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(71) **Applicants** *(for all designated States except US)*: **TELECOM ITALIA S.P.A. .** [IT/IT]; Piazza degli Affari, 2, I-20123 Milano (IT). **PIRELLI & C. S.p.A.** [IT/IT]; Viale Piero e Alberto Pirelli, 25, 20126 Milano (IT).

(72) **Inventors; and**

(75) **Inventors/Applicants** *(for US only)*: **COLERI ERGEN, Sinem** [TR/US]; Telecom Italia Sparkle of North America Inc., 1995 University avenue, Suite 225, Berkeley, CA 94704-1074 (US). **GUEYE, Assane** [SN/US]; Telecom Italia Sparkle of North America Inc., 1995 University avenue, Suite 225, Berkeley, CA 94704-1074 (US). **BOREAN, Claudio** [IT/IT]; Telecom Italia S.p.A., Via G. Reiss Romoli, 274, I-10148 Torino (IT).

(74) **Agents**: **MACCALLI, Marco** et al.; Via Settembrini, 40, I-20124 Milano (IT).

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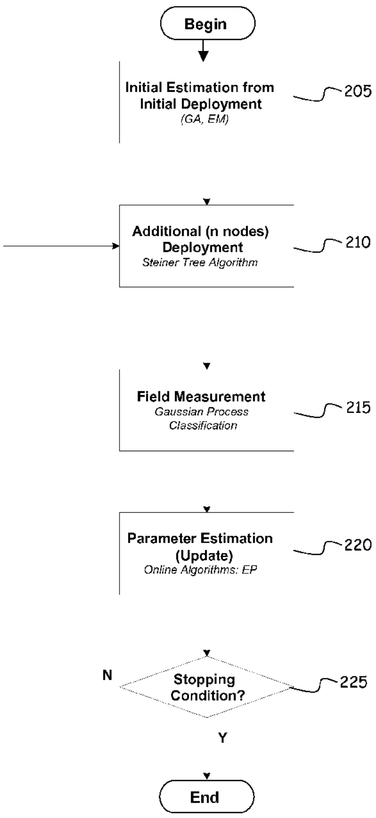

(57) Abstract: A method for the deployment of nodes (105,110,305) of a wireless communication network (100), comprising: a) obtaining (205) an initial estimation of parameters indicative of a quality of the communications between the nodes in the network in respect of an initial deployment of nodes; b) based on the parameters estimation, estimating (210) a physical position of at least one additional network node to be deployed; c) after the at least one additional network node has been deployed in a physical position in the network, monitoring and recording communication activities (215) between the nodes in the network; d) deriving (220) an updated estimation of the parameters indicative of the quality of the communications between the nodes in the network based on the recorded communication activities, and e) either iterating said steps b), c) and d) or not depending on an assessment of the updated parameters estimation.

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METHOD AND SYSTEM FOR THE DEPLOYMENT OF NODES OF A WIRELESS COMMUNICATIONS NETWORK

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DESCRIPTION

Background of the invention

Field of the invention

The present invention generally relates to wireless communications networks, particularly, although not limitatively, to Wireless Personal Area Networks (WPAN) or short-range WPAN, even more particularly, but still not limitatively, to Wireless Sensor Networks (WSN) and Wireless Sensor and Actuator Networks (WSAN). More specifically, the present invention relates to the deployment of network nodes, particularly of those nodes (like relay nodes of wireless sensor networks), which are deployed to guarantee connectivity between the network nodes and a base station, where for example the data sensed by the sensor nodes are collected and processed.

Description of the related art

Wireless sensor networks are wireless networks made up of spatially distributed, autonomous devices using sensors (sensor nodes) to cooperatively monitor physical or environmental conditions, such as temperature, voltage, current, sound, vibration, pressure, motion or pollutants, at different locations. Wireless sensor networks are nowadays used in many application areas, including environment and habitat monitoring, monitoring of industrial plants/telecommunication centrals, healthcare applications, home automation, traffic control, just to mention some.

Each sensor node includes, in addition to one or more sensors adapted to sense one or more physical quantities, a radio transceiver or other wireless communications device.

Wireless sensor networks typically include, in addition to sensor nodes, relay nodes which act as routers to guarantee connectivity between the targets (*i.e.*, the sensor nodes) and a base station, where the sensed values of the physical quantities sensed by the various sensor nodes are gathered and processed for, *e.g.* monitoring or control purposes.

Finding an effective deployment strategy of the network nodes, particularly of the relay nodes is rather challenging. In order to find the best placement of the nodes, a good knowledge of the wireless communication channel is required; however, a strategy that requires to first learn the characteristics of the wireless communication channel and then deploys the nodes is not always desirable, because of cost and scalability issues.

The problem of nodes deployment in wireless sensor networks has been extensively studied in the sensor network community. While deploying the nodes, the goal is to find the best placement thereof, particularly of the nodes which have a routing function, while optimizing some cost related to the specific application, such as the number of sensors, the communication cost, and the coverage. Thus, a natural approach for the nodes deployment problem is to model it as a constrained optimization problem.

In general terms, known solutions are based on one of two approaches: a first, classical approach based on the assumption of a "communication range" model, and a more recent approach that considers a "communication cost".

The "communication range" assumption states that the network nodes can perfectly communicate within a fixed range, and will not communicate outside that range.

Solutions based on this approach are for example discussed in K. Chakrabarty *et al.*, "Grid Coverage of Surveillance and Target location in Distributed Sensor Networks", IEEE Transactions on Computers, Vol. 51, No. 12, December 2002, pages 1448-1453 (ref. 1), Chakrabarty; H. *et al.*, "Coding theory framework for target location in distributed sensor networks", International Symposium on Information Technology: Coding and Computing, 2001 (ref. 2), Kenan Xu *et al.*, "Optimal wireless sensor networks (WSNs) deployment: minimum cost with lifetime constraint" WiMob 2005 (ref. 3), and Seapahn Meguerdichian *et al.*, "Coverage Problems in Wireless Ad-hoc Sensor Networks" IEEE Infocom 2001 (ref. 4). In ref. 1, the sensor nodes placement problem is modeled as an Integer Linear Programming problem to minimize the cost of sensors for complete coverage of the sensor field. Ref. 2 proposes a set covering approach to determine the minimum number of sensors needed to cover a certain area. Set covering techniques are also used in ref. 3 to explore the problem of optimal deployment in a WSN where the goal is to minimize the network cost under lifetime constraints. In ref. 4, computational geometric method and graph theory techniques are used to solve the coverage problem.

The "communication cost" model considers the probabilistic nature of the wireless communication channel, and introduces a communication cost that depends on the probability distribution of the channel. Either the probability distribution is assumed to be known, or it is assumed that there exists a pilot nodes deployment from which the probability distribution can be learned.

Examples of the "communication cost" approach can be found in S. Dhillon *et al.*, "Sensor Placement for Grid Coverage under Imprecise Detections", Proceedings of the International Conference on Information Fusion 2002 (ref. 5), and in A. Krause *et al.*, "Near-optimal Sensor Placements: Maximizing Information while Minimizing Communication Cost", IPSN'06, April 19–21, 2006, Nashville, Tennessee, USA (ref. 6).

Ref. 5 introduces a notion of sensing probability in which a sensor node senses its surrounding environment with some probability p that decays exponentially with the distance. Based on that notion, the authors propose a sensor placement (or coverage) algorithm that maximizes the probability that any given point in the field is sensed. In ref. 6, the authors proposed a novel approach where a sensing quality and a communication cost were introduced. The sensing quality is defined as the amount of predictive information that a given sensor placement/positioning provides about the region where no sensors are placed. The communication cost is defined as the expected number of retransmissions between any two nodes. Gaussian Process (GP) techniques are used to both model and learn the spatial phenomenon and the variability of the wireless link. The authors use data from a pilot deployment to learn the GP model and propose a polynomial algorithm to find the optimal sensor placement under communication cost and sensing quality constraints.

U.S. patent No. 7,006,889 discloses a sensor placement algorithm based on the sensor data such that the data for particular process disturbances are significantly different from the sensor data for other disturbances. A set of one or more decision trees in a distributed parameter manufacturing system is constructed. Each of the trees has inputs from multiple ones of the sensors and has an output indicating one of the disturbances.

Summary of the invention

The Applicant has observed that known strategies for approaching the nodes placement problem in wireless sensor networks are not completely satisfactory.

In particular, the Applicant observes that the "communication range" assumption is unrealistic for wireless communications channels like those employed in wireless sensor networks. For example, because of the presence of obstacles, sensor nodes might not be able to sense an area that is very close by; furthermore, the region of communication of a sensor node does not have a hard frontier: the communication quality decreases with the distance while being closely dependent on the environment around the communicating devices due to interference and shadowing.

The "communication cost" model tries to be more realistic, however, assuming that the (probability distribution of the) wireless channel is known, is unrealistic; on the other hand, launching a pilot deployment can be undesirable, as it involves high cost and scales very poorly, or it may also be impossible to be made.

In view of the state of the art, outlined above, the Applicant has tackled the problem of finding a more effective approach to the deployment of nodes in a wireless communications network, particularly, although not limitatively, useful in the context of WPAN, WSN, WSAN.

Essentially, the present invention proposes an iterative approach to the nodes deployment problem. Starting from an initial placement of a limited number of nodes, the method of the present invention makes an initial estimation of parameters indicative of a quality of the communications in the network in respect of such an initial nodes placement. Additional nodes are incrementally placed at each iteration, their positions being determined based on the estimation of the parameters indicative of a quality of the communications in the network; the estimation of these communication quality parameters is updated after each placement of additional nodes, based on a monitoring of communication activities between the nodes in the network.

According to a first aspect of the present invention, a method is provided for the deployment of nodes of a wireless communication network, the method comprising:

a) obtaining an initial estimation of parameters indicative of a quality of the communications between the nodes in the network in respect of an initial deployment of nodes;

b) based on the parameters estimation, estimating a physical position of at least one additional network node to be deployed;

c) after the at least one additional network node has been deployed in a physical position in the network, monitoring and recording communication activities between the nodes in the network;

d) deriving an updated estimation of the parameters indicative of the quality of the communications between the nodes in the network based on the recorded communication activities, and

e) either iterating said steps b), c) and d) or not depending on an assessment of the updated parameters estimation.

Step a) may include modeling a probability of successful wireless communications between the nodes in the network as a Gaussian process.

Step a) may also include estimating mean and covariance of probability distribution functions of Gaussian random variables characterizing a wireless communications link between any two nodes in the network.

Said estimating mean and covariance of the probability distribution functions may include calculating a maximum likelihood estimation.

Said calculating the maximum likelihood estimation may include approximating the maximum likelihood estimation by means of a gradient ascent algorithm, or by means of an expectation maximization (EM) algorithm.

Step b) may include solving a minimum-cost Steiner tree problem.

Said solving the minimum-cost Steiner tree problem may be approximated by a vertex algorithm.

Step c) may include monitoring and recording sequences of communications successes and/or failures between any two nodes in the network.

Said monitoring and recording communications activities may include scheduling the communications between the nodes in the network according to a TDMA schedule.

Said scheduling may include assigning to each node in the network a respective time slot for transmission.

Step d) may include approximating a maximum likelihood estimation by means of either a gradient ascent algorithm or a maximum expectation algorithm.

Step d) may include exploiting an online learning technique.

Said exploiting the online learning technique may comprise applying an expectation propagation algorithm.

Step e) may include deciding to terminate said iterating the steps b), c) and d) when a predetermined low cost for the communications between the nodes of the network is attained.

According to another aspect of the present invention, a system is provided for determining positions of deployment of nodes of a wireless communication network, the system being configured for performing the steps of the method according to the first aspect of the invention.

Still another aspect of the present invention relates to a computer program loadable into a memory of a computer, comprising computer program code modules adapted to implement the method of the first aspect of the invention.

The present invention is useful in scenarios where a certain number of nodes, *e.g.*, sensor nodes of a WSN or WSAN, have already been deployed in fixed and known positions, and additional nodes, like relay nodes, need to be deployed to guarantee connectivity while maintaining a low communication cost between the sensor nodes and a base station.

An advantage of the present invention resides in that it is not based on unrealistic assumptions like that of the “communication range” approach, but rather associates to the wireless channel a communication cost that changes tracking the changes in the network configuration during time.

Another advantage is that the method of the present invention does not assume the existence of a pilot deployment. Instead, it proposes an iterative approach that incrementally deploys the network nodes while learning the characteristics of the wireless communication channel.

Mathematical models and algorithms are used to both learn the characteristics of the wireless communication channel and find the best placement for the additional nodes to be deployed.

Brief description of the drawings

These and other features and advantages of the present invention will be made clearer by the following detailed description of some embodiments thereof, provided merely by of non-limitative examples. The description that follows should be read in conjunction with the attached drawings, wherein:

Figure 1 schematically shows a wireless communication network, particularly a wireless sensor network in which the present invention can be advantageously exploited;

Figure 2 is a schematic flowchart of a method according to an embodiment of the present invention;

Figures 3A, **3B** and **3C** give a pictorial overview of the iterative method of **Figure 2**, in a simple case;

Figure 4 is a schematic flowchart of a Gradient Ascent (GA) algorithm used in one embodiment of the present invention;

Figure 5 is a schematic flowchart of an Expectation Maximization (EM) algorithm that is used in another embodiment of the present invention, as an alternative to the GA algorithm;

Figure 6 depicts an exemplary result of an activity of monitoring and recording transmissions between nodes in the network;

Figure 7 is a schematic flowchart of an expectation propagation algorithm used in an embodiment of the present invention; and

Figure 8 schematically shows a gateway node of the network of **Figure 1** configured for implementing the method according to the present invention.

<u>Detailed description of invention embodiments</u>

Making reference to the drawings, in **Figure 1** there is schematically shown a scenario wherein the present invention is advantageously (albeit not limitatively) applicable. In greater detail, the considered scenario is that of a wireless sensor network **100**, including a plurality of sensor nodes **105**. Each sensor node **105** comprises one or more sensors of physical quantities, *e.g.* temperature, voltage, current, sound, vibration, pressure, motion or pollutants. The sensor nodes **105** are placed at various, different locations of a selected environment, *e.g.* an industrial plant or a telecommunication central, said locations being for example selected depending on the monitoring requirements. Each sensor node **105** also includes a wireless transceiver, adapted to wirelessly communicate with other nodes of the network based on a wireless communication protocol, for example, and not limitatively, a ZigBee protocol, or other mesh networking protocols.

The wireless sensor network **100** further includes one or more relay nodes **110**, which act as wireless routers between the sensor nodes **105** (the “targets”) and a gateway **115**; the relay nodes **110** have the function of guaranteeing the connectivity between the sensor nodes **105** and the gateway **115**. It is pointed out that nothing prevents that one or more of the sensor nodes **105** also perform the functions of relay nodes, *i.e.* of routers between other sensor nodes and the gateway.

The gateway **115** interfaces the wireless sensor network **100** with an external network **120**, *e.g.* a Metropolitan Area Network (MAN), a Wide Area Network (WAN), the Internet, an intranet, to which the gateway **115** is connected *via* a wired and/or wireless connection **125**.

Within the external network **120**, a base station **130** is provided (for example, implemented by a server computer in the external network **120**); the base station **130** is operable to collect the data sensed by the sensor nodes **105**, process them, and *e.g.* performing a monitoring/supervision of the environment where the sensor nodes **105** are placed based on the processed data. It is pointed out that nothing prevents that the functions of base station are performed by the gateway **115**, or by an entity within the wireless network **110**.

As discussed in the foregoing, the present invention deals with the problem of deploying nodes in a wireless communication network, particularly a wireless sensor network, and in particular relay nodes of the wireless network.

According to an embodiment of the present invention, a solution to the nodes deployment problem is based on an iterative method that, starting from an initial placement of a limited number of nodes, possibly including only one relay node **110**, incrementally places additional (relay) nodes so as to ensure a desired connectivity between the sensor nodes **105** and the gateway **115** / base station **130**.

In particular, the framework considered in the invention embodiment herein described is one in which (at least some of) the targets **105** and of the relay nodes **110** have already been deployed, and further relay nodes **110** (and/or sensor nodes having a routing capability) are to be added to guarantee connectivity between the targets **105** and the gateway **115** / base station **130**.

By way of overview, the present invention uses an iterative method to learn the unknown characteristics of the wireless communication channel based on an estimation of the communication cost throughout the network. The proposed iterative procedure alternates between placing a fixed number of nodes, particularly nodes having a routing function (relay nodes), and updating the knowledge about the quality of the communications in the network. At the beginning, an initial nodes deployment is assumed to exist, and, based on measurements obtained from this initial deployment, a first estimation of the wireless communication channel is computed, using a

Maximum Likelihood (ML) criterion; to this purpose, a Gradient Ascent (GA) or an Expectation Maximization (EM) algorithm may be advantageously exploited, for reducing the computational burden. Once a first estimate is obtained, one or more additional relay nodes (for example, a predetermined, fixed number of relay nodes) is deployed, by solving a Minimum Cost Steiner Tree Problem; a heuristic algorithm (Vertex Algorithm) based on the minimum spanning tree algorithm may be advantageously exploited for this purpose. After having deployed the new relay node(s), another set of measurements is carried out, and the estimate of the communication channel parameters is updated using Online Learning techniques, particularly an Expectation Propagation algorithm.

In greater detail, according to an embodiment of the present invention, to each wireless communication link in the wireless sensor network **100** a communication cost is associated; in particular, the communication cost that is associated to each wireless communication link corresponds, *e.g.* it is equal to the expected number of retransmissions needed to send a data packet over that communication link. It is assumed that the probability θ_{st} of successfully transmitting a data packet from the generic network node *s* (either a sensor node **105** or a relay node **110**) to the generic node *t*, is a function of an underlying Gaussian process of the wireless communications field, *W*, with unknown parameters, *i.e.* unknown mean and covariance. In order to compute the communication cost, *i.e.* the expected number of needed retransmissions, the parameters of the Gaussian process need to be known. The method according to an embodiment of the present invention does not rely on the assumption that the Gaussian process parameters are known *a priori*, nor that a pilot nodes deployment is available; the proposed solution provides for an iterative deployment of additional (relay) nodes and exploits online algorithms to update the estimate of the Gaussian process parameters as more data becomes available.

A schematic flowchart of a method according to an embodiment of the present invention is depicted in **Figure 2**. Hereinafter, an overview of the main steps of the method will be presented. The individual method steps will be described in detail later.

Since at the beginning there is no available estimate of the parameters of the field corresponding to the initial nodes deployment, an indicator that can be used is the distance between the nodes: the nodes, particularly the relay nodes **110**, are initially placed at distance *d* apart (in the directions sensor node - gateway), where the distance *d* is chosen small enough that there is a non-zero probability of successful transmission from any sensor node **105** to the gateway **115**/ base station **130**, but large enough such that the number of deployed (relay) nodes is minimized.

Firstly (block **205** in the figure), an initial estimation is obtained of the parameters of the Gaussian process corresponding to the initial deployment of sensor nodes **105** and relay nodes **110** in the network **100**.

Then (block **210**), at least one additional relay node **110**, possibly a fixed, predetermined number *n* of relay nodes **110** are deployed in the wireless sensor network **100**, at optimal locations, which are determined based on the results of the initial parameters estimation.

After the placement of the additional nodes, communication activities between the nodes in the field are then monitored and recorded (block **215**); in particular, the recorded communication activities include sequences of transmissions successes and failures between the already placed nodes and the gateway **115** / base station **130** (*i.e.*, between the end points).

The estimate of the field parameters is then updated (block **220**) using online algorithm techniques based on the recorded communication activities.

The steps of blocks **210**, **215** and **220** are iterated (block **225**, exit branch **N**) until the reaching of a predetermined stopping condition is assessed (block **225**, exit branch **Y**). In other words, if the stopping condition is not met, the deployment of another set of additional relay nodes **110** is performed based on the new field parameters estimates. The stopping condition may for example correspond to the reaching of a predetermined maximum number of deployable relay nodes **110**, or to the attainment of a minimum cost for sending the packets from the sensor nodes **105** to the gateway **115** / base station **130**.

Considering block **205** in **Figure 2**, an initial estimate of the wireless communications field parameters can be obtained by computing a Maximum Likelihood (ML) estimate of the parameters based on the data gathered from the initial deployment of the nodes **105** and **110**. With the underlying Gaussian process model, this can be done using Gaussian Process for Classification (GPC) techniques. However, computing an exact ML estimate is computationally demanding. Thus, according to a preferred embodiment of the present invention, approximated algorithms are used to limit the computational burden. A possible approximated algorithm that can be advantageously exploited is the Gradient Ascent (GA) algorithm. Another approximated algorithm that can be advantageously exploited is the Expectation Maximization (EM). A detailed description of the two approximated algorithms will be provided in the following.

Considering block **210**, an optimal placement of the next additional *n* relay nodes **110** is computed, based on the estimated values of the Gaussian process parameters. The number *n* of additional (relay) nodes to be deployed may for example be a design parameter (in principle, a single additional relay node could be placed at each step of the iteration), and should be properly chosen. For small values of *n* (*e.g.* *n* = 1), the amount of new information about the network that is gained after each step of the iteration is limited: this may limit the performance of the learning process. On the other hand, if *n* is large (*e.g.*, equal to the total number of relay nodes that the network designer is allowed/ready to deploy), the placement algorithm cannot be optimal, because the estimate of the field parameters is not good enough.

According to an embodiment of the present invention, finding the best placement of the next, additional *n* relay nodes is modeled as a Steiner Tree problem. Since a Steiner Tree problem is computationally intractable, according to an embodiment of the present invention a vertex heuristic is proposed. The vertex algorithm, described in greater detail in the following, adds the *n* nodes one-by-one.

Considering block **220**, the parameters of the underlying Gaussian process model are updated using Online Learning techniques. These techniques are based on combining the old distribution of the Gaussian process parameters with the new available data for the update of the distribution, without the need of keeping all the previous, old data. Since the posterior distributions (which are conditional probability distributions) do not have a simple form, according to an embodiment of the present invention such distributions are projected onto a Gaussian family to get a good approximation of the parameters. According to an embodiment of the present invention, an Expectation Propagation (EP) method is proposed to be used for this purpose.

Figures 3A, **3B** and **3C** give a pictorial overview of the iterative approach according to the present invention. A simple case is considered in which the network **100** comprises four sensor nodes **105a**, **105b**, **105c** and **105d**, placed in different locations, and, at the beginning, one relay node **110a** is present; it is assumed for simplicity that only relay nodes **110** are added to the network **100**, and that, at each iteration, one additional relay node **110** is deployed. These are however not to be construed as limitations for the present invention, which from one hand can be applied to the iterative deployment of any network node, be it a relay node or a sensor node or a sensor node with routing capability, and, from the other hand, support the deployment of any number of additional nodes at each iteration (either equal or different from iteration to iteration). Initially (**Figure 3A**), the single relay node **110a** allows the communication between the sensor nodes **105a** and **105b** and the gateway **115** / base station **130**; as schematically depicted in the figure, the connectivity between the two sensor nodes **105c** and **105d** and the gateway **115** / base station **130** is not guaranteed by the single relay node **110a**. At the first run of the iterative method, the relay node **110b** is thus added (**Figure 3B**). Recording the communications activities of the nodes in the network **100** after the placement of the relay node **110b**, it is ascertained that the sensor node **105c** can now communicate with the gateway **115** / base station **130**, while the sensor node **105d** is still not reachable. At the second run of the iterative method, the relay node **110b** is thus added (**Figure 3C**). Recording again the communications activities of the nodes in the network **100** after the placement of the further relay node **110c**, it is ascertained that also the sensor node **105d** can now communicate with the gateway **115** / base station **130**. This signals the attainment of the stopping condition, and the procedure ends. As mentioned above, the method is not limited to the deployment of additional relay nodes **110**, but to the deployment of network nodes in general irrespective of their nature, and this is schematized in **Figure 3C**, where reference numeral **305** denotes, by way of example, a sensor node with routing capability that may be added at the generic iteration of the method.

The individual steps of the method described above will be now described in detail, making reference to exemplary and non-limitative embodiments of the present invention.

<u>First step (block **205**): initial estimation</u>

As mentioned in the foregoing, the general model on which the first step is based is the Gaussian Process for Classification (GPC). In the GPC model, the probability of successfully sending a data packet between any two points over a wireless communication link in the field is a function of an underlying Gaussian process of the link:

$$P(Y_{s,t} = y \mid W_{s,t} = w) = g(y, w)$$

where $Y_{s,t}$ is the indicator random variable that takes value 1 if a data packet is successfully sent from the generic node *s* to the generic node *t*, and -1 otherwise (*i.e.* in case of transmission failure), and $W_{s,t}$ is the underlying Gaussian random variable that characterizes the wireless communication link (*s*, *t*). The function $g(y, w)$ which lies in the interval [0,1] is called the likelihood function, and it is assumed to be equal to the cumulative distribution of a standard normal random variable: $g(y, w) = \Phi(yw)$, where:

$$\Phi(x)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{x}e^{-t^2/2}dt\ .$$

As was observed in ref. 6 mentioned in the foregoing, the communication cost *C*(*s*,*t*) between the nodes *s* and *t*, which is defined as the expected number of retransmissions needed to successfully send the data packet, can be computed as:

$$C(s,t)=\int\frac{1}{\theta_{s,t}(w)}f_{W_{s,t}}(w)dw$$

where $f_{W_{s,t}}(w)$ is the probability distribution function of the underlying random variable $W_{s,t}$, which in the exemplary embodiment of the invention here considered is assumed to be Gaussian, and $\theta_{s,t}(w)=P(Y_{s,t}=1\mid W_{s,t}=w)=g(1,w)$ is the probability of successful transmission given $W_{s,t}=w$. The parameters of the distribution $f_{W_{s,t}}(w)$ are however not known, so they have to be estimated by observing the communications between the nodes in the field.

It is assumed that a certain number of transmissions in the field have been observed and recorded. For the observed communication links, the value $\mathrm{Y}=[Y^{(1)},...Y^{(N)}]$ is recorded, where $Y^{(i)}=(y_1^{(i)},...,y_m^{(i)}),i=1,...N$ are independent, $y_j^{(i)}\in\{-1,+1\}$ indicates whether the data packet in the *i*-th transmission in communication link *j* was received or not, *m* is the number of communication links involved. Given Y, it would desirable to compute the predictive communication cost $\overline{C}(s,t)$, which requires computing the posterior distribution of $W_{s,t}$ for any link (*s*, *t*). A Maximum Likelihood (ML) criterion can be used to estimate the parameters of the posterior distribution of $W=(w_1,...,w_m,w_{m+1},...,w_{m+n})$ given $\mathrm{Y}=(Y^1,...,Y^N)$. Observations are available only from the first *m* links *(1,...,m)*, links *(m+1,...,m+n)* being not observed.

$$\begin{aligned}\hat{\Theta}&=\arg\max_{\Theta}\left(E_W\left[P(\mathbf{Y},\mathbf{W}\mid\Theta)\right]\right)\\&=\arg\max_{\Theta}\log\left(\left(E_W\left[P(\mathbf{Y},\mathbf{W}\mid\Theta)\right]\right)\right)\end{aligned}$$

where $\Theta=(\mu,\Sigma)$ are the parameters of the Gaussian process, mean and covariance functions,

$$\mathbf{W}=(W^{(1)},...,W^{(N)}),$$

where $W^{(i)}=(w_1^{(i)},...,w_m^{(i)},w_{m+1}^{(i)},...,w_{m+n}^{(i)}),i=1,...N$ are independent realizations of

$W = (w_1, ..., w_m, w_{m+1}, ..., w_{m+n})$, $Y_j^{(i)}$ depends on the unobserved random variable $w_j^{(i)}$; $\mathrm{P}(\mathrm{Y}^{(i)}, W^{(i)} \mid \Theta)$ is the joint distribution characterizing the model and is given by:

$$P(Y^{(i)}, W^{(i)} \mid \Theta) = P(W^{(i)} \mid \Theta) \prod_{j=1}^{m} g(y_j^{(i)}, w_j^{i})$$

for a network with *m+n* links of which only *m* are being used.

Considering that the observation data have been generated from independent and identically distributed ("iid") realizations of the underlying Gaussian process, it can be obtained:

$$P(\mathbf{Y}, \mathbf{W} \mid \Theta) = \prod_{i=1}^{N} P(Y^{(i)}, W^{(i)} \mid \Theta)$$

Computing the exact ML estimate in the herein considered model may be a difficult task, from the computational viewpoint. Thus, according to preferred embodiments of the invention, two different approximate algorithms are proposed that are adapted to approximate the ML estimate: the Gradient Ascent algorithm and the EM algorithm.

Gradient Ascent (GA) Algorithm

The GA algorithm is based on the observation that a differentiable function $F(x)$ in the neighborhood of x_0, increases fastest when going in the direction of the gradient $\nabla F(x_0)$. Thus, by forming the sequence $x_o, x_1, ..., x_t, ...$ where $x_{i+1} = x_i + \delta \nabla F(x_i)$, it is obtained $F(x_{i+1}) \geq F(x_i)$ for all $i \geq 0$ and for a suitable scaling factor δ. If the scaling factor δ is small enough and there is a local maximum around x_0, then the sequence will converge to that local maximum.

In the problem considered herein, the function to be maximized is:

$$F(\Theta) = \log\left(E_W\left[P(\mathbf{Y}, \mathbf{W} \mid \Theta)\right]\right)$$

Starting from an initial guess Θ_0, the estimates of the parameters are obtained by iteratively computing:

$$\Theta_{t+1} = \Theta_t + \delta \nabla_\Theta F(\Theta_t)$$

where the gradient is taken with respect to $\Theta = (\mu, \Sigma)$; Θ_{t+1} is composed of the "partial gradients" with respect to μ and Σ as given by:

$$\nabla_{\Theta} = \begin{pmatrix} \nabla_{\mu} \\ \nabla_{\Sigma}[:] \end{pmatrix}$$

In general, the gradient with respect to Σ is a matrix. In the formula above, the term $\nabla_{\Sigma}[:]$ is the $m^2 \times 1$ matrix formed by the columns of the $m \times m$ matrix ∇_{Σ}.

The components of the gradient are given by the partial derivative with respect to the mean μ:

$$\nabla_{\mu} F(\Theta) = -\frac{N}{2} \sum (I+\Sigma)^{-1} \overline{Y}^{(i)} \left(I + \overline{Y}^{(i)} \Sigma \left(\overline{Y}^{(i)} \right)^T \right)^{1/2} \overline{\alpha}^{(i)}(\Theta)$$

and the partial derivative with respect to the covariance matrix Σ:

$$\begin{aligned}
\nabla_{\Sigma} F(\Theta) = & \frac{N}{2} \left(-(I+\Sigma)^{-1} + \mu\mu^T - \Sigma^{-1}\mu\mu^T\Sigma^{-1} \right) \\
& + \frac{N}{2} \sum_{i=1}^{N} (I+\Sigma)^{-1} \overline{Y}^{(i)} \left(I + \overline{Y}^{(i)} \Sigma \left(\overline{Y}^{(i)} \right)^T \right)^{1/2} \overline{\alpha}^{(i)}(\Theta) \mu^T (I+\Sigma)^{-1} \\
& + \frac{N}{2} \sum_{i=1}^{N} (I+\Sigma)^{-1} \mu \overline{\alpha}^{(i)}(\Theta)^T \left(I + \overline{Y}^{(i)} \Sigma \left(\overline{Y}^{(i)} \right)^T \right)^{1/2} \overline{Y}^{(i)} (I+\Sigma)^{-1} \\
& + \frac{N}{2} \sum_{i=1}^{N} (I+\Sigma)^{-1} \overline{Y}^{(i)} \left(I + \overline{Y}^{(i)} \Sigma \left(\overline{Y}^{(i)} \right)^T \right)^{1/2} \Upsilon^{(i)}(\Theta) \left(I + \overline{Y}^{(i)} \Sigma \left(\overline{Y}^{(i)} \right)^T \right)^{1/2} \overline{Y}^{(i)} (I+\Sigma)^{-1}
\end{aligned}$$

where

$$\overline{\alpha}^{(i)}(\Theta) = \frac{\int_{\mathbf{U}^{(i)}} U \exp\{-U^T U/2\} dU}{\int_{\mathbf{U}^{(i)}} \exp\{-U^T U/2\} dU}, \qquad \Upsilon^{(i)}(\Theta) = \frac{\int_{\mathbf{U}^{(i)}} U U^T \exp\{-U^T U/2\} dU}{\int_{\mathbf{U}^{(i)}} \exp\{-U^T U/2\} dU}$$

The sets over which the integrals are taken are given by:

$$\mathbf{U}^{(i)} = \left\{ U \in \mathbf{R}^m \mid \left(\left(I + \overline{Y}^{(i)} \Sigma \left(\overline{Y}^{(i)} \right)^T \right)^{1/2} U \right)_j > -y_j^{(i)} \mu_j ; \quad j = 1, 2, \ldots, m \right\}$$

where $\overline{Y}^{(i)} = \lfloor diag(y_1^{(i)}, y_2^{(i)},..., y_m^{(i)}), 0_{m,n} \rfloor$ is defined to be the matrix composed with the *m-by-m* diagonal matrix having the measurement data $y_j^{(i)} \in \{-1,+1\}$ in its diagonal and the *m-by-n* null matrices. The index *j* = 1,..., *m* designates the link number while the index *I* = 1,.., *N* denotes the measurement instance.

A schematic flowchart of the GA algorithm is depicted in **Figure 4**. The GA algorithm iteratively approaches the ML estimate by using a gradient method (block **405**), until a convergence condition is reached (block **410**, exit branch **Y**).The convergence condition can be set in several ways, for example depending on the network designer. For example, the convergence condition can be set equal to a certain number iterations, or to cause the iterations to stop whenever the change in the estimated parameters from one iteration to the other becomes small enough.

<u>Expectation Maximization (EM) Algorithm</u>

The EM algorithm is an approximate algorithm that iteratively maximizes a lower bound of the log- likelihood obtained by using Jensen's inequality.

$$\mathbb{E}_W[log(P(Y,W|\Theta))]$$

As schematized in the flowchart depicted in **Figure 5**, the EM algorithm computes an approximation of the solution of the maximization problem by alternating between an E-Step (Expectation Step – block **505**), where an expectation of the likelihood is computed based on the current estimate of the parameters, and an M-Step (Maximization Step – block **510**), where this expectation is maximized to update the parameter estimation. The E-step and the M-step are iterated until a convergence condition is reached (block **515**, exit branch **Y**).

In the E-Step, assuming a current estimate Θ_t of the parameters at time *t*, an expectation of the likelihood is computed as:

$$Q(\Theta,\Theta_t) = \mathbb{E}_{(W|\Theta_t,Y)}[log(P(Y,W|\Theta))|Y,\Theta_t]$$

where the expectation is taken with respect to the posterior distribution of *W* given *Y* and the prior distribution of *W* with parameters Θ_t. Once $Q(\Theta,\Theta_t)$ is computed, an update of the estimate is obtained in the M-Step by maximizing it over all the values of Θ.

$$\Theta_{t+1} = argmax_{\Theta} Q(\Theta, \Theta_t)$$

To compute $Q(\Theta, \Theta_t)$, the posterior probability distribution of *W* given *Y* and the prior distribution of *W* at time *t* are needed; the latter has the form:

$$\mathbb{P}(\mathbf{W}|\mathbf{Y}, \Theta_t) = \prod_{i=1}^{N} \frac{\mathbb{P}(W^{(i)}|\Theta_t)\mathbb{P}(Y^{(i)}|W^{(i)})}{\mathbb{P}(Y^{(i)}|\Theta_t)} = \prod_{i=1}^{N} \mathbb{P}(W^{(i)}|Y^{(i)}, \Theta_t)$$

If the terms $P(W^{(i)} \mid Y^{(i)}, \Theta_t)$ (which are posterior distributions of the different field realizations given the observation data) can be written as Gaussian distributions with parameters $\hat{\Theta}_t^{(i)} = (\hat{\mu}_t^{(i)}, \hat{\Sigma}_t^{(i)})$, then the updates $\Theta_{t+1} = (\mu_{t+1}, \Sigma_{t+1})$ are given by:

$$\mu_{t+1} = \frac{1}{N}\sum_{i=1}^{N} \hat{\mu}_t^{(i)}, \quad \Sigma_{t+1} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{\Sigma}_t^{(i)} + \left(\hat{\mu}_t^{(i)} - \mu_{t+1}\right)\left(\hat{\mu}_t^{(i)} - \mu_{t+1}\right)^T\right)$$

To derive these formulas, it should be firstly noticed that since the different realizations $W^{(i)}$ of the Gaussian process are *iid*, the expected likelihood $Q(\Theta, \Theta_t)$ is:

$$Q(\Theta, \Theta_t) = \sum_{i=1}^{N} \mathbb{E}_{W^{(i)}|\Theta_t, Y^{(i)}} \left[\log\left(\mathbb{P}(Y^{(i)}, W^{(i)}|\Theta)\right) | Y^{(i)}, \Theta_t\right]$$

Each term of the summation above can be written as:

$$\mathbb{E}_{W^{(i)}|\Theta_t, Y^{(i)}}[\cdot] = -\frac{1}{2}|\Sigma^{-1}| + \frac{1}{2}\left(Tr(\Sigma^{-1}\hat{\Sigma}_t^{(i)}) + (\hat{\mu}_t^{(i)} - \mu)^T\Sigma^{-1}(\hat{\mu}_t^{(i)} - \mu)\right) + fct(\hat{\mu}_t^{(i)}, \hat{\Sigma}_t^{(i)})$$

The last term of the summation does not depend on the parameter $\Theta = (\mu, \Sigma)$. Taking the partial derivatives with respect to μ and Σ and setting them equal to zero yields the formulas given above.

However, the posterior distributions $P(W^{(i)} \mid Y^{(i)}, \Theta_t)$ are not in general Gaussian, but they can be approximated by Gaussian distributions. These approximations can be obtained by projecting each posterior onto the Gaussian family. Projecting onto the Gaussian family corresponds to minimizing the KL (Kullback-Leibler) divergence. Thus the parameters of the Gaussian distribution that best approximate $P(W^{(i)} \mid Y^{(i)}, \Theta_t)$ can be determined by solving the following equation:

$$\tilde{\Theta}_t^{(i)} = argmin_{\Theta} KL\left(P\left(W^{(i)} \middle| Y^{(i)}, \Theta_t\right) \middle|\middle| P\left(W^{(i)} \middle| \Theta\right)\right)$$

where $P(W^{(i)} \mid \Theta)$ is a Gaussian density with parameter Θ. This minimization can be solved by exploiting the moment matching principle; this principle states that the mean and the covariance matrix of the Gaussian projection are given by:

$$\tilde{\mu}_t^{(i)} = \mathbb{E}_{\left(W^{(i)} | Y^{(i)}, \Theta_t\right)}\left[W^{(i)}\right]$$

$$\tilde{\Sigma}_t^{(i)} = \mathbb{E}_{\left(W^{(i)} | Y^{(i)}, \Theta_t\right)}\left[W^{(i)}\left(W^{(i)}\right)^T\right] - \mathbb{E}_{\left(W^{(i)} | Y^{(i)}, \Theta_t\right)}\left[W^{(i)}\right]\left(\mathbb{E}_{\left(W^{(i)} | Y^{(i)}, \Theta_t\right)}\left[W^{(i)}\right]\right)^T$$

where the expectations above are taken with respect to the posterior distribution $P(W^{(i)} \mid Y^{(i)}, \Theta_t)$.

In general, computing these values is not easy because it requires integrating over the posterior distribution itself (which is known to have a complicated form). However, assuming to adopt a probit model (as known, the probit function is the inverse cumulative distribution function, or quantile function associated with the standard normal distribution), closed-form expressions can be found for these moments. In fact, the probit function can be rewritten as:

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \delta(u \geq 0) e^{-\frac{(u-x)^2}{2}} du$$

Using this formula for the probit, the mean and the covariance matrix of the Gaussian projection are given by:

$$\tilde{\mu}_t^{(i)} = \mu_t + \Sigma_t\left(\bar{Y}^{(i)}\right)^T A \bar{\alpha}^{(i)}(\Theta_t)$$

$$\tilde{\Sigma}_t^{(i)} = \Sigma_t - \Sigma_t\left(\bar{Y}^{(i)}\right)^T A\left(A^{-1} + \bar{\alpha}^{(i)}(\Theta_t)\left(\bar{\alpha}^{(i)}(\Theta_t)\right)^T - \Upsilon^{(i)}(\Theta)\right) A \bar{Y}^{(i)} \Sigma_t$$

where $\bar{Y}^{(i)} = diag(y_1^{(i)}, y_2^{(i)}, \ldots, y_m^{(i)})$ is defined to be the diagonal matrix having the measurement data $y_j^{(i)} \in \{-1, +1\}$ in its diagonal. The index j = 1,..., m designates the communication link number.

The matrix $A^{(i)}$ is given by:

$$A^{(i)} = \left(I + \bar{Y}^{(i)}\Sigma_t\left(\bar{Y}^{(i)}\right)^T\right)^{-1}$$

where

$$\bar{\alpha}^{(i)}(\Theta) = \frac{\int_{\mathbf{U}^{(i)}} U \exp\{-U^T U/2\} dU}{\int_{\mathbf{U}^{(i)}} \exp\{-U^T U/2\} dU}, \qquad \Upsilon^{(i)}(\Theta) = \frac{\int_{\mathbf{U}^{(i)}} U U^T \exp\{-U^T U/2\} dU}{\int_{\mathbf{U}^{(i)}} \exp\{-U^T U/2\} dU}$$

The sets over which the integrals are taken are given by:

$$\mathbf{U}^{(i)} = \left\{ U \in \mathbf{R}^m \mid \left(\left(I + \bar{Y}^{(i)}\Sigma\left(\bar{Y}^{(i)}\right)^T \right)^{1/2} U \right)_j > -y_j^{(i)}\mu_j; \quad j = 1,2,\ldots,m \right\}$$

where $\bar{Y}^{(i)} = \left\lfloor diag(y_1^{(i)}, y_2^{(i)}, \ldots, y_m^{(i)}), 0_{m,n} \right\rfloor$ is defined to be the matrix composed with the *m-by-m* diagonal matrix having the measurement data $y_j^{(i)} \in \{-1,+1\}$ in its diagonal and the *m-by-n* null matrixs. The index j = 1,..., m designates the link number while the index I = 1,.., N denotes the measurement instance.

In general, the EM algorithm converges to a local maximum of the likelihood function. However, if the function has nice properties, such as concavity, then EM algorithm will converge to the optimal value.

<u>Second step (block **210**): Deployment of additional relay nodes</u>

Once the parameters of the underlying Gaussian process have been learned and updated, *n* additional relay nodes **110** are deployed to improve the communication cost between the sensor nodes and the gateway **115** / base station **130**. Choosing the new *n* nodes placement positions that minimizes the communication cost is equivalent to solving a Minimum Cost Steiner Tree problem. Such problems are known to be NP-hard from the computational viewpoint. According to an embodiment of the present invention, a heuristic algorithm based on the minimum spanning tree algorithm is proposed.

Several implementation of the spanning tree algorithm are possible. The Adjacency Matrix implementation runs in *O*(|*V*|^2), Binary Head implementation runs in *O*(|*E*|log(|*V*|)), while the Fibonacci Heap method runs in *O*(|*E*|+log(|*V*|)), where |*E*| is the number of edges and |*V*| the number of vertices.

According to a preferred embodiment of the present invention, a vertex algorithm based the minimum spanning tree algorithm is used. Using a spanning tree of complexity $K(|V|,|E|)$, the vertex algorithm runs in $O(nM\,K(|V|,|E|))$ where M is the number of all possible locations.

An exemplary pseudocode of the heuristic algorithm is shown below. A penalty has been introduced in the cost of the tree to force the algorithm to explore new positions. The penalty is taken to be proportional to the 2-norm of the covariance matrix. In fact, when estimating the parameters of the underline distribution, better estimates will be obtained in regions where the links are observed, resulting to higher variances in regions where there was no observation. As a consequence, the Steiner Tree algorithm will tend to choose Steiner points in regions where nodes have been deployed (because the cost of the links in the other regions is high). To avoid this phenomenon and force the algorithm to "*explore new regions*", we introduce a penalty $-\lambda\|\Sigma\|_2$ that favors "*non-yet explored regions*". :

Given: Graph $G = (V,E)$, set of terminal nodes X subset of V, a Steiner Tree $T_{bs}(X,Y)$ that spans all terminals in X using nodes in Y as Steiner points (or relays)

Find: n Steiner points $p_1,...p_n$ in V, such that the Steiner Tree $T_{bs}(X,Y \cup \{p_1,...,p_n\})$ is of minimum cost.

R = empty set

For i from 1 to n

1. $p_i = argmin_{v' \in V-\{XUYUR\}}\left(C\left(T_{BS}(X,YURU\{v'\})\right) - \lambda\|\Sigma\|_2\right)$

2. $R = RU\{p\_i\}$

End (for)

Return R

Essentially, the new n relay nodes **110** are added one-at-a-time, and each time the best position of the newly added relay node **110** is obtained by running the spanning tree algorithm for all possible positions and choosing the best position.

Third step (block **215**): recording communications activities

In the third step of the method according to the present invention, after each deployment of additional relay nodes the communication activity over each communication link is recorded, in terms of a sequence of successes and failures of transmissions between the end points (sensor nodes **105** and gateway **115** / base station **130**) over such a link. The reason of a transmission failure over a certain communication link may be either the poor quality of the link or collisions. Since the goal of recording the communication activities at this step is to understand the communication link quality, the collisions should be avoided. One way to do that is to use a TDMA (Time Division Multiple Access) schedule.

The communication activities are recorded over a certain number of transmission frames. Each frame consists of time slots such that the nodes transmitting in the same slot do not conflict with each other and each node transmits one data packet in the assigned slot of the frame. One way to do that is to assign a separate time slot to each node in the network, such that each frame consists of m slots for m nodes.

Let N be the number of transmission frames. The output of this step is then the binary vector of length N for each communication link (i,j): vij=[sij1, sij2,...,sijN], where sijk=1 if the k-th transmission in link (i,j) is successful and sijk=0 otherwise.

Figure 6 shows an example for recording communication activities over a network of three sensor nodes **105** for four transmission frames. “t”, “r” and “x” denote the transmission, successful packet reception and no reception, respectively. The binary vectors V_{12}, ..., V_{32} for each link are as shown in the figure.

Fourth step (block **220**): updating the parameters estimates

As described in the foregoing, GA or EM algorithms are preferably used to compute an initial estimation of the parameters of the underlying Gaussian process. Once the Gaussian process parameters are estimated, another set of relay nodes is deployed based on the current value of the estimate. Then new observations are made, and, based on these new observations, the new value estimates of the Gaussian process parameters are computed.

To compute the new value of the Gaussian process parameters estimates, one of the methods described in the foregoing for computing a Maximum Likelihood Estimator (MLE) may be used. However, to compute the best MLE, it would be necessary to consider the old and the new observations. Doing this would require to store a large amount of data, which becomes an issue as more data becomes available. Furthermore, such method ignores the old estimates and computes completely new ones based on the entire data set.

According to a preferred embodiment of the present invention, online learning techniques are exploited, whereby approximated update algorithms can be derived that use the old estimate and do not need to store the old data. Online learning and the Expectation Propagation (EP) algorithm for approximating a complex distribution by a Gaussian distribution are presented next; a schematic flowchart of the EP algorithm is depicted in **Figure 7**.

Let $D^{(t)}$ be the total amount of data observed up to time *t* and let Θ_t be the estimate of the parameters at time *t*, computed from the data $D^{(t)}$. The goal is to find a way to update the parameters estimate Θ_{t+1} after a new observation $\mathbf{Y}^{(t+1)} = (Y_1^{(t+1)},...,Y_N^{(t+1)})$ is made, where $D^{(t+1)} = (D^{(t)}, \mathbf{Y}^{(t+1)})$ and $D^{(0)}$ is equal to the empty set (it is assumed that the observations $Y_i^{(t+1)}$ are iid given Θ). A slight change of convention in the notation has been here adopted compared to the foregoing: superscripts denote the iteration number in the nodes deployment procedure and subscripts denote the instance number of observations within that iteration. $Y_i^{(t)}$ is a vector containing the information about whether there is a success or failure of transmission in each communication link at the *i*-th instance of *t*-th iteration. To find the update, the GP model can be considered as a parameterized Bayesian model where the parameter (the Gaussian random process) has infinite dimension.

Having an old posterior distribution of $P(W \mid D^{(t)})$, it is possible to compute the new posterior distribution $P(W \mid D^{(t+1)})$ as a function of $P(W \mid D^{(t)})$ by applying the Bayes' rule. Directly applying the Bayes' rule requires the knowledge about the different field realizations $W_1^{(t+1)},...,W_N^{(t+1)}$ that generate the observations $Y_1^{(t+1)},...,Y_N^{(t+1)}$ respectively. Trying to compute these values may be very demanding. Thus, for deriving the posterior distribution it is assumed that the prior distribution of *W* is known to be Gaussian with parameter Θ at the beginning, $P(W \mid \Theta)$ (block **705** – in this block of the flowchart, other initializations are shown, *e.g.* of the indexes used for controlling the subsequent iterations), *e.g* computed from the initial deployment. The following describes how the data $\mathbf{Y}^{(1)} = (Y_1^{(1)},...,Y_N^{(1)})$ is used to obtain the posterior probability distribution at the end of the first iteration. The posterior distribution at the end of each iteration is then used as a prior probability distribution for the following iterations.

1. Data $\mathbf{Y}^{(1)} = (Y_1^{(1)},...,Y_N^{(1)})$ are considered to arrive one at a time, *i.e.* $Y_1^{(1)}$, then $Y_2^{(1)}$ and so on (this assumption is reflected in the iteration loop controlled by block **725**).

2. After $Y_1^{(1)}$ is received, the posterior distribution $P_{1,1}^{(1)}(W) = P(W \mid D^{(0)}, Y_1^{(1)})$ is computed by using the "prior" distribution $P(W \mid D^{(0)}) = P(W \mid \Theta)$, assuming that $Y_1^{(1)}$ was generated by sampling $W_1^{(1)}$ from this "prior" distribution. Thus (block **710**):

$$P_{1,1}^{(1)}(W) = \frac{P(W|\Theta)P(Y_1^{(1)}|W)}{P(Y_1^{(1)}|\Theta)}$$

The above probability density does not have in general a "nice" form. To be able to easily manipulate it in subsequent operations, according to a preferred embodiment of the invention it is approximated by a Gaussian distribution $q_{1,1}^{(1)}(W)$ with parameter $\Theta_{1,1}^{(1)}$. Since the posterior distribution is the product of a Gaussian distribution by a probit function, the mean and covariance matrix of the Gaussian projection are calculated using the moment matching principle, as described in the foregoing.

In the notation adopted here (*e.g.* $\Theta_{1,1}^{(1)}$), the superscript *(1)* indicates the iteration number where the data set is collected (here $\mathbf{Y}^{(1)} = (Y_1^{(1)},...,Y_N^{(1)})$), the first index in the subscript designates the instance number of the particular data within that iteration and the second index in the subscript indicates that these data are being considered for the first time.

3. The parameters of this approximate Gaussian distribution are now considered to be the new estimates of the parameters of the field distribution (*i.e.* the Gaussian distribution is considered to be the prior probability distribution of the field).

4. Once the data $Y_2^{(1)}$ becomes available, the new posterior distribution $P_{2,1}^{(1)}(W) = P(W \mid D^{(0)}, Y_1^{(1)}, Y_2^{(1)})$ can be computed and projected to the Gaussian family to get $q_{2,1}^{(1)}(W)$. In general, after data $Y_{i+1}^{(1)}$ is received, the posterior distribution is updated as:

$$P_{i+1,1}^{(1)}(W) = \frac{\tilde{q}_{i,1}^{(1)}(W)P(Y_{i+1}^{(1)}|W)}{P(Y_{i+1}^{(1)}|\tilde{\Theta}_{i,1}^{(1)})}$$

where $q_{i,1}^{(1)}(W)$ is the Gaussian approximation of the posterior distribution $P_{i,1}^{(1)}(W) = P(W \mid D^{(0)}, Y_1^{(1)},...,Y_i^{(1)})$ obtained after considering data $Y_i^{(1)}$ and $\tilde{q}_{i,1}^{(1)}(W) = q_{i,1}^{(1)}(W)$ since the data is considered for the first time within the iteration. The parameters of $\tilde{q}_{i,1}^{(1)}(W) = q_{i,1}^{(1)}(W)$, $\tilde{\Theta}_{i,1}^{(1)} = \Theta_{i,1}^{(1)}$, can be computed using the moment matching principle.

The effect of considering each data $Y_i^{(1)}$ is captured in the following distribution:

$$t_{i,1}^{(1)}(W) = q_{i,1}^{(1)}(W)/q_{i-1,1}^{(1)}(W)$$

5. After observing data $Y_N^{(1)}$, the posterior distribution can be similarly computed and a first approximation $q_{N,1}^{(1)}(W)$ of the complete posterior distribution $P_{N,1}^{(1)}(W) = P(W \mid D^{(0)}, Y_1^{(1)},...,Y_N^{(1)})$ is obtained.

The procedure then restarts from step 2 considering the data $\mathbf{Y}^{(1)} = (Y_1^{(1)},...,Y_N^{(1)})$ a second time. However, the observation $Y_1^{(1)}$ has already been used to estimate $q_{N,1}^{(1)}(W)$. Thus, before using it again in the approximation, its effect needs to be removed first. This can be done by computing (block **710**):

$$\tilde{q}_{1,2}^{(1)}(W) = q_{N,1}^{(1)}(W)/t_{1,1}^{(1)}(W)$$

Considering $\tilde{q}_{1,2}^{(1)}(W)$ to be the new "prior" distribution, the posterior distribution given $Y_1^{(1)}$ can now be computed as (block **715**):

$$P_{1,2}^{(1)}(W) = \frac{\tilde{q}_{1,2}^{(1)}(W)P(Y_1^{(1)}|W)}{P(Y_1^{(1)}|\tilde{\Theta}_{1,2}^{(1)})}$$

Using the moment matching principle, this posterior distribution can be approximated by a Gaussian distribution $q_{1,2}^{(1)}(W)$ having parameters $\Theta_{1,2}^{(1)}$. The effect of re-considering data $Y_1^{(1)}$ is captured in the distribution (block **720**):

$$t_{1,2}^{(1)}(W) = q_{1,2}^{(1)}(W)/\tilde{q}_{1,2}^{(1)}(W)$$

Now the data $Y_2^{(1)}$ can be reconsidered by first removing its effect as it was done for $Y_1^{(1)}$.

6. By repeating this procedure a certain number *M* of times (block **730**) for the data set $\mathbf{Y}^{(1)} = (Y_1^{(1)},...,Y_N^{(1)})$, the complete posterior distribution $P^{(1)}(W) = P(W \mid D^{(0)}, Y_1^{(1)},...,Y_N^{(1)})$ can be closely approximated by a Gaussian density $q_{N,M}^{(1)}(W)$.

The same procedure is applied whenever a new data set $\mathbf{Y}^{(t)} = (Y_1^{(t)},...,Y_N^{(t)})$ for *t* > 1 is available. The prior distribution at each iteration is the posterior distribution from the previous iteration: $q_{0,1}^{(t+1)}(W) = q_{N,M}^{(t)}(W)$. A “good” update of the estimate of the parameters of the field distribution is computed without actually having to store all the data.

The procedure is iterated until a convergence condition is reached. The convergence condition may correspond to the reaching of a predetermined maximum number of iterations, or when the change in absolute value from the values calculated in the previous iteration and those calculated in the current iteration is below a predetermined threshold.

The method according to the described embodiment of the invention can be implemented by the base station **130**, or directly by the gateway **115**.

Figure 8 schematically shows the architecture with the main functional blocks of a gateway **115** according to an embodiment of the present invention, adapted to implement the above described method.

The gateway **115** comprises a power unit **805** (POW) for supplying electric power to the gateway circuitry, either through a battery or main power line.

A transceiver **810** (RTX), connected to an antenna **815**, allows communication of the gateway **115** with the other nodes in the network **100**. This communication will transfer the communication activities in the network, mainly a sequence of transmissions successes and failures between the gateway **115** and the already placed nodes.

The iterative algorithm described above is implemented by a control and processing unit **820** (CPU) that is connected to the transceiver **810**; the control and processing unit **820** is also connected to a storage unit **825** (*e.g.* a memory – MEM) for storing data and programs, in particular a software/firmware that includes modules allowing the control and processing unit **820** implement the iterative algorithm described above.

The storage unit **825** comprises in particular a table **830** (TAB) that stores information about the recorded communication activities for each communication link in the network **100**.

The gateway **115** also includes a timer **835** (TM) receiving a clock signal **CLK**, generated for example by a quartz oscillator **840** (X), for timing its operation, such that the gateway **115** can record the communication activities after the deployment of additional nodes for a certain time duration, which can be notified by input from technicians deploying the additional nodes, by means of a signal **ST_i** (start signal for deployment i). Once a certain time is passed, the gateway **115** implements the iterative algorithm and determines the next best *n* positions for the additional relay nodes **110**; the determined positions **BEST_i** (best *n* positions at deployment i) are provided to the technicians that have to deploy the new nodes.

The present invention has been here described in detail making reference to exemplary embodiments thereof. Those skilled in the art will recognize that several changes to the described embodiments, as well as other embodiments of the invention are possible, without departing from the protection scope defined in the appended claims.

CLAIMS

1. A method for the deployment of nodes (**105**,**110**,**305**) of a wireless communication network (**100**), comprising:

a) obtaining (**205**) an initial estimation of parameters indicative of a quality of the communications between the nodes in the network in respect of an initial deployment of nodes;

b) based on the parameters estimation, estimating (**210**) a physical position of at least one additional network node to be deployed;

c) after the at least one additional network node has been deployed in a physical position in the network, monitoring and recording communication activities (**215**) between the nodes in the network;

d) deriving (**220**) an updated estimation of the parameters indicative of the quality of the communications between the nodes in the network based on the recorded communication activities, and

e) either iterating said steps b), c) and d) or not depending on an assessment of the updated parameters estimation.

2. The method of claim 1, wherein step a) includes modeling a probability of successful wireless communications between the nodes in the network as a Gaussian process.

3. The method of claim 2, wherein step a) includes estimating mean and covariance of probability distribution functions of Gaussian random variables characterizing a wireless communications link between any two nodes in the network.

4. The method of claim 3, wherein said estimating mean and covariance of the probability distribution functions includes calculating a maximum likelihood estimation.

5. The method of claim 4, wherein said calculating the maximum likelihood estimation includes approximating the maximum likelihood estimation by means of a gradient ascent algorithm.

6. The method of claim 4, wherein said calculating the maximum likelihood estimation includes approximating the maximum likelihood estimation by means of an expectation maximization (EM) algorithm.

7. The method of any one of the preceding claims, wherein step b) includes solving a minimum-cost Steiner tree problem.

8. The method of claim 7, wherein said solving the minimum-cost Steiner tree problem is approximated by a vertex algorithm.

9. The method of any one of the preceding claims, wherein step c) includes monitoring and recording sequences of communications successes and/or failures between any two nodes in the network.

10. The method of claim 9, wherein said monitoring and recording communications activities includes scheduling the communications between the nodes in the network according to a TDMA schedule.

11. The method of claim 10, wherein said scheduling includes assigning to each node in the network a respective time slot for transmission.

12. The method of any one of the preceding claims, wherein step d) includes approximating a maximum likelihood estimation by means of either a gradient ascent algorithm or a maximum

expectation algorithm.

13. The method of any one of claims 1 to 11, wherein step d) includes exploiting an online learning technique.

14. The method of claim 13, wherein said exploiting the online learning technique comprises applying an expectation propagation algorithm.

15. The method of any one of the preceding claims, wherein step e) includes deciding to terminate said iterating the steps b), c) and d) when a predetermined low cost for the communications between the nodes of the network is attained.

16. A system for determining positions of deployment of nodes (**105**,**110**,**305**) of a wireless communication network (**100**),the system being configured for performing the steps of the method of any one of the preceding claims.

17. A computer program loadable into a memory of a computer, comprising computer program code modules adapted to implement the method of any one of claims 1 to 15 when executed on the computer.

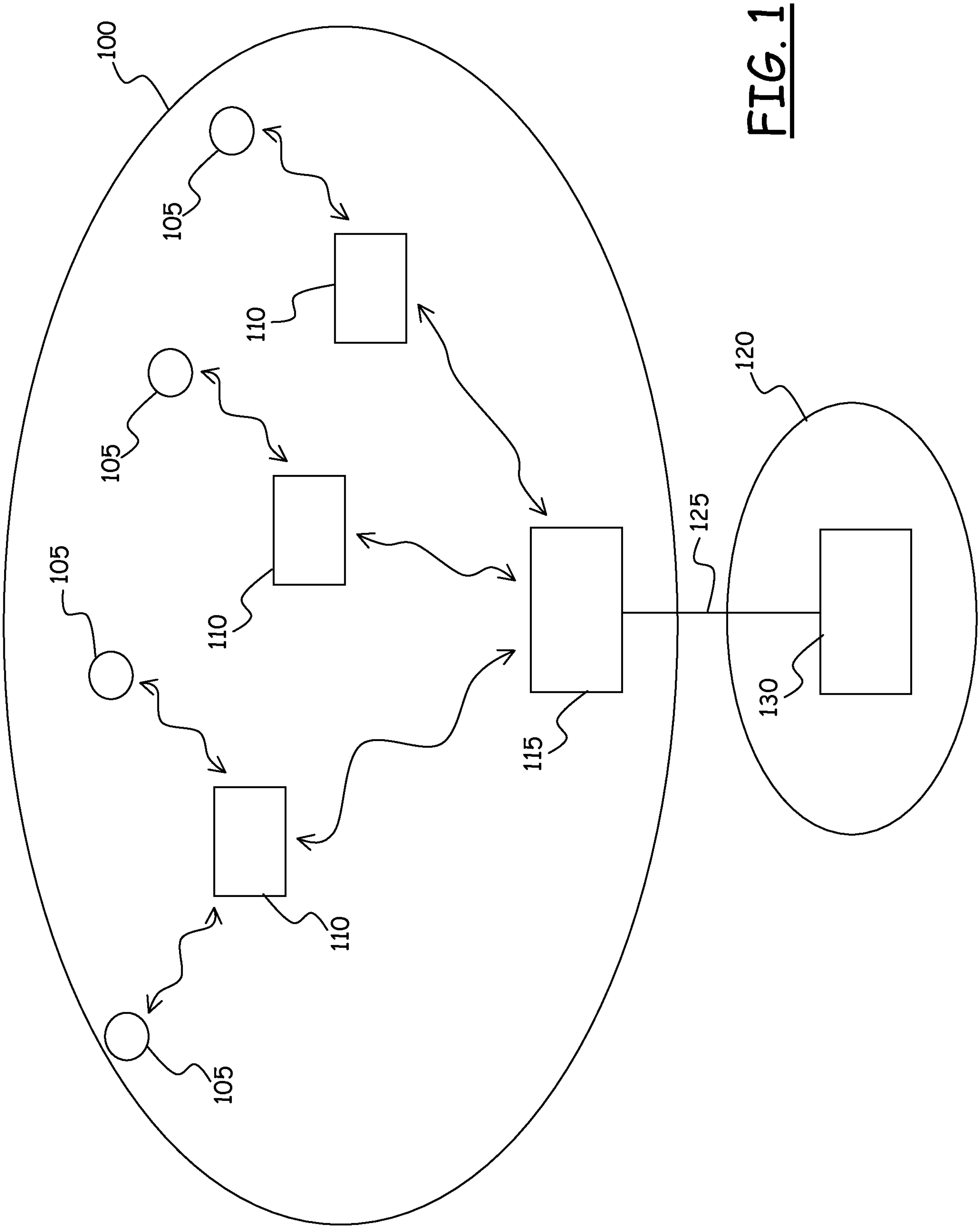

FIG. 1

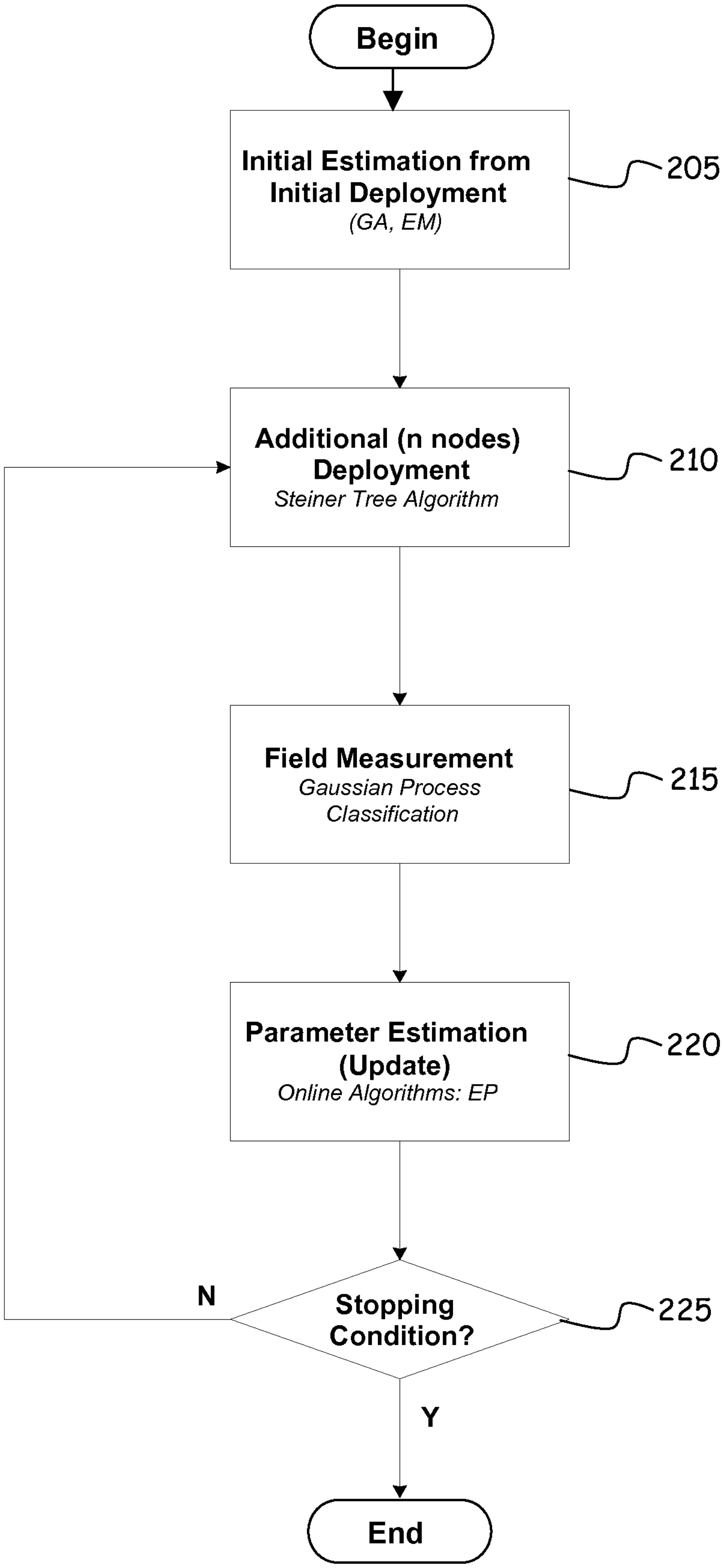
Begin
Initial Estimation from Initial Deployment
(GA, EM)
205
Additional (n nodes) Deployment
Steiner Tree Algorithm
210
Field Measurement
Gaussian Process Classification
215
Parameter Estimation (Update)
Online Algorithms: EP
220
Stopping Condition?
225
N
Y
End

FIG. 2

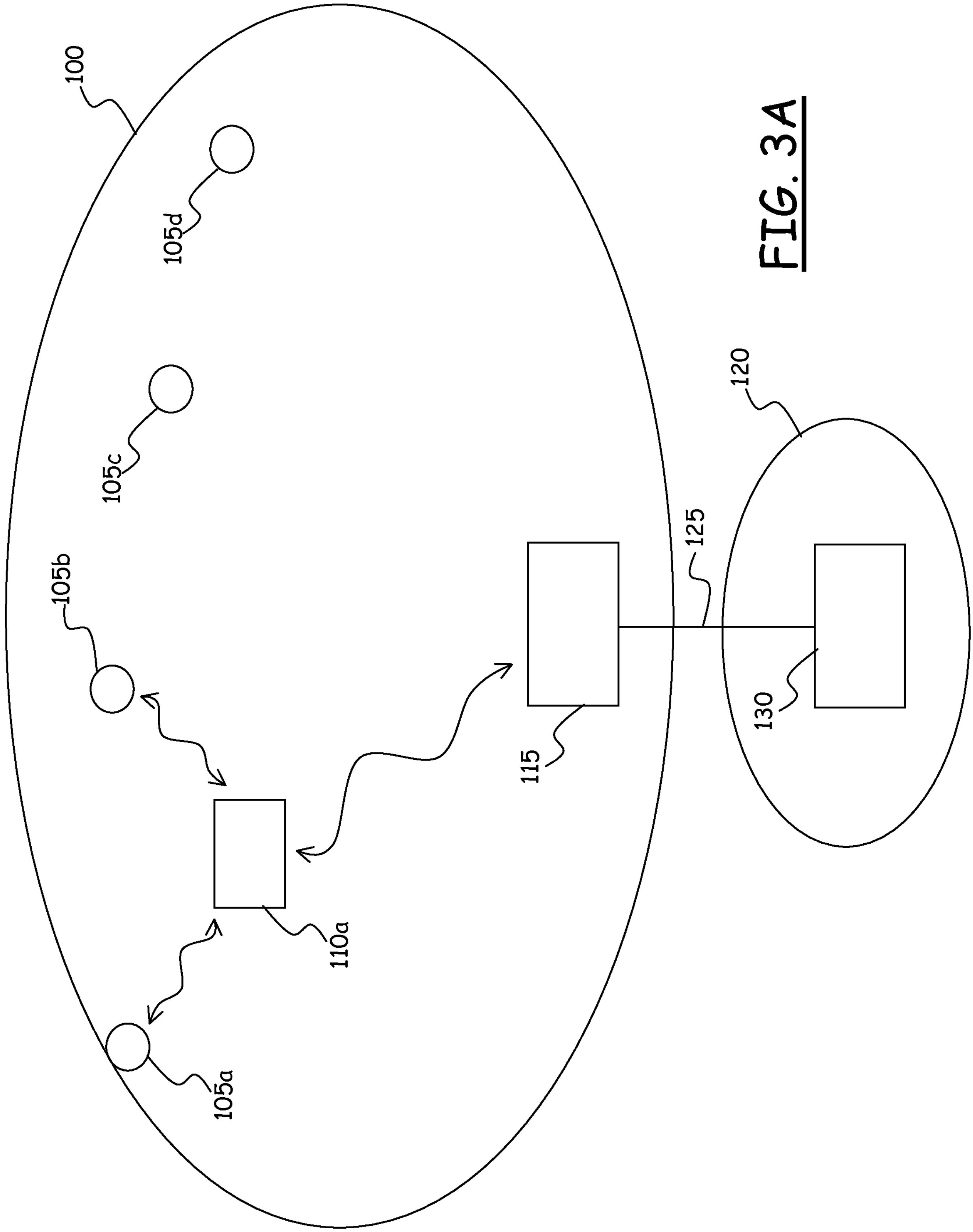

FIG. 3A

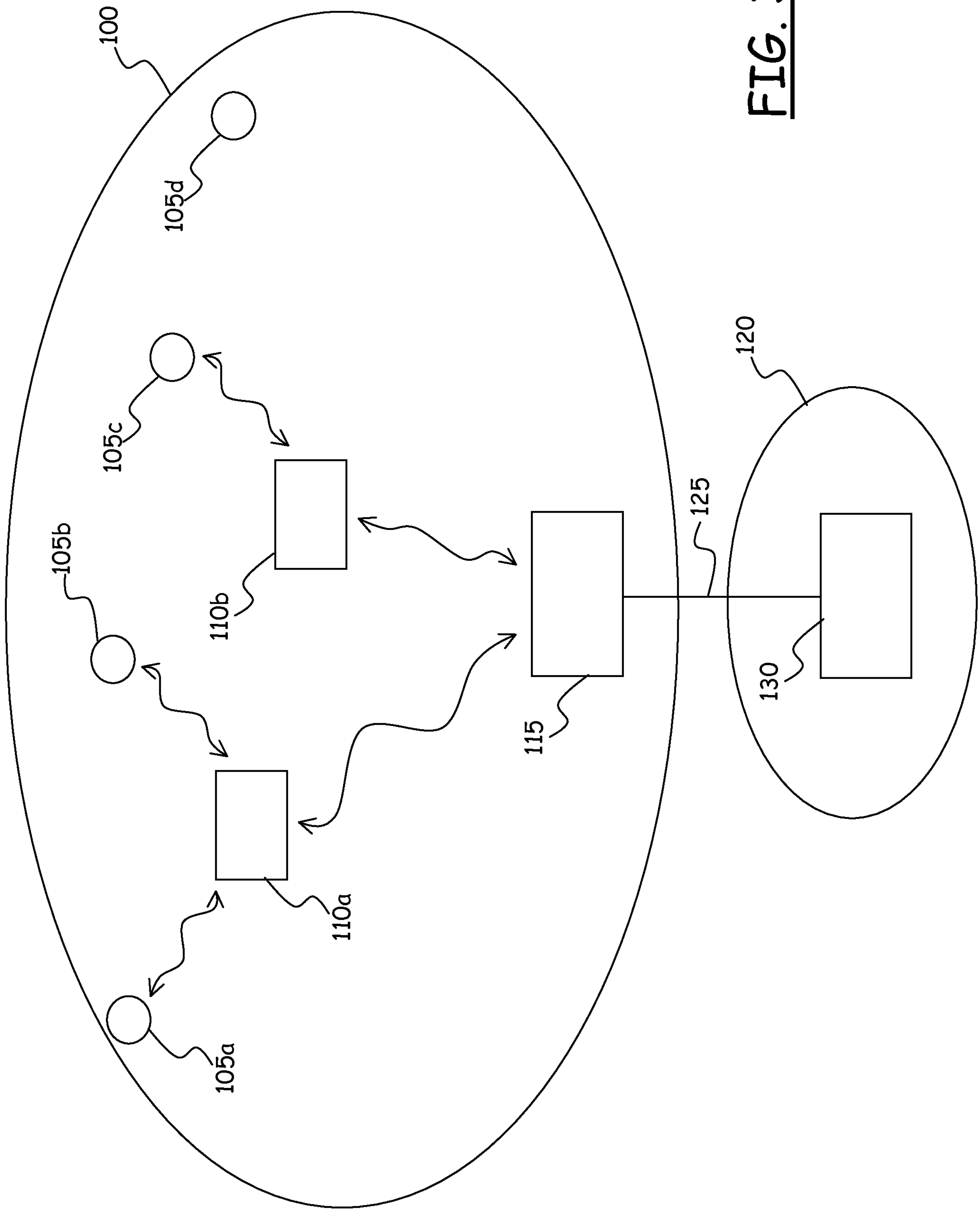

FIG. 3B

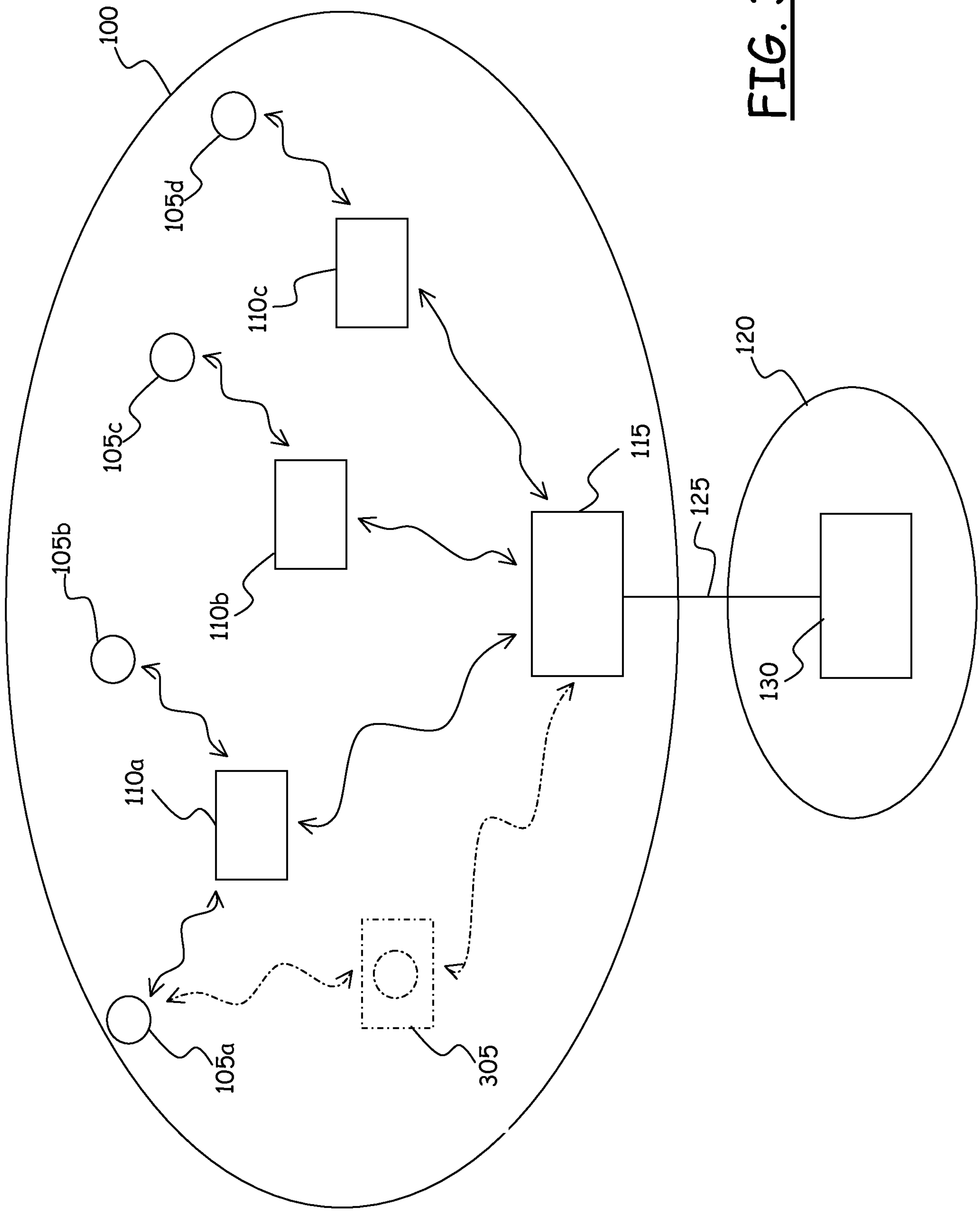

FIG. 3C

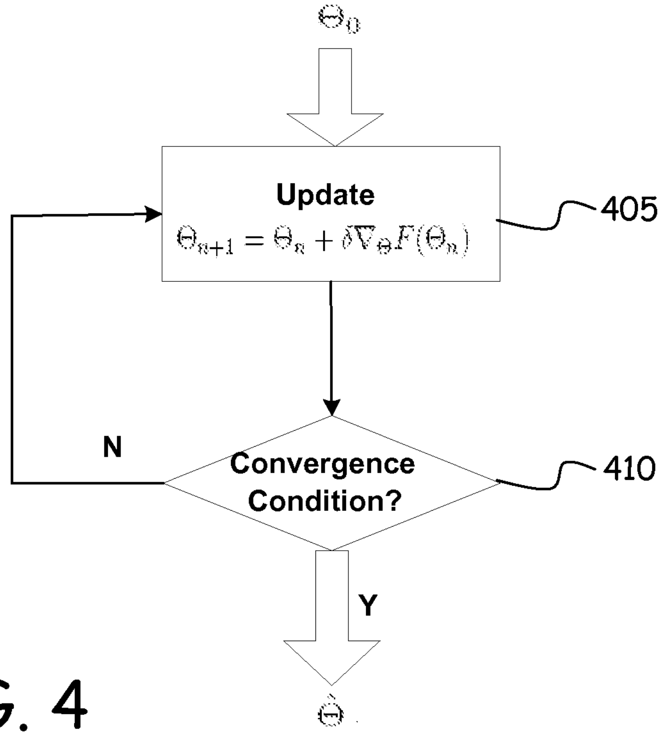
Θ_0
Update
$\Theta_{n+1} = \Theta_n + \delta \nabla_\Theta F(\Theta_n)$
405
N
Convergence Condition?
410
Y
$\hat{\Theta}$

FIG. 4

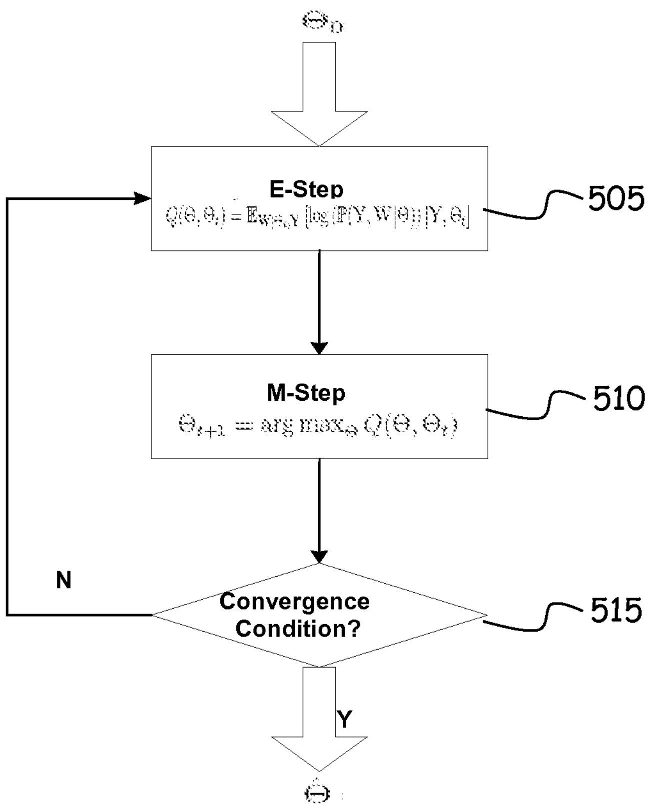
Θ_0
E-Step
$Q(\Theta,\Theta_t) = \mathbb{E}_{W|\Theta_t,Y}[\log(\mathbb{P}(Y,W|\Theta))|Y,\Theta_t]$
505
M-Step
$\Theta_{t+1} = \arg\max_\Theta Q(\Theta,\Theta_t)$
510
N
Convergence Condition?
515
Y
$\hat{\Theta}$

FIG. 5

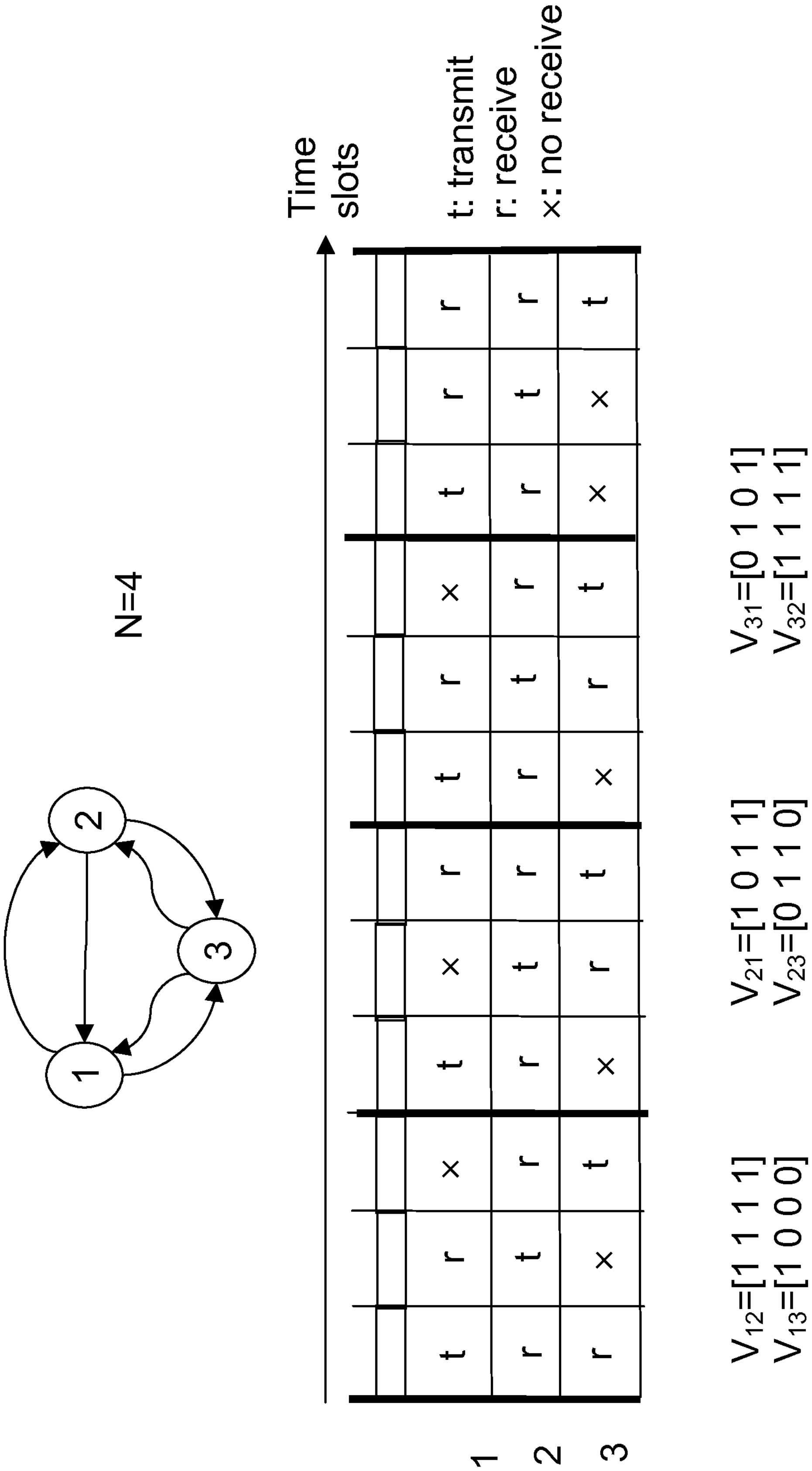
N=4
Time slots
t: transmit
r: receive
x: no receive
V_{12}=[1 1 1 1]
V_{13}=[1 0 0 0]
V_{21}=[1 0 1 1]
V_{23}=[0 1 1 0]
V_{31}=[0 1 0 1]
V_{32}=[1 1 1 1]
1
2
3

FIG. 6

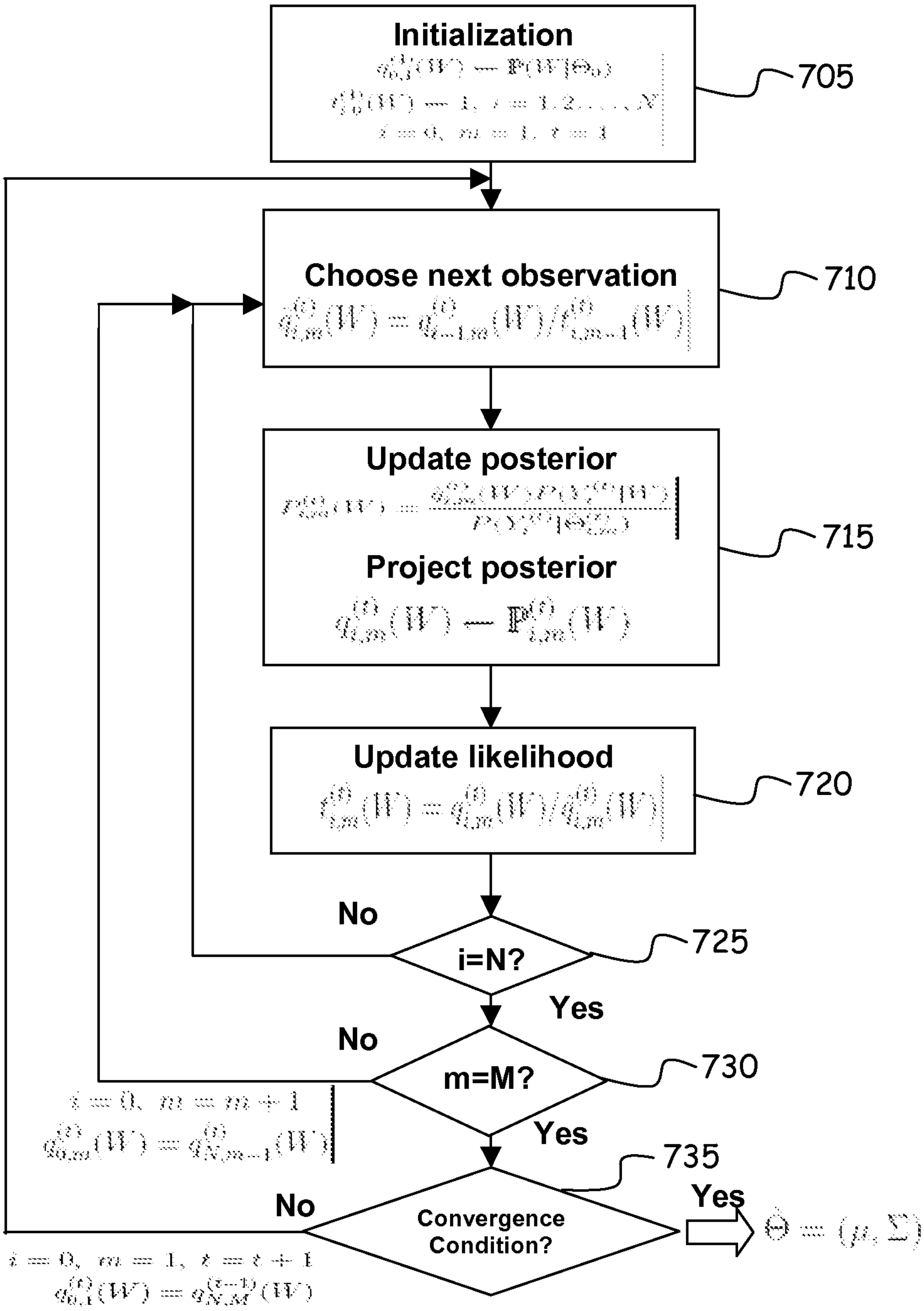
Initialization
705
Choose next observation
710
Update posterior
Project posterior
715
Update likelihood
720
No
i=N?
725
Yes
No
m=M?
730
Yes
735
No
Convergence Condition?
Yes

FIG. 7

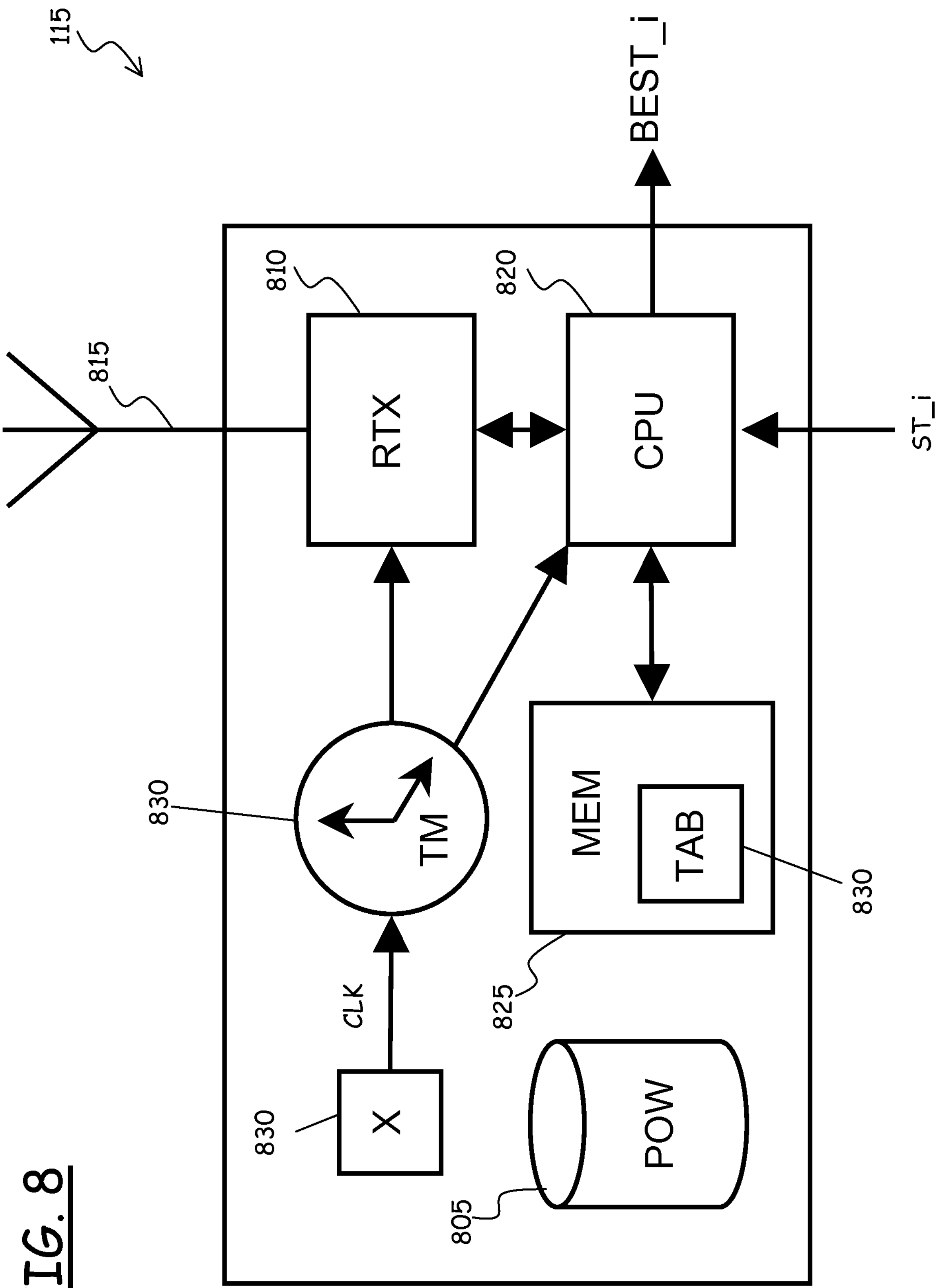
115
BEST_i
810
820
815
RTX
CPU
ST_i
830
TM
MEM
TAB
830
825
CLK
830
X
POW
805

FIG. 8

INTERNATIONAL SEARCH REPORT

International application No
PCT/EP2008/064279

A. CLASSIFICATION OF SUBJECT MATTER
INV. H04L29/08 H04L12/24 H04W84/18

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
H04L H04W

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practical, search terms used)

EPO-Internal

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	KRAUSE A ET AL: "Near-optimal Sensor Placements: Maximizing Information while Minimizing Communication Cost" INFORMATION PROCESSING IN SENSOR NETWORKS, 2006. IPSN 2006. THE FIFTH INTERNATIONAL CONFERENCE ON NASHVILLE, TN, USA 19-21 APRIL 2006, PISCATAWAY, NJ, USA,IEEE, 19 April 2006 (2006-04-19), pages 2-10, XP010932163 ISBN: 978-1-59593-334-8 cited in the application abstract sections 1., 2.2, 2.3, 5., 7. -----	1-17

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[X] Further documents are listed in the continuation of Box C.

[X] See patent family annex.

* Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier document but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art.

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
3 September 2009	11/09/2009

Name and mailing address of the ISA/	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL – 2280 HV Rijswijk Tel. (+31-70) 340-2040, Fax: (+31-70) 340-3016	Buhleier, Rainer

2

Form PCT/ISA/210 (second sheet) (April 2005)

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	DHILLON S S ET AL: "Sensor placement for grid coverage under imprecise detections" INFORMATION FUSION, 2002. PROCEEDINGS OF THE FIFTH INTERNATIONAL CONFE RENCE ON JULY 8-11, 2002, PISCATAWAY, NJ, USA,IEEE, vol. 2, 8 July 2002 (2002-07-08), pages 1581-1587, XP010594382 ISBN: 978-0-9721844-1-0 cited in the application abstract section 3 -----	1-17
A	MEGUERDICHIAN S ET AL: "Coverage problems in wireless ad-hoc sensor networks" PROCEEDINGS IEEE INFOCOM 2001. CONFERENCE ON COMPUTER COMMUNICATIONS. TWENTIETH ANNUAL JOINT CONFERENCE OF THE IEEE COMPUTER AND COMMUNICATIONS SOCIETY (CAT. NO.01CH37213) IEEE PISCATAWAY, NJ, USA; [PROCEEDINGS IEEE INFOCOM. THE CONFERENCE ON COMPUTE, vol. 3, 22 April 2001 (2001-04-22), pages 1380-1387, XP010538829 ISBN: 978-0-7803-7016-6 abstract figure 7 section VI. B -----	1-17
A	HAINING SHU ET AL: "Distributed Sensor Networks Deployment Using Fuzzy Logic Systems" INTERNATIONAL JOURNAL OF WIRELESS INFORMATION NETWORKS, KLUWER ACADEMIC PUBLISHERS-PLENUM PUBLISHERS, NE, vol. 14, no. 3, 29 March 2007 (2007-03-29), pages 163-173, XP019527810 ISSN: 1572-8129 abstract page 163, left-hand column, paragraph 1 - page 164, right-hand column, paragraph 1 -----	1-17
A	TAYLOR C ET AL: "Simultaneous Localization, Calibration and Tracking in an ad Hoc Sensor Network" INFORMATION PROCESSING IN SENSOR NETWORKS, 2006. IPSN 2006. THE FIFTH INTERNATIONAL CONFERENCE ON NASHVILLE, TN, USA 19-21 APRIL 2006, PISCATAWAY, NJ, USA,IEEE, 19 April 2006 (2006-04-19), pages 27-33, XP010932166 ISBN: 978-1-59593-334-8 abstract page 27, left-hand column, last paragraph - page 29, left-hand column; table 1 ----- -/--	1-17

International application No
PCT/EP2008/064279

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	US 2006/253570 A1 (BISWAS PRATIK [US] ET AL) 9 November 2006 (2006-11-09) abstract paragraphs [0005], [0030], [0037], [0046], [0050] -----	1-17

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No
PCT/EP2008/064279

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
US 2006253570 A1	09-11-2006	WO 2006110199 A2	19-10-2006