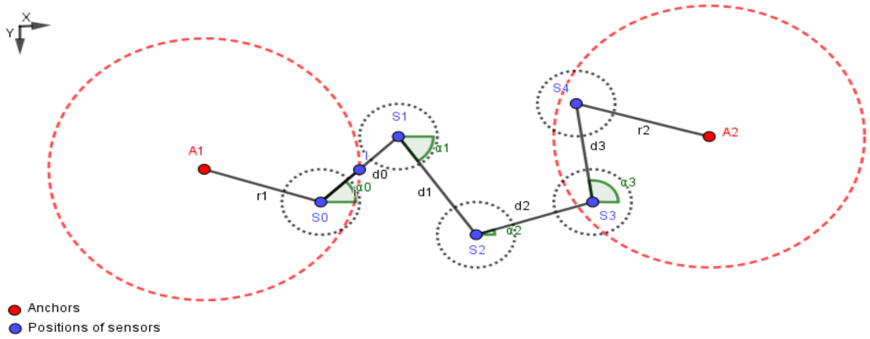

Figure 1: Illustration of sensor behavior

The sensors then hold in memory a table to save the history of its journey. In order to limit the number of data to back up, the sensor will start saving the history of its journey after receiving the first message from an anchor and will stop when it obtains its current location.

When the sensor receives a message from an anchor, it will use RSSI to calculate the distance between him and the sending anchor.

Indeed, given that most wireless devices have the ability to measure signal strength, we can use this to measure the strength of the signal received by a sensor, from neighboring sensors, [4], [11], [8].

The strength of the wireless signal received by a sensor from another sensor is a decreasing monotonic function of their distance. This relationship between received signal strength and distance is modeled by the normal log model below.

$$P_r(d) = P_0(d_0) - 10nlog_{10}\left(\frac{d}{d_0}\right) + X_\alpha \qquad (1)$$

With $P_0(d_0)$ a reference power in milliwatts dB at a reference distance d_0 from the transmitter;n is the path loss parameter which measures the rate at which the received signal strength decreases with distance; X_α is a random variable with mean Gaussian distribution zero with the standard deviation σ which represents the random effect caused by shading (walls, people, intermediate layers, ...). n and σ are environment dependent.

From the equation 1, the real distance separating a transmitter from a receiver is given by the following equation 2, [14]:

$$d = d_0 * 10^{\frac{P_r(d)-P_0(d_0)-X_\alpha}{10n}} \qquad (2)$$

3.3 Presentation of HI-RSSI localization process

The process will be executed from Figure 1. The process begins when the sensor in position S_0, intercepts a message broadcast by the anchor A_1. On receipt of this message, it evaluates by the RSSI method the distance r_1 which separates it from the sending anchor A_1. The sensor will then memorize the coordinates of A_1 received and the distance r_1 evaluated.

But the sensor being worn by the patient does not necessarily remain stationary. When the patient is moving, the sensor saves the angle and the speed of movement at that time. This is how it will do to have in memory the different distances d_i and the different angles α_i.

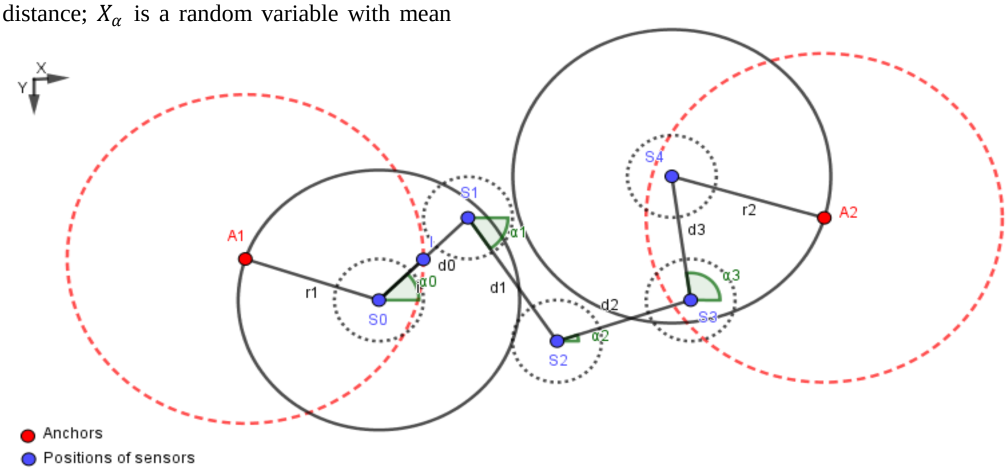

Figure 2: Illustration of sensor behavior when receiving a message from anchor

Starting from the points $A_1(x_{a1}, y_{a1})$,$A_2(x_{a2}, y_{a2})$,and $S_i(x_i, y_i)$, the equations of the circles at time 0 when the sensor receives the first message and at time n when it receives the second message from an anchor will be:

$$\begin{cases}(x_{a1} - x_0)^2 + (y_{a1} - y_0)^2 = r_1{}^2 \\ (x_{a2} - x_n)^2 + (y_{a2} - y_n)^2 = r_2{}^2\end{cases} \qquad (3)$$

However, in real environments, the distance measured by RSSI is corrupted by the shading effect called Gaussian noise σ [12]. Thus, for real considerations, the measured distance r_i will be increased by three times Gaussian effect: $\check{r}_i = r_i + 3\sigma$. So (3) will now be:

$$\begin{cases}(x_{a1} - x_0)^2 + (y_{a1} - y_0)^2 = \check{r}_1{}^2 \\ (x_{a2} - x_n)^2 + (y_{a2} - y_n)^2 = \check{r}_2{}^2\end{cases} \qquad (4)$$

However, being in the plane and in an orthonormal coordinate system, and knowing the angles and the distances between the different positions of the sensor, the following equation 5 can bewritten:

$$\begin{cases}x_n = x_0 + \sum_{i=0}^{n-1} d_i \cos(\alpha_i) \\ y_n = y_0 + \sum_{i=0}^{n-1} d_i \sin(\alpha_i)\end{cases} \qquad (5)$$

Let's pose:

$$\begin{cases}f_1 = \sum_{i=0}^{n-1} d_i \cos(\alpha_i) \\ f_2 = \sum_{i=0}^{n-1} d_i \sin(\alpha_i)\end{cases} \qquad (6)$$

Thus,$x_n = x_0 + f_1$ and $y_n = y_0 + f_2$. By replacingthese values in equation 4, the new system is:

$$\begin{cases}x_0{}^2 + y_0{}^2 - 2 * x_{a1} * x_0 - 2 * y_{a1} * y_0 = g_1 \\ x_0{}^2 + y_0{}^2 + 2 * x_0 * (f_1 - x_{a2}) + 2 * y_0 * (f_2 - y_{a2}) = g_2\end{cases} \qquad (7)$$

Where:

$$\begin{cases} g_1 = \check{r}_1{}^2 - x_{a1}{}^2 - y_{a1}{}^2 \\ g_2 = \check{r}_2{}^2 - x_{a2}{}^2 - y_{a2}{}^2 + 2 * x_{a2} * f_1 + 2 * y_{a2} * f_2 - f_1{}^2 - f_2{}^2 \end{cases} \quad (8)$$

The subtraction of the two equations of system 7 gives:

$$x_0 * (f_1 - x_{a2} + x_{a1}) + y_0 * (f_2 - y_{a2} - y_{a1}) = \frac{1}{2}(g_2 - g_1) \quad (9)$$

The following can therefore be written:

$$x_0 = \varrho - y_0 * \zeta \quad (10)$$

With:

$$\begin{cases} \varrho = \dfrac{g_2 - g_1}{2 * (f_1 - x_{a2} + x_{a1})} \\ \zeta = \dfrac{f_2 - y_{a2} - y_{a1}}{(f_1 - x_{a2} + x_{a1})} \end{cases} \quad (11)$$

Thus, the following quadratic equation 12 can be obtained by replacing $x_0$by its value in the first equation of (7):

$$(\zeta^2 + 1) * y_0{}^2 + 2 * (x_{a1} * \zeta - \varrho * \zeta - y_{a1}) * y_0 + \varrho^2 - 2 * x_{a1} * \varrho - g_1 = 0 \quad (12)$$

The equation 12 can be clearly expressed as $A * y_0{}^2 + B * y_0 + C = 0$ with the following solutions:

$$\begin{cases} y_0 = \dfrac{-B \pm \sqrt{B * B - 4 * A * C}}{2 * A} \\ x_0 = \varrho - (\pm y_0) * \zeta \end{cases} \quad (13)$$

(13)gives us two locations of the sensor when it first received the signal or the message from an anchor: $S_0(x_0, y_0)$and$S'_0(-x_0, -y_0)$.
It is now necessary to choose among these two solutions the one which is correct to express the location of the sensor.

To choose which of the two points is correct, the sensor will calculate the distance separating each of these points from the anchor A_1. Then, it will compare each of them with $\check{r}_i$which represented the distance between the anchor A_1 and itself. It will therefore choose the point for which these distances will be substantially equal.

So, the sensor will calculate the distances $[A_1S_0]$ and$[A_1S'_0]$ and compare them to $\check{r}_i$. The result will allow it to choose either S_0 or S'_0as its location at time 0. And from there, it will be able to calculate its current position, i.e. its location at the current time n according to the system. (5).

3.4 Possible sources of error

In the proposed approach, three elements can be considered as possible sources of localization errors.

Wrong anchor configuration: If an anchor is wrongly configured it is possible that it transmits wrong position information to the sensor. Indeed, the position of the anchor is assigned to it manually after the users have made a position statement in the environment using a GPS for example. If when the anchor is deployed the position is incorrectly configured then the anchor will be placed in the wrong location and will also broadcast position coordinates in the network.

Calculation of the distance between the sensor and the anchor: The sensor uses RSSI to deduce at the reception of the signal of an anchor, the distance which separates it from this anchor. The RSSI measurement may generate errors depending on the quality of the signal received by the sensor.

Calculation of the displacement angle and the distance traveled: If the sensor does not correctly calculate its inclination and its distance traveled at each inclination, the various values d_i and α_i will be incorrect. This will impact on determining the location of the sensor.

4. SIMULATION AND INTERPRETATION OF THE RESULTS

In order to evaluate HI-RSSI approach, simulations and comparisons have been carried out with five previous works ([5], [13], [9], [1]) using the Monte Carlo methods or the particle swarms. In these simulations, anchors and sensors are deployed randomly over the work area. To carry out these simulations, the following parameters were used:

Table 1: Simulation parameters

Parameters	Values
Dimensions of the environment (m^2)	10x10
Number of anchors	5-10-20-30
Number of mobile sensors	20
Gaussian noise σ	0.02-0.04-0.06-0.5
Communication radius of anchors (m)	1-2-4-6
Maximum speed of sensors (m/s)	2
Maximum inclination of sensors (rad)	2π

For the simulation, sensors move randomly by randomly choosing a speed and an angle of movement.

In general, two parameters are used to evaluate the proposed approach: the average localization error and the average localization time.

The location error of a sensorrepresents the difference between its estimated (x_e, y_e) position and its real position (x_r, y_r). The average network location error for N sensors is therefore evaluated by:

$$\xi = \frac{1}{N}\sum_{i=0}^{N} \sqrt{(x_e^i - x_r^i)^2 + (y_e^i - y_r^i)^2} \quad (14)$$

The average localization time represents the average of the localization time of each sensor. This parameter for N sensors is therefore evaluated by:

$$\Gamma = \frac{1}{N}\sum_{i=0}^{N} \tau_i \quad (15)$$

Where τ_i denotes the localization time of the sensor i.

4.1 Impact of environmental noise

Figure 3 presents the impact of the Gaussian noise effectσ of the environment on the localization error.

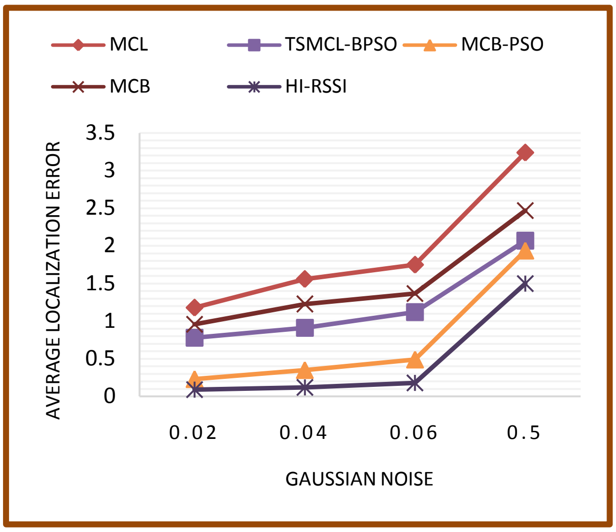

Figure 3: Impact of environment Gaussian noise on localization error

Results ofFigure 3 show that the localization error increases when the Gaussian noise also increases. But in each of the cases evaluated, the proposed approach HI-RSSI obtains better localization accuracy.

4.2 Impact of anchor transmission range

The communication range of anchors can influence the quality of a position estimate. Figure 4 shows that the communication radius of the anchors does not have too much influence on the precision of localization in the proposed approach HI-RSSI. On the other hand, there is a variation of precision in the other approaches.

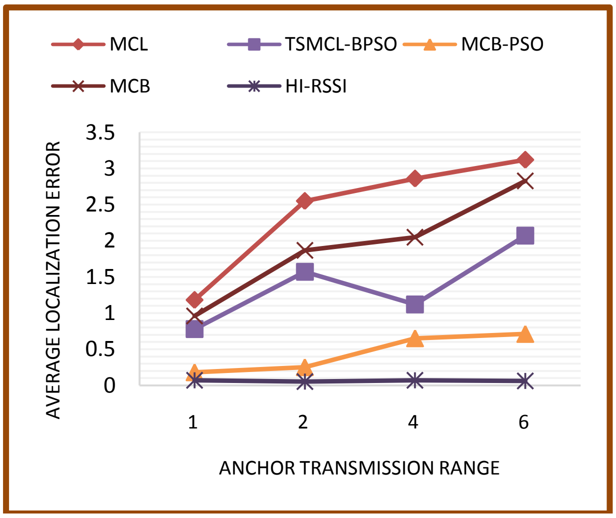

Figure 4: Impact of anchor transmission range on localization error

However, Figure 5shows that the communication radius of the anchors influences the localization time of the proposed approach. Indeed, the greater the radius, the faster the localization because the sensors will receive signals from the anchors more quickly. On the other hand, the curves of the other methods tend to increase with the communication radius. Indeed, in the methods based on the MCL and MCB algorithms, a large communication radius implies a greater number of neighbors to be considered during the localization process.

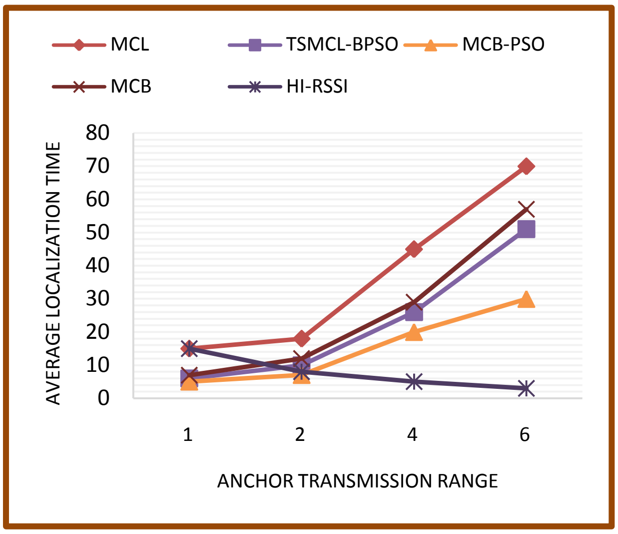

Figure 5: Impact of anchor transmission range on localization time

4.3 Impact of anchors number

Figure 6, shows us that the more the number of anchors increases, the faster the process of locating the network. Indeed, a high number of anchors allows the sensors to receive signals from the anchors more quickly because this allows them to find themselves more quickly in the transmission range of the anchors.

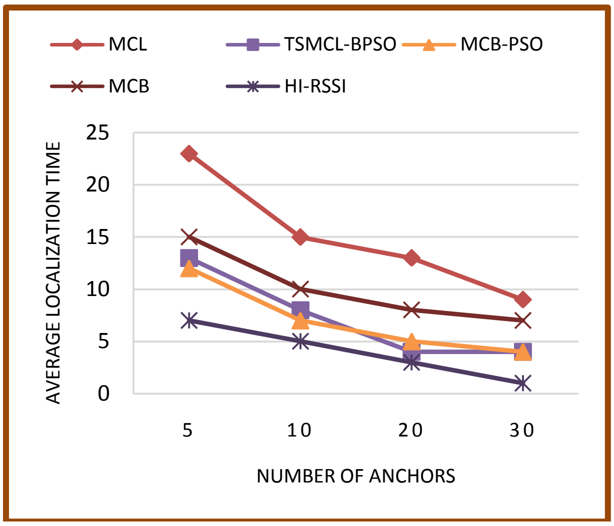

Figure 6: Impact of anchors number on localization time

It can be seen that the HI-RSSI approach is the best in terms of time on this evaluation. In fact, in the MCL and MCB techniques, the more the number of anchors increases, the more the sensors receive much more information to process in their localization process.

4.4 Impact of sensors speed

The sensors movement speed is also an important parameter in a mobile sensors network. Indeed, very fast sensors make localization more difficult. For the simulation, sensors have the same maximum movement speed v_{max}. But each has its own speed when moving, randomly selected between 0 and v_{max}. Figure 7 shows that even if the speed of the sensors influences the accuracy of the approaches represented, HI-RSSI approach obtains better results.

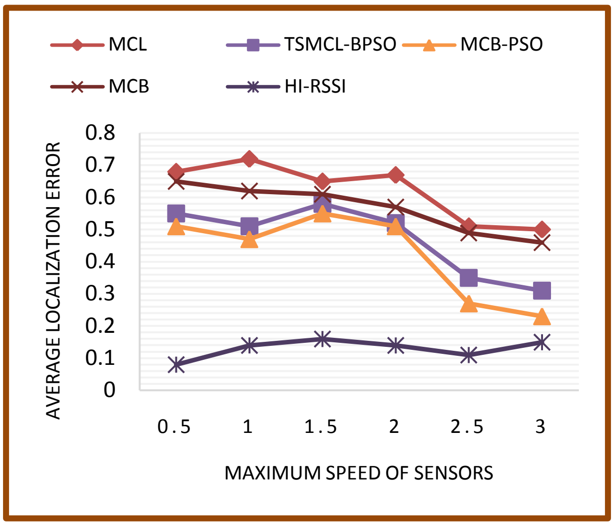

Figure 7: Impact of sensors speed on localization error

The speed of the sensors also influences the localization time of the network. On Figure 8, HI-RSSI approach as well as the TSMCL-BPSO and MCB-PSO approaches obtain not very distant results. But HI-RSSI is faster than the others.

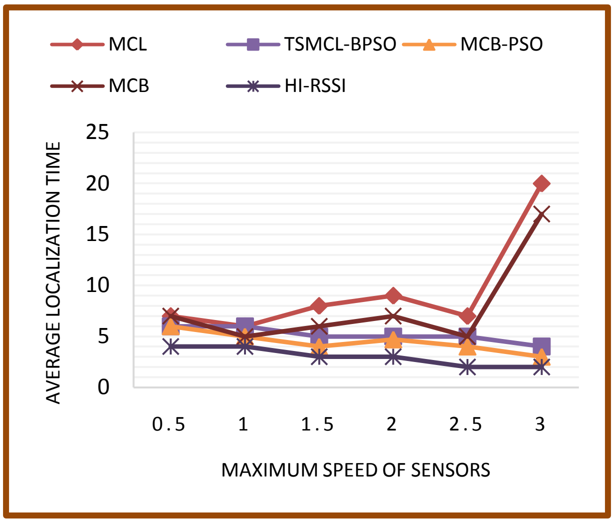

Figure 8: Impact of sensors speed on localization time

5. CONCLUSION

This workproposed an approach to localize patients in a psychiatric center. Patients are located through sensors worn on their wrists and using information provided by fixed anchors in the environment. Anchors are fixed entities knowing their positions and periodically broadcasting them in the network. The proposed approach called HI-RSSI therefore falls within the category of localization approaches based on static anchors and mobile sensors. In this category, several works use the Monte Carlo methods, sometimes coupled with the optimization of particle swarms to estimate the position of the sensors. But in view of their limitations, HI-RSSIwas proposed based on received signal strength indicator and sensor information history. The simulations carried out made it possible to assess the efficiency of HI-RSSI in terms of accuracy and localization time.

In the following, this work plan to analyze the impact of anchor placement on the location of sensors. Indeed, we noticed during the simulations that the placement of the anchors influenced in a certain way the obtained results.

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