Abstract—This paper deals with a wireless pervasive communication system to support advanced healthcare applications. The proposed system is based on an ad hoc interaction of mobile body sensor networks with independent wireless sensor networks already deployed within the environments in order to allow a continuous and context aware health monitoring for patients along their daily life scenarios with an unprecedented precision and flexibility of sensing. After an accurate protocol characterization, simulation results are provided, underlining remarkable performance with respect to existing solutions, for different mobility models and node density values.

Index Terms—Body Sensor Networks, Context Awareness, Communications Protocols, Localization.

I. INTRODUCTION

O
ter the past decade, the miniaturization and cost reduction brought about by the semiconductor industry have made feasible the realization of smaller and more powerful computers, paving the floor to the ubiquitous computing era.

Similarly, advances in wireless communication, sensor design, and energy storage technologies have enabled the concept of a truly pervasive wireless Body Sensor Network (BSN) to rapidly become affordable [1]. This specialized family of WSN has the potential to reshape the general practice of clinical medicine by supporting a continuous health monitoring and diagnostic. In fact, the mere monitoring of the patients in a hospital, an intensive care unit or simply an ambulatory might not be able:

1) to capture exceptional episodes or transient abnormalities during real life physiological states;
2) to prevent the onset of a fatal illness initially for at-risk patients;
3) to support long term rehabilitation or therapies for chronic diseases, as the personalized drug delivering with a continuous feedback;
4) to help applied life science research.

This novel sensing paradigm involves a couple of key research topics that are still open; first of all, host mobility needs to be addressed and possibly managed by tracking the patient’s physical location in typical daily life environments (work, home entertainments). In addition to that, in order to improve the appropriateness of gathered data, information related to the context need to be extracted and correlated with the on body sensing. This property, usually referred as context awareness, could be achieved by means of spontaneous networking with WSNs embedded into different environments and idle as long as a mobile BSN is out of their range.

To this purpose, the most relevant issues to be addressed are the efficient power management to prevent battery depletion by managing sleep and active states, an efficient use of directional antennas and localization information of mobile BSNs. As these aspects belong to both the Physical (PHY) and Medium Access Control (MAC) layers, they might be integrated to achieve overall energy efficiency: the way to accomplish this goal effectively relies on the so called cross-layer protocol design principle [2]. However, the increased system complexity needs to be addressed and possibly limited as well as the capability of quickly setting up an end-to-end communication path, even in the presence of unpredictable mobility.

The paper is organized as follows: in Section II, the main features of context-aware sensing for health care applications are presented, whilst the characteristic of the proposed communications framework protocol are subsequently described. In particular, the overall functional architecture, the MD-STAR MAC protocol together with its cooperative localization capabilities are addressed in Section III. The overall communications protocol performance is presented, in terms of network life time gain, setup latency, collision probability in Section IV. Finally some conclusions are drawn explaining the future directions of the present research activity.

II. CHALLENGES OF CONTEXT-AWARE SENSING

Albeit context awareness in BSNs can tap the tool box developed for WSN, there are some specific needs which are to be met by ad hoc methods. First, in indoor environments, the quality of data can be significantly degraded in unpredictable
ways since the absorbing effect of wall’s construction materials may interfere with high frequency radio signals: therefore we need an observation model general and robust enough to accommodate missing data, uncertain information and also malicious behaviors. Second, the state transition model must be flexible enough to capture the generally continuous nature of human behavior and to detect significant deviations from the common pattern of activities.

The first step toward context awareness is exploratory data analysis consisting of clustering and feature selection. The clustering approach more suitable for BSN is Self Organizing Maps (SOM) driven by a $k$-means clustering [3], [4] which does not require fixing a priori the number of clusters. This approach is fairly general, basically unsupervised and does not need any prior information: this character is bound to make it relatively inefficient in that it does not exploit contextual information and training examples usually available in fields like health monitoring.

For this reason, more principled approaches based on Bayesian theory have been recently suggested. To apply these methods, the minimum subsets of features which are relevant to recognize the context need to be selected. This also allows a reduction in data transmissions and therefore in energy consumption that is of paramount importance for wireless monitoring devices used in healthcare applications. The simplest Bayesian approaches are the naive classifiers which, based on the assumption of conditional independence of the features, can perform surprisingly well, but suffer when some features can be referred to multiple contexts [5].

In this paper we focus on more general probabilistic models of particular interest for pervasive communications systems to allow high quality healthcare. In particular, Bayesian Networks (BN), outlined in Section C, permits to have an unambiguous factorization of joint probability distributions. While BN are best suited for representing the causal interrelationships, Hidden Markov Models (HMMs) focus on representing the mechanism of context transition: the state sequence is hidden and only the observations are visible. HMMs can also be structured in multiple layers to model the hierarchical nature of complex human activities [6]. The advantages of these two approaches could be reaped using Dynamic Bayesian Networks: we have now tools, which will be discussed later on, for performing inference, probability updating and therefore context recognition also for streaming data.

A further step not be discussed in this paper is the use of relational models which do not require problem instances to be independent identically distributed (iid [7]): BSNs due to their localized and highly correlated features seem to offer an ideal challenge for RDBN (Relational Dynamic Bayesian Networks).

III. DYNAMIC COMMUNICATIONS PROTOCOLS

A. Overall functional architecture

The reference application scenario is a special case of the Ambient Intelligent (AmI) vision represented by a continuous and ubiquitous patient health monitoring. In particular, it is assumed the presence of at least one BAN comprised of heterogeneous sensors, worn by a person, and connected to a cluster head (CH) that is in charge of collecting and pre-processing data.

Moreover, CH are able to dynamically connect with stand alone WSNs deployed in the environment and to interact with them in order to get a high degree of context awareness. In particular, some WSN nodes act as gateway allowing CH to remotely deliver data to a Remote Control Center (RCC). Within this module, priorities and rules are established enabling a Decision Support System (DSS) to achieve a situation awareness. At DSS, the data coming from BSN are organized into a Data Base (DB) which supports complex, intertemporal probabilistic queries and the basic function of localization, enabling tracking and detection of anomalous behavior and analysis of time-spatial correlations. The outcome of these applications allows inference of ADL (Activities of Daily Living), detection of anomalies and support to the operator the optimal diagnosis or treatment [8]. Within the operating strategy, BSNs can operate autonomously. The overall architecture is pointed out in Fig. 1.

This involves a careful system design, with particular regard to the communications and control protocols. To this end, some promising issues to be addressed are the management of sleep and active states, the on board integration of directional antennas and the addressing of nodes mobility [9]. In particular, the adoption of smart antennas allows the gain maximization toward the desired directions by concentrating the energy in a smaller area. In addition to this, the higher antenna gain might compensate the reduced coverage range due to higher frequencies (for realizing small size nodes) or preserve connectivity in networks and efficiently use the node energy thus increasing its lifetime. However, the increased system complexity needs to be limited; in particular, the requirements related to in vivo sensors miniaturization make feasible the adoption of directional antennas only on fixed WSN gateway hardware onboard.

As these aspects belong to both the Physical (PHY) and Medium Access Control (MAC) layers, they might be integrated to achieve overall energy efficiency: it could be

![Fig. 1. Functional architecture pointing out the pervasive and context aware patient health monitoring.](image)
feasible by jointly managing the duty cycle and the transmitting (receiving) antenna gain, together with implicit nodes localization according to the context aware paradigm. The way to accomplish this goal effectively relies on the so-called cross-layer protocol design principle [2], which allows effectively controlling the capability of quickly setting up an end-to-end communication path, even in the presence of unpredictable mobility.

B. Proposed communications framework

The proposed MD-STAR MAC protocol permits to achieve space-time synchronization for mesh topology in the presence of node or even sub-networks mobility, as it represents the more general case of ad hoc networking. According to the basic scheme (D-STAR) [10], each node (periodically sends to its neighbors its own phase φ, i.e., the time in which it will be available for data exchange (time synchronization). The destination node, upon the reception of a packet, can identify the relative angular position θ of the sender with respect to its own angular reference system (space synchronization). This information can be regarded as a ranging metric useful for localize the mobile BSN, i.e. its local data sink, as explained in Section III.C. Moreover the proposed protocol is inspired to the cross-layer principle as specified in [11]. This mechanism is very effective for a predefined pause time (T_{up}) broadcasting a HELLO message per sector in search of connectivity by notifying its presence. Once T_{c} is expired, it keeps moving again.

The channel access is managed by means of the carrier sense multiple access with collision avoidance (CSMA/CA) scheme, as specified in [11]. This mechanism is very effective in reducing collisions, while the problem of hidden node [12] is still partially unsolved [13].

Each node remains in the regime phase until there is at least one neighbor, otherwise if there are no active neighbors (i.e., the number of empty angular sectors is equal to N_{s}) it reenters the discovery phase in search of connectivity. In Figure 4, the signaling occurring within the regime phase is pointed out following the previously introduced in the case of a mobile node.

To complete the protocol characterization, whenever a node battery is depleted, this node turns off, entering an off phase. This is again represented in Figure 2.

C. Cooperative Localization Protocols

The quality of radio signals is affected by many factors in addition to the distance between transmitting and receiving devices; for instance, RSSI (Received Signal Strength Indication) and S/N (signal/noise ratio) are dependent on the number of walls or other obstacles, the relative humidity, interference with other RF devices, etc. All of these variables are usually unknown and make the location problem a challenging task in a real-world environment. Such problem is commonly solved using predictive statistical methods such as Bayesian Networks combined with Markov Chain Monte Carlo. In this paper we propose the use of Dynamic Bayesian Network in order to take into account not only the uncertainty but also the

2It might be due to the fact that a node could have joined the network extremely late or even have changed its position.
dynamic of the system and make fully use of the information given by the previous estimated localization. BNs and other probabilistic graphical models have been regarded as a tool for WSN configuration and management [14]. Only very recently Bayesian modeling has matured to the point of providing online computation of posterior probability, through sequential Monte Carlo methods, making possible their efficient application to complex dynamical models [15]. In this paper, following [16], we propose a scheme for dynamic localization based on Dynamic Bayesian Networks (DBN). We represent the area in which a BSN can move as a two-dimensional space; to localize the BSN we need to know its position w.r.t. a set of \(N\) waypoints, whose coordinates are known (location-aware points). To this purpose, MD-STAR communications framework capabilities of self-diagnosis and message exchange can be used; once a mobile CH enters the the discovery phase, it broadcasts HELLO messages to all possible neighbor WSN gateways. This procedure can be regarded as a special case of multilateration approach according as each HELLO message contains the unique identifier \(i\), \(1 \leq i \leq N\), of its emitter and an implicit information concerning the solid angle which it subtends w.r.t. to each fixed gateway 3.

Transmitted ranging information signals can be affected by several sources of noise and it is practically impossible to develop a closed equation set to solve for location in a real-world environment. Accordingly, such problems are commonly solved using predictive statistical methods such as Bayesian networks, an extension of Kalman Filters, which are able to deal with missing data and distributions more complex than the Gaussian, using Markov Chain Monte Carlo simulations to improve the accuracy and precision of the target location estimation.

1) Dynamic Bayesian Networks for localization: A Bayesian Network (BN) models real world’s data as realizations of stochastic variables \(\text{(nodes)}\). Nodes and their dependencies define the \(\text{BN structure}\), represented by a Directed Acyclic Graph (DAG) meaning that, if a node depends on another, either directly or through a chain of dependencies, then the reverse cannot be true. Following the \text{conditional independence principle}, each variable is independent on its non-descendants in the graph given the state of its parents. To each node \(Z\) is associated a CPD \(\text{(Conditional Probability Distribution)}\) \(\Theta_{Z_i|\Pi_i} = P_B(Z_i|\Pi_i)\), where \(\Pi_i\) denotes the set of parents of \(Z_i\). Using the independence statements encoded in the network, the joint probability distribution is uniquely determined by these local conditional distributions [17]:

\[
P_B(Z) = \prod_{i=1}^{k} P_B(Z_i|\Pi_i) = \prod_{i=1}^{k} (\Theta_{Z_i|\Pi_i})
\]

A Dynamic Bayesian Network (DBN) is a BN that describes a temporal dynamic model; it represents sequences of values produced by complex stochastic processes evolving over time. Every time slice of a DBN corresponds to a state of the system and movements between time slices reflect a change of state. Two assumptions limit the complexity of the model: process stationarity (i.e., CPDs does not change over time) and first order Markov hypothesis, i.e., the value of state \(Z\) at time \(t\) depends only on the previous state \(Z_{t-1}\). The conditional probability \(P(Z_t|Z_{t-1})\) describes the transition model, while the sensor model \(P(o_t|Z_t)\) describes how the observation variables \(o_t\) (sensor) are affected by the actual state \(Z_t\). The complete formulation includes also the initial state distribution \(P(Z_0)\).

The structure of our localization DBN is depicted in Figure 5. \(X_t\) is the position of the BSN at time \(t\), represented by coordinates \((x_t, y_t)\). \(O_t\) is a vector containing the \(R_t\) of DoA measurements from the message sent by location-aware points and the vector \(P_t\) of signal powers. Links between subsequent positions \(X\) are governed by the transition model; edges between \(X\) and observation \(O\) are described by the observation model. Learning consists in estimating transition and observation models from observations, it is executed offline from training data; in particular, the CPDs are estimated through likelihood maximization by using the EM algorithm [18]; this a has heavy computational requirements. An efficient version of EM is presented in [19], in which learning can be executed online by selecting input data through an adaptive sliding window.

2) Inference of position through Particle Filtering: Executing the inference over the DBN consists in obtaining a posterior distribution over \(X_t\) of the model, conditioned to \(R_t\) and \(P_t\). In particular, the recursive estimation of location probability is given by the formula:

\[
P(X_t|R_t, P_t) = \eta P(R_t|X_t, P_t) \left| \int P(X_{t-1}|X_{t-1}, P_{t-1}) P(X_{t-1}|R_{t-1}, P_{t-1}) dX_{t-1} \right|
\]

where \(\eta\) is a normalization constant. We execute inference by applying a particle filtering probabilistic algorithm. The idea [20]–[22] is to draw an identical independently distributed set of \(S\) samples (particles) from a target probability distribution function (PDF), namely \(P(X_{t-1}|R_{t-1}, P_{t-1})\). By following the transition model \(P(X_t|X_{t-1})\) these samples evolve and once observations \(O_t\) become available, they are weighted according to their likelihood, following the sensor model \(P(R_t|X_t, P_t)\). The weighted particles are then sampled to approximate the target PDF \(P(X_t|R_t, P_t)\) with the

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3This information can be considered a sort of Direction of Arrival (DoA) estimation.
empirical point mass function. It is possible to proof that this algorithm is consistent, i.e. it gives correct states probabilities for \( N \) that goes to infinity. The computational complexity of particle filtering is proportional to the number of particles that we want to produce; empirical experiments show that this procedure is efficient and effective [23], since often it can give a good approximation of the real posterior distribution of the variables also using a reduced number of samples.

3) Probabilistic querying of location: We empower the localization system through a procedure inspired by [24], which allows replying to probabilistic queries over the estimated positions as if they were stored into a database. We apply a model-based view of a database, i.e., an abstraction of relational tables whose content is fed by the inference model, either periodically through Particle Filtering or online, only when queries are posed. In our model, the Position Table (Figure 6) contains the following attributes:

- Time: the time \( t \) to which the position refers;
- \( x_t \) and \( y_t \): probability distribution of the coordinates \((x, y)\) in the position vector \( X_t \) of the BSN at time \( t \);
- \( R_i^t \): measurement extracted from message received from location \( i \) at time \( t \);
- \( P_i^t \): power of the signal emitted by location \( i \) at time \( t \).

Associated to the Position Table, a Particle Table holds for each time instant the particles are sampled \((1 \leq s \leq S)\), from which the location distributions and the corresponding weight \( w_{is}^t \) have been estimated. A portion of the Particle Table is depicted in Figure 7.

The Position Table can be queried to extract, e.g., the position at a given time or the most probable position in a time interval. Queries, formulated in standard querying language, like SQL, are processed and converted into single or multiple queries over the probabilistic position table. This scheme allows replying also to queries over a probabilistic attribute and/or confidence value, e.g., to filter out less probable localization hypotheses.
A. System model

To evaluate the performance of the proposed MD-STAR protocol as for the power consumption and latency minimization, extensive numerical simulations have been conducted over a realistic scenario. In fact, it focuses on a challenging scenario comprised of stationary and mobile nodes, which can effectively model a continuous and seamless health monitoring application where the adoption of a novel and cross-layer inspired approach is recommended, representing an evolution of [25]. The most relevant simulation parameters assumed in deriving numerical results are summarized in Table I. In particular, it has been assumed a typical indoor scenario for what the signal propagation is concerned (with a Packet Error rate equal to 5%) and a pedestrian mobility model with velocity in the range [2 - 4] m/s. The adopted antenna model is an ideal switched beam antenna, adopting a group of N almost non-overlapping beams that together result in omnidirectional coverage, so that the patterns main lobes are adjacent. The microcontroller at each node is able to scan the channel according to the MD-STAR protocol, switching to the correct beam corresponding with the user wishing to communicate at that time. In particular, an antenna is able to radiate in a fixed arc or sector of, say, $\frac{2\pi}{N}$ radians, thus providing increased gain over a restricted range of azimuths as compared to an omnidirectional antenna.

B. Numerical results

To give an insight on the protocol energy efficiency, in Figure 8, the relative lifetime as a function of the number of network nodes is presented in the case of directive receiving antennas with two, four, six and eight angular sector, respectively, normalized to the lifetime achieved by using omnidirectional antennas. The remarkable gain provided by the introduction of directive antennas on the fixed WSN gateway nodes is evident in the figure. In particular, it increases at the increasing of the node density (underlying an optimal scalability property), reaching a maximum value of 800%.

The energy efficiency of the proposed MD-STAR protocol can be evaluated by also focusing on the collision probability that depends mainly upon the node density and the presence of the hidden node effect. The underlying CSMA/CA mechanism might fail indeed if neighbor nodes get extremely close or if two or more nodes not belonging to the same coverage area might overlap with a third node when transmitting and the hidden node effect can be evaluated by also focusing on the collision probability that depends mainly upon the node density and the presence of the hidden node effect. The underlying CSMA/CA mechanism might fail indeed if neighbor nodes get extremely close or if two or more nodes not belonging to the same coverage area attempt to transmit toward the same node. To get an insight on this aspect, in Figure 9, the collision probability as a function of the number of network nodes is depicted, again in the case of omnidirectional antennas and directive antennas with two, four, six, eight possible angular sectors, respectively. It could be noticed that the adoption of omnidirectional antennas minimizes the residual packets collisions, even in the case of densely deployed nodes, while the converse is true for directive antennas mostly due to the presence of hidden nodes, since the coverage area gets smaller in terms of azimuth and the increasing number of nodes become invisible. However, as the angular resolution increases, a lower number of nodes might overlap with a third node when transmitting and the communication becomes really point-to-point. This effect is more evident in the case of directive antennas with a number

<table>
<thead>
<tr>
<th>Time</th>
<th>$x_t$</th>
<th>$y_t$</th>
<th>$R^1_t$</th>
<th>$R^2_t$</th>
<th>$P^1_t$</th>
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<tr>
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<td>$r^1_1$</td>
<td>$r^2_1$</td>
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<tr>
<td>2</td>
<td>$x^2_1$</td>
<td>$y^2_1$</td>
<td>$r^3_1$</td>
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Fig. 5. Structure of the localization DBN.

Fig. 6. Schema of Position Table.

IV. PERFORMANCE ANALYSIS

The underlying CSMA/CA mechanism might fail indeed if neighbor nodes get extremely close or if two or more nodes not belonging to the same coverage area attempt to transmit toward the same node. To get an insight on this aspect, in Figure 9, the collision probability as a function of the number of network nodes is depicted, again in the case of omnidirectional antennas and directive antennas with two, four, six, eight possible angular sectors, respectively. It could be noticed that the adoption of omnidirectional antennas minimizes the residual packets collisions, even in the case of densely deployed nodes, while the converse is true for directive antennas mostly due to the presence of hidden nodes, since the coverage area gets smaller in terms of azimuth and an increasing number of nodes become invisible. However, as the angular resolution increases, a lower number of nodes might overlap with a third node when transmitting and the communication becomes really point-to-point. This effect is more evident in the case of directive antennas with a number
of possible angular sectors greater than four, since a kind of spatial deafness occurs in the case of lower values. In this case, a mobile BSN might interact with a higher number of fixed WSNs without interfering. Nevertheless, the slight performance degradation does not affect the overall energy balance, as highlighted in Figure 8.

To conclude this analysis, latency has been investigated in Figure 10. According to these results, the omnidirectional scheme takes the longer time to deliver a packet, due to the higher probability of finding the channel busy. The last characteristic to be addressed is the mean localization error for a pedestrian mobility for an indoor residential scenario. In Figure 11, it is represented as a function of the number of available WSN gateway collecting the ranging information of mobile BSNs (or rather the CH worn by a patient). It is immediate to notice the satisfactory results in terms of the underlying application requirements in the light of the worst propagation characteristics in terms of non line of sight (NLoS) propagation regime.

V. CONCLUSION

The BSNs application is widely considered as the most promising concept for providing an intelligent, context aware sensing architecture for the development of pervasive health care monitoring systems; however, this could be pursued by means of effective protocols design, since wearable or implantable sensor nodes present specific constraints, as far as the limited resources and size, while having a high degree of mobility. In particular, a scenario comprised of a mobile BSN dynamically joining with deployed WSNs has been focused on to allow a context aware monitoring paradigm capable of data and alarm delivering together with target localization. Moreover, the paper has considered a communications framework able to energy effectively manage sleep/active states, together with integrate the presence of directional antennas, according to a cross-layer design. A novel MAC layer protocol, namely MD-STAR, has been proposed, aiming at improving the capabilities of synchronization/localization in a scenario in which a mobile BSN interacts with fixed WSNs, without excessively affecting the setup latency, but achieving a reduction in energy consumption. MD-STAR protocol has been characterized in terms of functional characteristics, together with presenting the overall performance, in terms of network lifetime gain, collision probability setup latency, and localization accuracy, pointing out a remarkable gain with respect to the existing approaches and makes it suitable for applications in a wireless pervasive communication network devoted to facilitate high quality healthcare.

REFERENCES


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