A NOVEL APPROACH FOR OPTIMAL WIRELESS SENSOR NETWORK DEPLOYMENT

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ABSTRACT

Wireless Sensor Networks (WSN) limited resources in terms of processing capability and power supply raise a variety of challenges which make them a fertile ground to numerous investigation efforts. Increasing the sensing range, maintaining and improving the connectivity, or extending the lifetime represent the main objectives of WSN researches. In this paper we propose an approach for the deployment of WSN based on the use of simulated annealing to obtain close to optimal solutions for the placement of sensors in terms of minimizing the number of hops between all the nodes of the target region and the sink node while covering as much of the interest area as possible. By reducing the number of hops, the energy saving is also improved. Finally, this paper shows the flexibility of this technique for studying the influence of different parameters of interest at a design stage of the network, prior to the real deployment of WSN nodes.

Index Terms— WSN, Connectivity, Optimal Deployment, Simulated Annealing Algorithm, Energy Saving.

1. INTRODUCTION

A WSN consists of a high number of wireless sensor devices deployed in a target region which operate cooperatively using ad hoc communication architecture. The WSN tasks combine sensing, computing and communicating all into a single small device. Through advanced protocols in terms of sensing configuration and mesh communication, these devices collaborate and exchange information to reach the global task of the network.

The sensing coverage of a sensor is defined as an area formed by a set of points within the sensor's sensing radius. Regarding connectivity of a WSN, there are different definitions: one refers to the fact that no part of the network is isolated, that is, that all the nodes of the target region can forward the information collected to the sink. But also; connectivity refers to the quality of the communication paths between nodes: number of hops; redundant paths and so on. In this paper we refer to the latter meaning. We define the sensing coverage area and the transmission range of a sensor, R_c and R_t respectively. Each point existing within the radius R_c can be covered by the sensor and each sensor node placed within the radius R_t can communicate with the sensor.

Various works have approached the problem of guaranteed connectivity in WSN by controlling the transmission power [1] or the sensing coverage range by improving the event detection probability [2]. In terms of the connectivity the majority of efforts have intended to optimize the routing protocols [3] to maintain the connectivity and decrease the overload that happen in the sensor nodes of relay mission. The relationship between sensing coverage and connectivity has been established in [4]: coverage implies connectivity if the transmission range is more than twice the sensing range of the sensor node.

This work starts from a previous approach on the problem of maximizing the sensing coverage problem in WSN which can be found in [5], in which the simulated annealing technique is used to obtain optimal solutions in terms of sensing coverage. Starting from the proposed objective function of [5], that is, the function to be optimized, we have improved it to take into account connectivity issues and, as a side effect, energy issues. We show that with minimum modifications we can improve the number of hops between nodes while covering a similar area of interest. In addition, it also confirms the flexibility of this technique for studying the influence of different parameters of interest in the deployment of WSN nodes: by adding new terms to the objective function and tuning its parameters, several network properties can be controlled.

This paper is organized as follows: related papers are discussed in section 2. Section 3 explains the optimal deployment of nodes based on simulated annealing. Section 4 describes the scenario of the problem and illustrates the alternative paths between all the nodes and the sink node. Section 5 defines the formulation and the model which improve the quality of the paths from all the nodes to the sink node. Section 6 shows the influence of the parameters on the simulation performance and discusses the results of improved connectivity. Section 7 concludes this work.

2. RELATED WORK

Different approaches have been proposed for the problems of coverage and connectivity in WSN. In [6] it is shown that the coverage of a given target area by a set of sensor nodes can be maintained if every point in this area is covered by at least k sensors, where k is the required degree of coverage. Figure 1, shows a coverage problem in WSN when the required degree of coverage is 1.

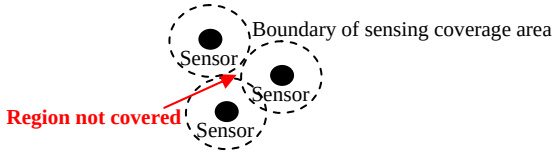


Figure 1. Coverage problem in WSN

The degree of coverage is dependent on application requirements. Various applications may require a high degree of coverage to provide a fault tolerance or accurate data and target localization. Figure 1 represents the sensing coverage of a sensor node as a unit disk model, usually assumed uniform in all directions. However, the authors of [7] explain that the coverage not only depends on the sensing capability of the sensor but also on the event characteristics. The relationship between coverage and connectivity for the single coverage requirement has been established in [4], and proves that if the communication range of the sensors is at least twice the sensing range, then we need just to guarantee that the coverage and the connectivity constraint will be satisfied. Several approaches have been proposed to achieve power-efficiency in terms of coverage and connectivity, [8, 9, 10], for instance decreasing the transmission power by correcting nodal radio transmission ranges while conserving necessary network capabilities. Other efforts [11, 12] have been based on the sleep period management approaches to save energy. A sleep management approach turn off unneeded nodes while keeping a minimum number of active nodes that will assure the required degree of coverage and the relay for multi-hop communication.

A modest number of approaches have been presented to resolve issues of deployment of nodes in WSN. The majority considers the coverage as its primary constraint and let the connectivity comes in a second place. The approach to deployment of nodes in [13] tries to maximize the network lifetime for a fixed quantity of energy power reserved to all the sensor nodes for deployment task and a static routing scheme. Finally, in [5] it has been presented an optimal solution based on simulated annealing for the deployment of nodes in order to collect the maximum information provided by a target area and guarantee one path between all nodes and the sink. We will focus on this work to explore further possibilities of this technique.

3. DEPLOYMENT OF NODES BASED ON SIMULATED ANNEALING

As said previously, in this work, we start from the approach to optimal deployment proposed in [5], which aims to select the optimal positions of a set of nodes in order to maximize the *interest* collected in a target area under the constraint that one path exists from all the nodes to the sink. An *interest function* assigns an interest value to any point of the target area. The proposed approach aims to maximize an objective function that computes the values of the interest collected by the set of nodes. As presented in equation (1), reproduced from [5], the objective function has two members; the first one computes the minimum distance between nodes and the second calculates the joint interest collected in all the regions of nodes.

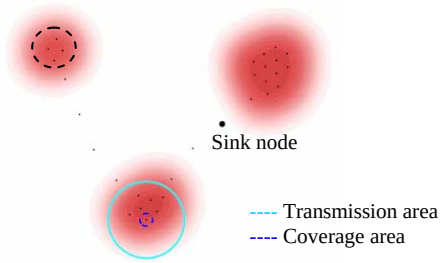
$$f^K(X) = \begin{cases} \gamma \cdot f_{\min}(X) + f_s(X), \text{ if X is K-survivable} \\ C, \text{ otherwise} \end{cases} \quad (1)$$

Where, X is a set of N nodes. X is said to be K-survivable if for any simultaneous failure of K nodes in X, every surviving node x_i lies at least within the communication coverage of another surviving node x_j, and every surviving node must be capable to communicate with the sink either directly or indirectly. Therefore, survivability can be considered a metric of robustness of the network. C is a suitable constant guaranteeing that only survivable solutions will be accepted. The maximization of the objective function implies the maximization of the sub function of minimum distance, and intends to ensure that the set of nodes of the solution be separated by the maximum possible distance. The function which computes the interest collected penalizes the overlapping which occurs by the intersection between the regions of sensing range of nodes.

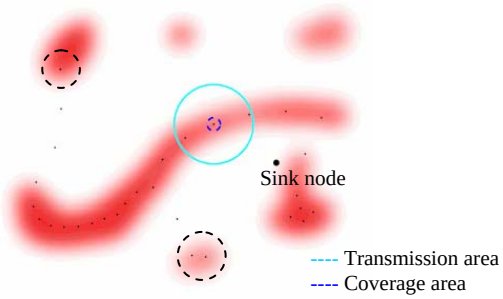
The optimization model proposed in [5] uses the Simulated Annealing Algorithm (SAA) to obtain a "good" (quasi-optimal) solution of the deployment of nodes. SAA [13] is a numerical optimization technique based on the principles of thermodynamics by an analogy to annealing in solids. The algorithm simulates the cooling process by gradually lowering the temperature of the system until it converges to a steady, frozen state. Similarly the proposed algorithm of [5] starts from a high temperature and the initial positions of the N nodes are identical to guarantee the K-survivability of the set at the beginning of the simulation. Next, the algorithm moves a node in a random direction within the target area and checks the survivability, if X is K-survivable then the algorithm computes the new value of the objective function and accept it as a new solution if is greater than the initial solution value of the current iteration of temperature, otherwise the algorithm uses the SAA formula based on a probability value to accept or refuse the new solution. Then the model decreases the temperature and moves next node and repeat the procedure until the temperature reach the cold state.

The algorithm established in [5] was tested on a picture of 640x480 pixels which simulates the target area. To represent the variation of the interest in the target region, each pixel takes a value from 0 to 255, where 0 means no interest and 255 indicate the maximum interest of the position. The interest has been distributed into two modes, convex and non convex regions. The total number of nodes that have been used is 30, including the sink node. The survivability has been checked for K=0 and K=1.

The results achieved in [5] as illustrated in Figure 2 cover all the regions of interest for both cases, convex and non convex regions, under the constraint that there is one path between all the nodes and the sink.



(a). Optimal deployment results of convex region

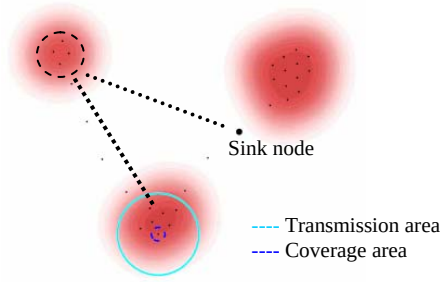


(b). Optimal deployment results of non convex region

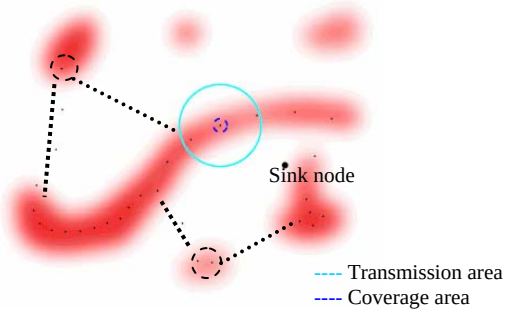
Figure. 2. Results of optimal deployment in WSN from [5]

4. PROBLEM DESCRIPTION

It can be noticed from Figure 2 that for both type of results, convex and non convex region, the nodes which are surrounded by an indent circle forward their packets to the sink node through a high number of hops.



(a). Optimal deployment results of convex region



(b). Short path of the non convex regions of interest

Figure 3. Scenario of the problem

In Figure 3, the two paths represented by the round points and the square points have an equal length. The path of square points represents the path of the optimal result of [5]. This path is used to forward the packets from the nodes of the interest regions surrounded by the indented circle to the sink node. If we replace this path, in both cases, by the path of the round points we can decrease the number of hops, in other words, we can reduce the total number of nodes which switch the packets between all the nodes and the sink. In that case the energy consumption of the set of nodes would improve. The paths of the round points would also meet the constraint of the survivability for the two values of K=0 and K=1, and thus preserve the optimal deployment of X.
Finally, according to this observation we intend to improve the connectivity by minimizing the length of paths between all the nodes and the sink while meeting the rest of constraints.

5. FORMULATION AND OPTIMAL MODEL

Normally the simulated annealing algorithm provides several solutions that permit to collect the maximum interest of the target area. Some of these solutions allow the forwarding of the packets from all the nodes to the sink with a minimum number of hops. It would allow a maximum coverage with improved connectivity properties for the deployed nodes. To obtain it, we have augmented the objective function of [5]. Therefore, we have added a new subfunction which computes the average of the number of hops between all the nodes and the sink. When the objective function moves towards its maximum value, the function of average hops will diminish then the number of hops between all the nodes and the sink will decrease. Equation (2) represents our new objective function as follows:

$$f(X) = \begin{cases} \gamma.f_{\min}(X) - \beta.f_a(X) + f_s(X), & \text{X is K-survivable} \\ C, & \text{otherwise} \end{cases} \quad (2)$$

Where, $f_a(X)$ is the function for the average number of hops defined by the equation (3) as follows:

$$f_a(X): \Re^{2N} \rightarrow \Re$$

$$f_a(X - \{x_i, s\}) \cup \{x_i + d\} = \frac{1}{N-1} \times \sum_{j=1}^{N-1} \frac{\sum_{p=1}^{p_j} nbr_hop(s, x_j)}{p_j} \quad (3)$$

Where, s is the sink node, p_j represents the total number of paths between s and x_j, $x_i + d$ is the randomly shifted position of x_i, where d is an arbitrary distance oriented in a random direction, and $nbr_hop(s, x_j)$ computes the number of hops between the sink and the node x_j. We also propose the following recursive algorithm "discover" which determines all the possible paths between x_j and the sink node and computes its total number of hops. We have used two tables named path and state table respectively. The path table is used to store all the possible paths between x_j and the sink. The state table is used to avoid loops in the paths.

depth = 0; numberOfPath = 0; numberOfHop = 0;
discover (x_j , depth) :

1) *path[depth] = x_j ;*
2) *if x_j is the sink node then:*
   a) *numberOfPath = numberOfPath + 1;*
   b) *numberOfHop = numberOfHop + depth;*
3) *state[x_j] = true;*
4) *for each node x_i in N*
   a) *if x_i is not a neighbor of x_j or if state[x_j] = true, then go to x_{i+1} in N;*
   b) *else discover (x_i ,depth+1);*
5) *state[x_j] = false.*

Then, we have carried out the classical simulated annealing algorithm as follows:

1) *T= T_0, X_0= { $x_0, x_1, ..., x_N$ } and i = 0, where T_0 and X_0 represent respectively the initial temperature and the initial deployment of X. i correspond to the index of the current node.*
2) *Let a node of the set X be denoted as the sink node with the label x_S ;*
3) *Compute the initial values of the function of minimum distance, joint interest value and average hops. Then compute the initial value of objective function $f(X_0)$.*
4) *While T > 0*
   a) *i = i+1;*
   b) *if i > N, then i = 0;*
   c) *if i = s, then i = i+1;*
   d) *Move xi within the target area to a random position;*
   e) *If X is not K-survivable then go to step d of 4);*
   f) *Compute the values of the function of minimum distance, joint interest and average hops. Next compute the value of objective function $f(X)$;*
   g) *If $f(X_0) - f(X) < 0$ then $f(X_0) = f(X)$*
   h) *Otherwise:*
      i. *Generate a random value r between 0 and 1;*
      ii. *If ($r < \exp(-\frac{f(X_0) - f(X)}{T})$), then $f(X_0) = f(X)$*
   i) *T=T-δ.*

We start the algorithm from an initial temperature T_0. The set X_0 represents the initial positions of the N nodes of X. The node x_S of X has be chosen as the sink node. Then we compute the initial values of: the minimum distance between two nodes of X, the joint interest values collected in the coverage area of all the nodes of X and the average of number of hops in all paths between each node of X and the sink. Next, we move one node different to the sink to a random position within the target area. If the set of nodes including the shifted position is K-survivable, then we compute the corresponding value of the objective function. The algorithm accepts the new solution if is greater than the initial one of the current iteration, otherwise the algorithm accepts or refuses the new solution based on the concept of SAA. Finally, we decrease the temperature and repeat again the procedure from the step a) until the temperature gets its lower value or the objective function remains constant.

6. RESULTS AND DISCUSSION

We have tested our model on a picture which represents the distribution of the interest on the target area. We have used in the objective function a coefficient α into the joint interest to control the penalty of overlapping that occurs in the intersection area of the sensing range between the neighboring sensor nodes. All the simulations presented in this work have been performed with $\alpha = 0.001$, $\beta = 1.5$, $\gamma = 0.0005$ and δ=0.0025. This parameters have been selected after running several simulations among which provide the better performance.

About the radius of coverage and transmission we have simulated our model with R_c = 10 and R_t = 60. Regarding survivability we have used during our simulations to K=1, because it ensures a higher number of paths between all the nodes and the sink.

6.1. Parameters of influence on the simulation performance

Our initial deployment as represented in Figure 4 distributes the N nodes in its initial positions to form a cross shape which covers the majority of the target area and let the model reach rapidly an optimal solution. Figure 5 depicts the variation of the positions of the nodes of all accepted solutions by SAA during the simulation. We have noted in this variation that the simulation which starts from spreaded initial positions of the nodes reaches far locations in the target area *in much less time for a given* δ. On the contrary the simulation in which nodes start from identical positions tend to stay in the same zone of the target area *unless we decrease* δ, *which increases the number of simulation steps and so the simulation time*. Figure 6-a illustrates that when we start the simulation from an initial deployment X_0 based on different positions of the N nodes, we reach rapidly an optimal deployment which cover all the regions of interest in the target area. Figure 6-b shows that when the simulation starts from initial identical positions with the same vaue of δ=0.0025, the sensor nodes discover only one interest region of the target area after the same number of steps.

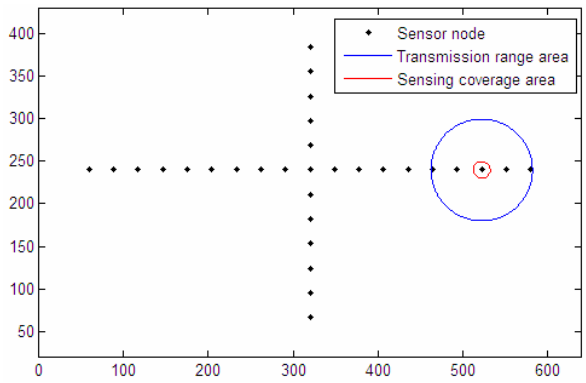


Figure 4. Initial deployment of nodes in our model

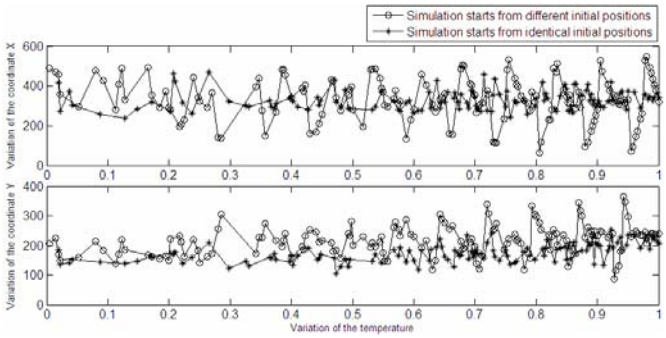
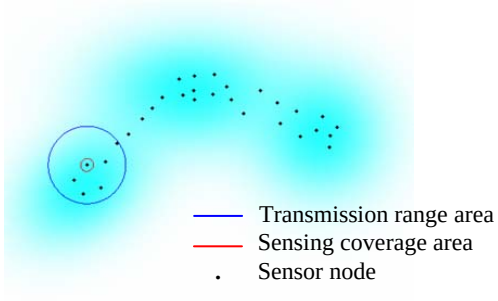
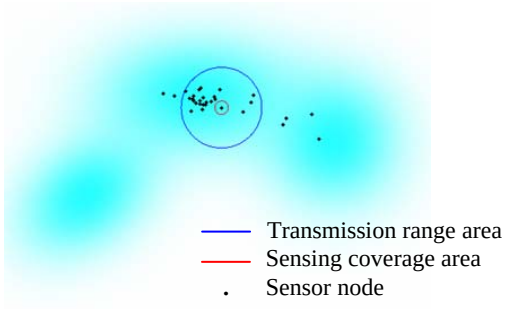


Figure 5. Position of nodes for all accepted solutions



(a). Solution of initial deployment with different positions



(b). Solution of initial deployment with identical positions

Figure 6. Solutions of optimal deployment model

6.2. Improved connectivity

In Figure 7, we have represented all the accepted solutions during the cooling process of the model which optimizes the number of hops between all the nodes and the sink with respect to the results of the optimal model of [5] which aims just to collect the maximum interest under the constraint that exists one path between all the nodes and the sink. From a given value of the temperature, our model accepts only the solutions with lower values of average hops, and at T = 0 our model has decreased the average number of hops by 8 hops fewer than the model of the previous approach. Also we have noted that when we continue to increase the coefficient β, the resulting average number of hops decreases until it reaches a constant value when β =2, after that, there is no significant improvement.

We have represented respectively in the Figures 8 and 9, the results of the deployment of 30 nodes in the target area using our model which uses the optimization of the average number of hops between all the nodes and the sink, and the model which only collects the maximum importance from the target region with the guarantee of existing one path between all the nodes and the sink. In both Figures 8 and 9, the sink node is the red one. We have set the same position for the sink node in both simulations to compare the deployment results of each model. We have also simulated both models of Figures 8 and 9 with equal parameters $\alpha = 0.001, \beta = 1.5$, $\gamma = 0.0005$ and δ=0.0025.

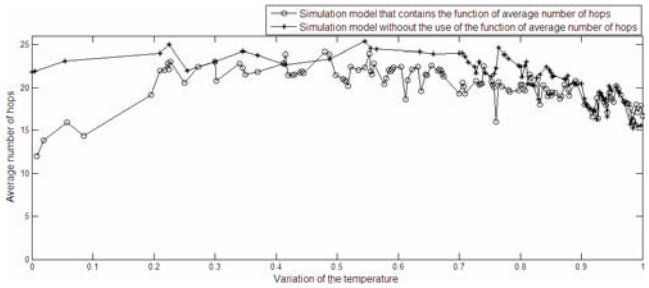


Figure 7. Average number of hops for models (using and not using the average number of hops)

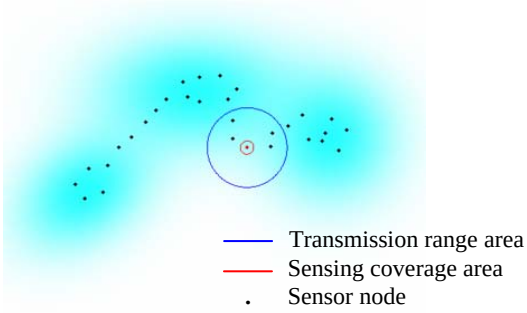


Figure 8. Deployment results of the model that uses the average number of hops optimization

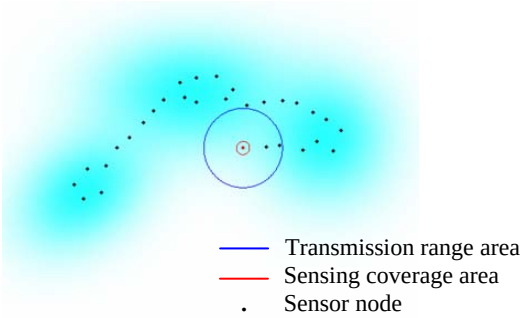


Figure 9. Deployment results of the model that not uses the average number of hops optimization

The ratio $\frac{f_s(X)}{f_{s_hop}(X)} = 0.995$ denotes the percentage of the joint importance function $f_s(X)$ result without optimization of the average number of hops to the joint importance function $f_{s_hop}(X)$ result with the optimization of the number hops. This value shows clearly that the new model

of average of hops preserves the interest collected in the model of the approach [5]. Therefore, it produces a solution with better properties. Besides, from both Figures 8 and 9, it can be observed that additionally the optimization of average number of hops between all the nodes and the sink provides alternative paths to connect all the interest regions of the target area. On the contrary, without the optimization of the average hops between all the nodes and the sink, the deployment results contain only one relay path that link all the regions of interest, which would increase the overload in the nodes which form the relay path and, therefore, would reduce their lifetime. In summary, the new approach, improves network connectivity in terms of robustness and energy consumption.

7. CONCLUSION

In this work, we have improved the connectity properties that we would obtain by an optimized and carefull design of the nodes deployment in a sensor network. We have used a Simulated Annaeling Algorithm (SAA) to obtain the position of the sensor nodes that would provide the better sensing coverage for a given interest area, while maintaining advantageous connectivity properties in terms of robustness, latency and energy.

By designing and tuning appropriately the objective function to be optimized by SAA, we can obtain the aforementioned properties. In this case, we have obtained solutions with a minimum average number of hops between nodes and sink.

Finally, these modifications confirm the flexibility of this technique for studying the influence of different parameters of interest at a design stage of the network, prior to the real deployment of WSN nodes: by adding new terms to the objective function and tuning its parameters, multiple network properties of interest can be controlled.

As future work, we will continue the study of optimal solutions in terms of coverage and other network properties of interest based on the nodes placement and density. In particular, we will study not only the position but also the number of nodes needed to meet certain requirements.

8. AKNOWLDGEMENT

This research has been supported by project grant TEC2007-67966-01/TCM (CON-PARTE-1), by Ministerio de Educación y Ciencia grant DEP2006-56158-C03, and it is also developed in the framework of “Programa de Ayudas a Grupos de Excelencia de la Región de Murcia, de la Fundación Séneca, Agencia de Ciencia y Tecnología de la RM”.
This research work has been also supported by Abdelmalek Essaâdi University of Tetuan, Morocco.

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