# Chapter 8
# Human Detection and Tracking in Healthcare Applications Through the Use of a Network of Sensors

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**Abstract** One of the most appealing applications of wireless sensor networks (WSNs) is in human detection and tracking. The aim of these applications is to detect if a person is in an area of interest, and to keep track of his location at every instant of time. In recent years, we have seen a growing interest in the development of proposals for the use of WSNs in detection and tracking applications for healthcare. In the particular case of a patient suffering from dementia, it is very important to detect him and keep track of his location at every time, to avoid that the patient may enter to a zone of risk without supervision. When an event of interest is detected, such as wandering, an action may be taken by sending out a notification to the caregiver personnel. In this chapter, we review the most important proposals regarding the use of WSNs for human detection and tracking in healthcare applications. Moreover, we introduce a model for detection of patients suffering from dementia, based on a WSN that uses binary sensors. The proposed model is able to detect if a patient leaves a secure zone without supervision, and to emit alerts directed to caregivers.

## 8.1 Introduction

Human detection and tracking is one of the most attractive fields of application of Wireless Sensor Networks (WSNs). The nodes of a WSN, known as *motes*, work together to monitor the presence of people in the sensed area, and to keep track of their location as they move. Since the motes have limited resources, an important

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design goal for these applications is to achieve a reliable detection of targets with minimal resources consumption. Examples of areas where they can be used are habitat monitoring, surveillance, intruder tracking, and healthcare.

New problems have emerged as a consequence of the fast growth of the urban population experienced during the past few years. Even though people now live longer, the number of deaths caused by neurodegenerative diseases has grown considerably [38]. Among them we have Psychiatric Illness, Dementia (of which Alzheimer's is the major cause), Parkinson's disease, and Autism Spectrum disorders [34]. Unfortunately, these diseases are starting earlier and affecting people under 55 years.

Most of the brain disorders are chronic and incurable, and may last for years or decades. Their economic costs are huge. In Europe, the 2010s total estimated cost was 798 billion euros, of which the 60 % was attributable to direct costs and 40 % to lost productivity [15]. For the family members that take care of patients with brain diseases, it can represent an enormous source of emotional, practical, and financial burden. As world's population ages, the healthcare systems may collapse.

Among brain disorders, one of the major health problems is dementia. Dementia describes a set of symptoms that includes loss of memory, mood issues, and problems with communication and reasoning. The causes of this disease may include a number of progressive illness that affect behavior and the ability to perform daily activities. Two of the most common types of dementia are the Alzheimer's disease and vascular dementia.

Accordingly to the Alzheimer's Disease International, 36 million people suffered from dementia worldwide in 2010, and it is estimated that this number will grow to 66 million by 2030, and to 115 million by 2050. Also, nearly two-thirds of these people live in middle and low-income countries. In addition, the global cost of dementia was estimated at $604 billion USD in 2010, and this cost is expected to grow in proportion to the number of people affected by this disorder [2]. Dementia is the main cause of dependency in the elderly, since they need constant monitoring, imposing a severe burden to caregivers.

To address these issues, the use of WSNs to implement ubiquitous systems to support healthcare activities has been the subject of intense research [1]. To ease the burden on caregivers, in-home and in-hospital WSN-based applications may provide continuous patient tracking, medical monitoring, medical data access, and emergency notifications [43]. In the case of people with cognitive and physical disabilities, the capability of continuous monitoring will increase the chance of early detection of emergency and risk conditions [24]. In addition to the elderly and patients with cognitive disorders, the care services for children may also benefit from these applications.

In this chapter, we review the most important proposals regarding the use of WSNs for human detection and tracking in healthcare applications. Moreover, we introduce a model for detection of patients suffering from dementia, based on a WSN that uses binary sensors. The proposed model is able to detect if a patient leaves without supervision a secure zone, and to emit alerts directed to caregivers.

The rest of the chapter is organized as follows. In Sect. 8.2 we briefly discuss the state of the art of the detection and tracking proposals that use networks of sensors.

Section 8.3 introduces the related work regarding human detection and tracking for healthcare applications. In Sect. 8.4, the proposed model for detection of patients suffering from dementia is presented, and in Sect. 8.5 this model is evaluated and the results are discussed. Finally, Sect. 8.6 is for conclusions.

## 8.2 Target Tracking Based on the Use of a WSN

Target tracking using wireless sensor networks has been the subject of intensive research in the last decade [9]. A WSN tracking application must periodically collect sensed data and use it to reconstruct the overall status of the monitored area using data fusion techniques. The centralized approach is the most commonly used in target tracking algorithms. In it, when the motes detect an event, they record it, and rely on a routing protocol to send the relevant and preprocessed information toward a base station or *sink*. The sink, which is a device with more resources than the motes, collects the data received from the sensor nodes, processes it, and takes the appropriate actions.

The algorithms designed to be used in WSN tracking applications are targeted for the network and application layers, and may assume a static or a mobile sink [8]. Regarding the application layer, two approaches have been used: coarse-grained and fine-grained [25]. Coarse-grained localization uses minimal information, which can include binary proximity [22] or near-far information [16]. In contrast, fine-grained approaches use more detailed information and are based on different types of measurements, such as the received signal strength (RSS) [37], angle of arrival (AOA) [14, 37], time of arrival (TOA) [35], time difference of arrival (TDOA) [36], extended Kalman filters (EKF) [30], and hybrid approaches [23, 47].

Concerning coarse-grained localization proposals, in [22] Kim et al. proposed a target tracking model that relies on the use of binary sensors. Such sensors provide only 1-bit information regarding the presence or absence of a target in the sensed area. Past and current sensor outputs are used to determine the trajectory of the target during small intervals. This trajectory is approximated by a straight line segment. In [41], Shrivastava et al. analyzed fundamental performance limits of target tracking using binary proximity sensors, and determined the accuracy with which a target's trajectory can be tracked. They introduced a geometric algorithm to derive linear paths that approximate the trajectory of the target, and they extended their proposal for multiple target tracking in [42]. The *Dynamical Object Tracking* (DOT) algorithm was introduced by Tsaia et al. [44]. It assumes a mobile sink since it was devised to guide a mobile user to chase a moving target. The motes that detect an intruder record the event. When the mobile user requires the target location, it sends queries that are replied by those motes that have tracking information, guiding the mobile user until he catches the target. The algorithm uses the knowledge of spatial neighborhood defined on a planar graph, where the face neighbors are identified by a Gabriel Graph. Bugallo et al. [7] addressed the problem of multiple target tracking using particle filtering. Under this approach, the algorithms need a very large number of particles when the sensed area is moderately large. To face this problem, they partition the state space of the system into different subspaces, and run a separate particle filter for each subspace.

In [12], Djuric et al. proposed the use of the auxiliary particle filtering (AFP) and the cost-reference particle filter (CRPF) algorithms for tracking a single target using data from binary sensors. The adopted model for sensor measurements was the signal strength. Vu and Zheng addressed the problem of target detection and tracking using binary proximity sensors with location uncertainty in [45]. The uncertainty was modeled as disks of possibly different radius around the nominal positions. They introduced the concept of order-$k$ max Voronoi Diagrams (VD) that tessellates the area of interest into regions that are closer to $k$ sensors in the worst case, to determine the minimum sensing radius needed to ensure worst-case $k$-coverage. Their work was extended in [46]. Le and Kaplan [27], proposed a probability hypothesis density (PHD) filter for multi-target tracking using proximity sensors. This method was able to estimate the number of targets and localize them regardless the target separation for sufficient sensor density.

Concerning the fine-grained detection approach, Arora et al. [4] introduced a surveillance system using inexpensive sensor nodes. In their model, intrusion data are processed locally at each node, and if an anomaly situation is detected, data are shared with neighboring nodes, and communicated to a gateway with wide area networking capability. The model considers three user requirements: target detection, classification, and tracking. The user may specify the QoS parameters that affect how well the system detects, classifies, and tracks targets. Sheng and Hu proposed a target location method using microphones in [40]. This method is based on a maximum likelihood estimation of both the source locations and corresponding acoustic energy readings. Since this method uses nonlinear optimization, two complementary methods were proposed to solve this nonlinear optimization problem.

He et al. proposed in [17] a monitoring system for use in military applications, such as a surveillance system, that is able to operate for long periods of time. Using magnetic sensors, the system allows a group of cooperating motes to detect and track the positions of moving vehicles. It is able to tradeoff between energy-awareness and surveillance performance by adaptively adjusting the sensitivity of the system. Based on this work, He et al. later developed *VigilNet* [18], a large-scale real-time WSN system that allows detecting, tracking, and classifying targets within a reasonable period of time, while making efficient use of energy. *VigilNet* is a system designed for spontaneous military operations in remote areas, where events of interest happen infrequently and with a short duration, such as intruder-related events. The system is organized into a layered architecture comprised of higher-level services and lower-level components. The latter includes time synchronization, localization, and routing, and forms the basis for implementing the higher-level services, such as aggregation and power management.

In [30], Lin et al. introduced an EKF-based distributed adaptive multisensor scheduling scheme for energy efficiency, to improve tracking accuracy. Since more sensors can achieve better tracking accuracy, the proposed scheduling scheme calculates the optimal sampling interval, selects the nodes that will conform the cluster, and designates one of them as the cluster coordinator. The sensor scheduling problem is formulated as an optimization problem and solved by a sequential three-step heuristic algorithm. Wang et al. proposed in [47] an approach for target tracking for WSN by combining maximum likelihood estimation and Kalman filtering using the distance measurement. The maximum likelihood estimator is used for pre-localization of the target and measurement conversion. The converted measurement and its associated noise statistics are then used in a standard Kalman filter for recursive update of the target state.

A method for RF tomographic tracking of a single target using a wireless sensor network was introduced by Li et al. [29]. RF tomographic imaging involves an image reconstruction step to estimate target locations. To avoid imaging processing, the proposed method uses a particle filtering (Sequential Monte Carlo) approach. In order to reduce the computational complexity of the algorithm, they introduced a new measurement model that does not *pixelize* the region of interest. In [49], Xu et al. addressed the problem of mobile target tracking based on a TOA measurement model. The signals emitted by the mobile target are collected by the sensor nodes, which records the signal's time of arrival (TOA). A mobile sensor also emits signals to allow the motes to collect the needed information to determine its location. This mobile sensor can also measure signal from the target. In the data fusion center, a mobile sensor controller directs the mobile sensor toward the target location. To track a moving target with a mobile sensor, the data fusion center must estimate the locations of both the target and the mobile sensor. The proposed model accounts for the measurement noise due to multipath propagation and sensing error. It uses a min-max approximation approach to estimate the targets location that can be efficiently solved by means of semidefinite programming (SDP) relaxation.

## 8.3 Human Detection and Tracking for Healthcare Applications

As the world's population ages, there has been a great interest in the development of ambient intelligence solutions to assist the elderly, particularly, those suffering from the Alzheimer's disease and related problems [24]. We can categorize the proposals regarding human detection and tracking for healthcare as invasive and non-invasive. In the former, the detection and tracking model considers the use of devices attached to the target's body. In contrast, in non-invasive models, the use of these devices is not required.

Regarding invasive proposals, the *Assisted Living Monitoring and Analysis System (ALMAS*), introduced in [33] by Marques et al., extended the concepts and ideas of the *CodeBlue* project [31] by incorporating RFID technology, and employing sophisticated video analysis algorithms for patient location, tracking, and monitoring. Wireless transceivers are located throughout the facility (e.g., a geriatric residence), which communicate with the RFID tags and wearable units worn by the patients to track and locate them. The video analysis software examines the information that is continuously recorded by the video cameras, in order to detect if there is any anomalous situation, such as when a patient leaves his room toward an unauthorized area, or if a patient has fallen down.

In [19], the location tracking *Ultra Badge* system was proposed to be used in a hospital setting, with the aim of detecting falls and wandering. The system was composed of two subsystems: an ultrasonic radar subsystem, and a wheelchair locator subsystem. The first one monitors the human head's position on and around the bed, in order to detect falls. The second one is used to detect wandering, assuming that the patient uses a wheelchair. The system consists of embedded ultrasonic receivers, embedded/wireless ultrasonic emitters (named *Ultra Badges*), and a WSN that connects receivers and emitters. In [21], Intille et al. introduced *PlaceLab*, which is part of the *House_n* project, and share some of their experiences in regard to constructing and operating the living laboratory. It included the use of hundreds of sensors deployed in a live in laboratory, in order to research the use of ubiquitous computer technologies in home settings. The laboratory was designed to support the collection of rich, multimodal sensor datasets of domestic activity, which are intended to be shared among researchers working on context-aware ubiquitous computing technology, preventive healthcare, energy conservation, and education.

Bardram et al. proposed in [6] a set of context-awareness applications and technologies to be used in hospitals. The proposed system consisted, among other components, of an indoor location tracking system that uses the Bluetooth technology, and a context-aware mobile phone application. The location and tracking system was designed to locate staff, patients, and equipment, using smartphones and Bluetooth tags.

*AlarmNet*, introduced in [48] by Wood et al., is a system for assisted living and residential monitoring which uses a WSN. *AlamNet* consists of wearable body networks, emplaced wireless sensors, user interfaces, and back-end processing elements. The body network includes sensors for heart rate, oxygen saturation, and ECG. Emplaced sensors are deployed in living spaces to sense environmental quality, such as temperature, dust, and light, or resident activities. Motion and tripwire sensors enable location tracking. However, it is not explained how the location and tracking processes are conducted. In [10], Corchado et al. proposed *GerAmi*, an intelligent environment that integrates multiagent systems, mobile devices, RFID bracelets, and Wi-Fi technologies, to facilitate the management and control of geriatric residences. To track the location of a patient, the signal emitted from the bracelets is used by the ID readers installed on the doors. The readers forward the data to a controller, which sends a notification to a system agent that manages and forwards the information to a mobile device, where the medical staff can identify the patient's location.

An indoor system for patient tracking and monitoring system was proposed in [13]. The system is capable of determining the location of a patient, and monitoring motion activity. In this proposal, patients must carry a mobile node comprised of a RF transceiver and a 3-axis accelerometer. A localization WSN is used, consisting of static nodes, placed at known positions throughout a house or geriatric residence. The mobile nodes transmit a beacon message every 50 ms. The static nodes that receive the message will forward it to the sink, where a localization module runs.

It uses the number of the received beacon messages per static node that has the same sequence number to determine which static nodes are in proximity to the mobile node. Delaunay triangles are used to create a grid of possible regions where the target could be located. If three static nodes are found to be in proximity, the corresponding Delaunay triangle is used to determine the position of the patient. A tracking system for the elderly is proposed by Yan et al. [50]. It is based on a mixed localization algorithm that relies on sensors attached to the wrist of the patients, and the received signal indicator (RSI). The system is able to track the location of a patient regardless of whether or not he is wearing the sensor node.

Armaini et al. proposed in [3] a tracking system based on the combination of wearable sensors and a video analysis module. The wearable sensor is a mobile node that is fixed on the belt of the patient. It embeds an Inertial Navigation System (INS) consisting of gyroscopes, accelerometers, and a compass. Data is fused using an Extended Kalman Filtering (EKF). Once the wearable node detects the patient's location, the corresponding video camera is activated to confirm the presence of the patient in the predicted area.

Concerning non-invasive proposals, Marco et al. introduced *ZUPS* in [32], a ZigBee and ultrasound-based positioning system. *ZUPS* was intended to emit an alarm when a risky situation is detected, such as wandering. The system uses ZigBee (radio-frequency) and ultra-sound to measure distances between tags carried by the patients, and beacons with known locations. Additionally, an accelerometer and a button are integrated into the devices worn by the patients, to detect falls. A similar approach was used in [20], where Huang et al. proposed a patient alert system for fall management. It is a ZigBee-based location awareness and fall detection system that provides immediate position information to the caregivers as soon as it detects that a patient fell. Redondi et al. proposed *LAURA*, the *Localization and Ubiquitous Monitoring of Patients for Healthcare Support* in [39], which is an integrated system based on wireless sensor networks for patient monitoring, localization, and tracking. In their paper, the authors discuss the two proposed approaches of the localization and tracking engine. The first one is a centralized implementation, where localization is executed centrally using the information collected locally. The second approach is a distributed solution, where the localization is performed at the mobile nodes and the outcome is delivered to the central controller. The personal localization and tracking subsystem (PLTS) uses a localization algorithm based on the received signal strength and the fixed distance between nodes.

In [26], Laoudias et al. discuss the proposal of an architecture which combines the sensor health state estimation together with fault tolerant localization algorithms, to be used in a binary WSN. The proposed architecture has three main components. The Sensor State Estimation component determines the health state of each sensor. The Localization component uses the information generated by the previous module, and ignores any information coming from what are thought as faulty sensors. Finally, the target location estimate is sent to the Smoothing component, which filters the current location estimate using a particle filter.

As it can be observed, most of the proposals described here require the use of physical devices attached to the person that is being monitored or tracked, such as

RFID bracelets. However, patients with dementia tend to reject noticeable gadgets. For this kind of patients, we need a device-free passive localization [51], which is able to detect and track persons that do not carry any device.

## 8.4 Architecture of the Proposed System

Healthcare applications may benefit greatly by the use of networks of sensors. For instance, since it is not necessary the existence of a previous infrastructure (e.g., cables) to deploy it, the system may have a high degree of flexibility. Additionally, they provide the possibility of implementing homogeneous systems by integrating almost any sensor to the nodes constituting the WSN. This means that using only the WSN it is possible to detect a large number of events. Also, they allow the development of ambient intelligence healthcare solutions through the integration of wireless sensor networks with pervasive computing, fusion information, and artificial intelligence techniques.

The aim of the proposed model is to support the care process of patients with dementia. It is an extension of the model introduced in [11]. In particular, the objective of the extended model is to add robustness to the former one, when detecting a patient leaving a safe location without supervision. The specific objective is to identify if a patient leaves a room, having arrived there by himself or by someone else, such as a nurse.

As discussed previously, some proposals that have been published to date also consider the use of ubiquitous computing to implement healthcare monitoring and tracking applications. However, most of them include the use of devices attached to the person that is being monitored, and that are hardly accepted by dementia patients. Our purpose has been to investigate how to monitor dementia patients using non-invasive techniques, as the one used in the system discussed in [51] for patient location, or the one discussed in [5] for falls detection. However, unlike these proposals that use the strength of the signal detected by the sensors, we wanted to develop a simpler solution using inexpensive binary sensors. In addition, the use of binary sensors reduces the processing overhead, allowing a faster system response. In our model, the sensors produce binary outputs without the need of filter them to achieve binary signals.

Non-invasive techniques are helpful when it is not possible or convenient use invasive methods. Additionally, the proposed model can be used together with an invasive model to improve the system's performance. It can be used also as a redundant system to detect events of interest, in case that the main systems fails. For instance, if the patient removed the RFID bracelet attached to him.

In order to select the most suitable sensors to successfully detect if a patient leaves a room, and taking into consideration the results published in the literature, we conducted several tests using different types of sensors. The choice was made based on the accuracy in detecting the changes in the environment, and their relationship with the amount of processing to be given to the output received from the sensor.

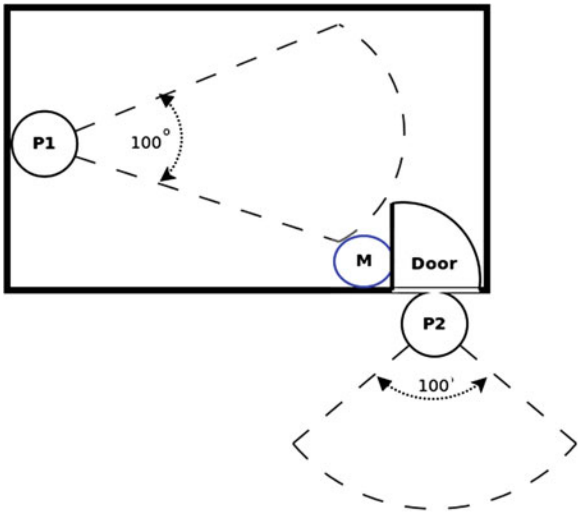


**Fig. 8.1** System deployment

Two of the sensors tested showed a very good performance: passive infrared sensors, and magnetometers.

Passive InfraRed (PIR) sensors measure the infrared light emanating from objects. They are cheap sensors that detect the presence of heat from an object or body nearby. They are also capable of detecting the movement of people when a temperature change occurs. Motion detectors usually use PIR sensors. On the other hand, magnetometers are sensors that detect the change of direction of a magnetic field. When placed on the doors of the rooms, it is possible to know if they were opened or closed. However, we require that the system would be able to decide if the door was opened because someone entered the room, or opened for a person to leave the room. For this, we propose an algorithm that uses information fusion techniques to combine the values measured by PIRs and magnetometers, to determine whether a person enters a room ($I$), or leaves a room ($O$).

Because there are many scenarios to consider for the detection of wander, we propose another algorithm that combines the measured values of the sensors, and the events $I$ and $O$, to determine if a patient leaves a room without authorization. The system deployment is shown in Fig. 8.1.

### 8.4.1 Non-invasive Tracking Algorithms

In order to be able to design a WSN-based algorithm to detect when a patient enters or leaves a room, it was important to understand the relationship between the data collected by the sensors. To achieve this, we conducted a set of experiments using the deployment shown in Fig. 8.1. As it can be observed, a node equipped with a magnetometer ($M$) was placed on the door of the room, whereas two nodes using a PIR sensor were placed on a wall inside the room ($P_1$), and on top of door ($P_2$), outside the room, respectively. It is important to note that the deployment of the sensors is important in our model. The PIR sensor placed on the wall ($P_1$) must detect any event around the room's door. The second PIR ($P_2$) must sense any movement close to the door, outside the room. The magnetometer must be able to detect any movement of the door.

The sensors were activated when an event of interest took place (e.g., motion is detected in the room). Afterward, they periodically sensed the environment until no activity was detected. The data collected by the sensors was sent to the sink.

An important observation from the analysis of the data obtained from the experiments, is that it is possible to differentiate the event of a *person entering the room* ($I$), from the event of a *person leaving the room* ($O$), using the values recorded from the sensors. To illustrate this, Fig. 8.2 shows the data collected from the sensors when a person enters the room, and later when a person leaves the room. We can observe that in the former case, we first got data from the magnetometer, followed by data received from both $M$ and $P_1$ sensors, and finally data from the $P_1$ sensor. In contrast, in the later case we first received data from the $P_1$ sensor, followed by data received from both $M$ and $P_1$ sensors, and finally we received data from the magnetometer, and also from the $P_1$ sensor if a person stays in the room. Using the above relationships between the values measured by the sensors as a function of the time, it was possible to design an algorithm based on information fusion techniques, to determine the type of event occurred (i.e., $I$ or $O$).

In our model, $S_t$ represents a sample recorded by a sensor node, where $t$ is the time when the event was detected. $S \in (M,\ P)$, where $M$ is a sample recorder by the

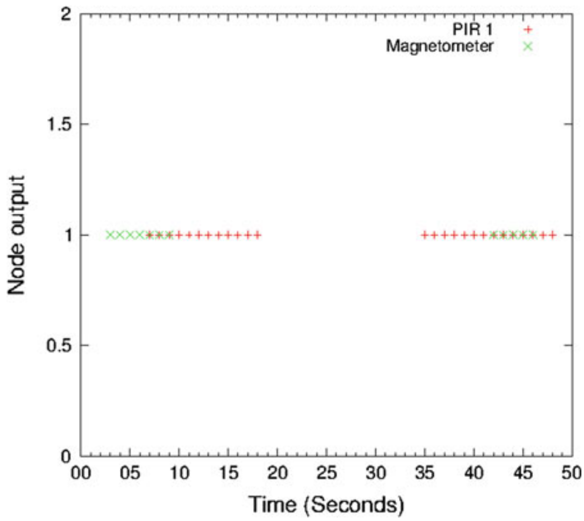


**Fig. 8.2** Values measured by the sensor when a person enters and leaves a room

magnetometer, and $P$ by the PIR sensor on the wall of the room, which are the only sensors needed to detect either $I$ and $O$ events. The events of interest are: $I$, a person entering the room, and $O$, a person leaving the room. For instance, considering the behavior of an $I$ event, and assuming, without loss of generality, that the event starts at $t = 1$, and that the sampling period $T$ is 1 second, the event can be represented as:

$$I = (M_1, M_2, \ldots, M_i, P_j, M_{i+1}, P_{j+1}, \ldots, M_k, P_{k+1}, \ldots, P_{n-1}, P_n).$$

As it can be observed, the event takes place in the interval $(1, n)$. The magnetometer detects activity in the interval $(1, k)$, whereas the PIR sensor detects it in the interval $(j, n)$. During the interval $(i, k)$, we have that the time elapsed between two consecutive samples, named $t$, satisfies the relationship $0 \leq t \leq T$. We call *intersection* the interval $(i, k)$. The samples $S_t$ are stored in a sliding window $W$ of size $ws$.

The characteristics of the patients can vary depending on the age, type of disease, among other things. Also, the conditions of the rooms vary considerably in size, distribution, weight, and orientation of the doors, just to name a few. Because of this reason, the proposed model requires a training stage, to determine the values of parameters of interest of the events that are used by the algorithm. The parameters of interest are: the mean and standard deviation of the number of samples of the $I$ and $O$ events, named $\bar{S_I}$, $\sigma_{S_I}$, $\bar{S_O}$, and $\sigma_{S_O}$, respectively. Also, the mean and standard deviation of the number of samples collected by the magnetometer before the intersection in an $I$ event, $\bar{M_I}$ and $\sigma_{M_I}$, respectively; the mean and standard deviation of the number of samples collected by the PIR sensor after the intersection in an $I$ event, $\bar{P_I}$ and $\sigma_{P_I}$, respectively; the mean and standard deviation of the number of samples collected by the PIR sensor before the intersection in a $O$ event, $\bar{P_O}$ and $\sigma_{P_O}$, respectively; and the mean and standard deviation of the number of samples collected by the magnetometer sensor after the intersection in a $O$ event, $\bar{M_O}$ and $\sigma_{M_O}$, respectively. Finally, the threshold values $TM_I$, $TM_O$, $TP_I$, and $TP_o$, which are of the maximum number of samples recorded by the magnetometer and PIR sensors, and their respective standard deviations, before and after an intersection, for both events. To obtain these parameters, data is collected in the training stage, from the $I$ and $O$ events, for each patient and a room.

When the nodes discover activity, they send the collected data to the sink, where each sample is stored in the sliding window. The algorithm detects the beginning of an event when the time elapsed between two consecutive samples is equal or less than $T$. The event finishes when the previous condition is not satisfied, or when the number of samples is large enough to conclude that an event of interest has taken place. To determine if an event $I$ or $O$ has taken place, the following expression is used,

$$E = 1 - \frac{\left|NS - \bar{S}_E\right|}{\lambda \cdot \sigma_{S_E}}, \tag{8.1}$$

where $NS$ is the number of samples of the event, and $\lambda$ is a constant. If $E \geq 0$, the algorithm concludes that an event has occurred.

The $NS$ parameter is the sum of the number of samples before, during and after the intersection. In the former and latter cases, if the number of samples are greater than a threshold, then the threshold value is used. The mean and the standard deviation of the number of samples can be used as a threshold value. The algorithm is described in Fig. 8.3. It can be observed that the function `event()` is used to determine the type of event, which can be $I$, or $O$.

For instance, consider the case of the $I$ event discussed previously. The algorithm first receives the data sent by the magnetometer collected in the interval $(1, i)$, followed by an intersection (data sent by both nodes) collected in the interval $(j, k)$, and finally the data sent by the PIR sensor, collected in the interval $(k+1, n)$. Then, it calculates the following, as shown in the algorithm of Fig. 8.3:

- $b = \sum_{t=1}^{i} M_t$ if $b \leq \bar{M}_I + \sigma_{M_I}$; $b = \bar{M}_I + \sigma_{M_I}$ otherwise;
- $m = \sum_{t=j}^{k} S_t$;
- $l = \sum_{t=k+1}^{n} P_t$ if $l \leq \bar{P}_I + \sigma_{P_I}$; $l = \bar{P}_I + \sigma_{P_I}$ otherwise; and
- $NS = b + m + l$.

To determine if an $I$ event has occurred, the algorithm evaluates the following expression:

$$E_I = 1 - \frac{\left|NS - \bar{S}_I\right|}{\lambda \cdot \sigma_{S_I}}. \tag{8.2}$$

Finally, if $E_I \geq 0$, the algorithm concludes that an $I$ event occurred.

The second algorithm uses the temporal relationship maintained by the order in which the sensors are activated, when someone leaves a room without supervision. Through various experiments, it was observed that this is the occurrence of events, or a change of states in the environment in a particular order. For instance, when a patient leaves a room, he first performs an activity within it (such as walking), later the door is opened, and finally, there is no activity in the room. We assume that only authorized individuals can enter the room through a security mechanism. The state machine (SM) shown in Fig. 8.4 depicts the proposed algorithm.

The SM has five states representing changes in the patient's environment. State 0 represents that the room is empty, while State 4 represents a patient left the room without supervision. States 1, 2, and 3 are transitional states, and represent: one or two people entered the room, another person entered the room with the patient inside, and that a person has left the room leaving inside the patient, respectively. State changes may occur as a consequence of the events produced by the sensor measurements, evaluated as a function of time. The events that cause state changes are: $I$, representing an input is detected; $O$, representing that an output was detected; $P_1$, which means that the PIR sensor placed on the wall detects activity in the room; $N_1$, which represents a period of inactivity inside the room, $P_2$, which means that the PIR sensor placed on the door detects activity outside the room; and finally $N_2$, which represents no activity is detected outside the room. In our former model [11],

```
/* Input: S_t, samples collected by sensors,
   conformed of a timestamp (ts) and node id. */
/* Output: e, type of event (I, O, P, or N) */
while (true) do
   i=b=m=l=0;
   b_node_id = l_node_id = NULL;
   w[i]=S_t;
   i++;
   w[i]=S_t;
   while ( w[i].ts - w[i-1].ts ≤T ) do
      b_node_id = w[i].id;
      b = 2;
      i++;
      w[i]=S_t;
      while [ ( w[i].ts - w[i-1].ts ≤T ) and
            (w[i].id == w[i-1].id) ] do
         b++;
         i++;
         w[i]=S_t;
      m = 1;
      i++;
      w[i]=S_t;
      while [ ( w[i].ts - w[i-1].ts ≤T ) and
         !( w[i].id == w[i-1].id == w[i-2].id ) ] do
         if(w[i].lastElement.id == P2)
               m++;
         i++;
         w[i]=S_t;
      l = 1;
      i++;
      w[i]=S_t;
      if(b_node_id == INPUT)
         b_threshold = b_thresholdInput;
         l_threshold = l_thresholdInput;
      else
         b_threshold = b_thresholdOutput;
         l_threshold = l_thresholdOutput;

      while [ ( w[i].ts - w[i-1].ts ≤T ) and
            (l ≤l_threshold) ] do
         l_node_id = w[i].id;
         l++;
         i++;
         w[i]=S_t;
      if (b ¿ b_threshold)
         b = l_threshold;
      e = event(b, m, l, b_node_id, l_node_id); // using Eqn. 1
      send_event(e);
   i++;
   w[i]=S_t;
```

**Fig. 8.3** Algorithm 1

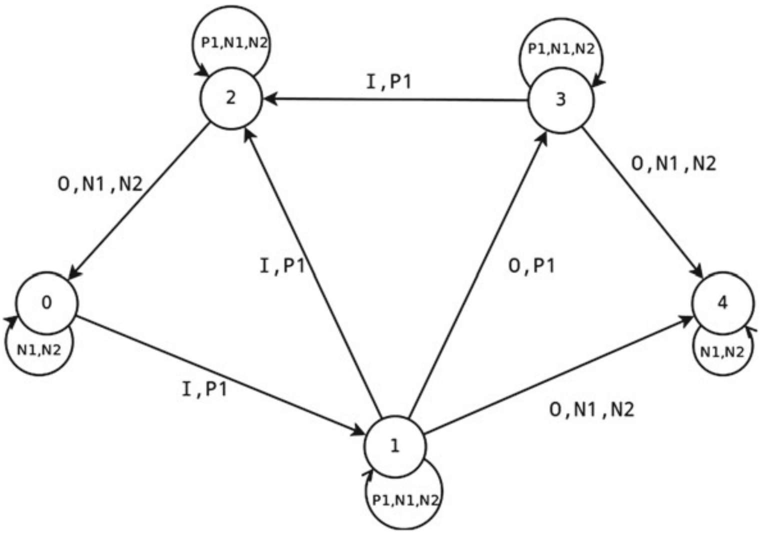


**Fig. 8.4** State machine

it was difficult to detect the transition from State1 to State2, and from State2 to State0. The inclusion of the PIR outside the room's door enables a more accurate detection of these cases. Additionally, the model is able to detect a patient leaving the room even when there are people standing or moving outside the patient's room.

We restricted our model to the scenarios described above since they represent common situations in geriatric residences, or at home, where family members take care of a person affected by the Alzheimer's disease. In these cases, the patient is under constant supervision, with the exception of special situations. For instance, when the patient goes to sleep, or when the caregiver is busy preparing meal. Our model is aimed to be used in these and similar cases. Otherwise, the system can be deactivated. It is important to note that our model is able to distinguish whether the patient or caregivers are leaving the room.

On the other hand, if the proposed system is deployed to be used in different scenarios, some minor modifications to the proposed algorithm are required, and perhaps it would be necessary the addition of more sensors. It is important to note that our purpose has been to show that is possible to define a non-invasive method to detect events of interest, using inexpensive binary sensors.

## 8.5 Evaluation

The proposed algorithms were evaluated using a room with only one access, and simulating various activity scenarios. We implemented a prototype of the proposed model and conducted a series of experiments to evaluate it.

To implement the prototype, the nodes used were equipped with two types of sensors. One was the PIR sensor, which can detect people's movement through the energy they emit. The PIR sensor used has a maximum radial detection distance (straight ahead) of 7 m, and a detection angle of 100°. The second PIR sensor was placed on the outside wall of the room, above the door. The other sensor used was the magnetometer, which detects the change in the magnetic field direction. This sensor is used in conjunction with a magnet integrated in the door, to detect when it is opened.

The WSN was composed of four nodes. Three of them used an IRIS hardware platform, which was programmed using the *nesC* language and the *TinyOS* operating system [28]. These nodes have a MTS300CA board, one of them containing a magnetometer and two of them containing PIR sensors. The third node was used as a sink, and was connected to a personal computer via an interface board MIB520.

We used a DYP-ME003 model PIR sensor. It is a digital sensor that has a *true* output when someone enters to its detection area. The PIR sensor output depends on the electric current in its power source. This implies that, when the magnitude of the current decreases, so it does the magnitude of the high level output of the PIR sensor.

To increase the lifetime of the PIR sensor node, and for a more certainty in its measurements, the PIR sensor was connected to an LM741C model operational amplifier (Opamp), which is connected using a magnitude comparator configuration. The amplifier output was connected to a MDA300CA board. This connection is illustrated in Fig. 8.5. Note that the values of resistors connected have 10 KΩ, and $V_{cc} = 5$ VDC.

We conducted a set of controlled experiments to evaluate our first algorithm. The goal of this set of experiments was to corroborate whether the algorithm was able to detect a person entering and leaving the room. From the training stage, we obtained the following parameters values: $\bar{S}_I = 18.45$, $\sigma_{S_I} = 1.67$, $\bar{S}_O = 21.9$, and

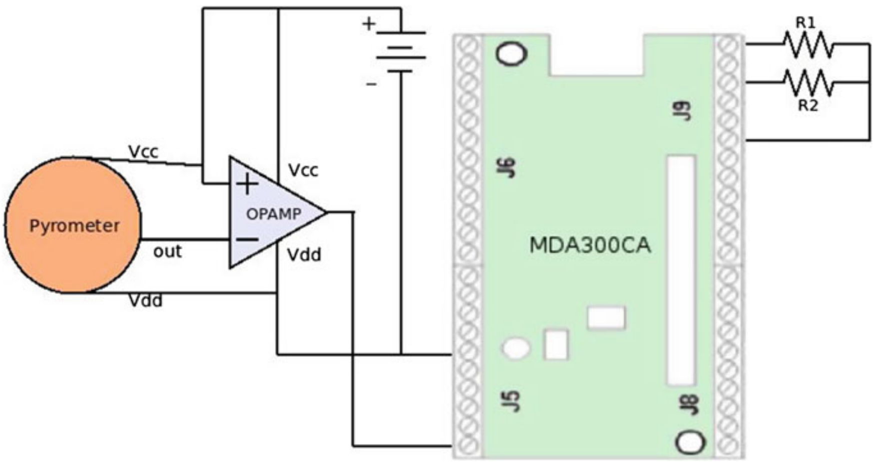


**Fig. 8.5** PIR sensor connected to aMDA300CA board

**Table 8.1** Results obtained from the evaluation of event $I$

| $\lambda$ | Detected | False negatives |
|---|---|---|
| 1 | 13 | 7 |
| 1.1 | 13 | 7 |
| 1.2 | 14 | 6 |
| 1.3 | 14 | 6 |
| 1.4 | 14 | 6 |
| 1.5 | 15 | 5 |
| 1.6 | 15 | 5 |
| 1.7 | 17 | 3 |
| 1.8 | 17 | 3 |
| 1.9 | 18 | 2 |
| 2 | 18 | 2 |

**Table 8.2** Results obtained from the evaluation of event $O$

| $\lambda$ | Detected | False negatives |
|---|---|---|
| 1 | 13 | 7 |
| 1.1 | 13 | 7 |
| 1.2 | 13 | 7 |
| 1.3 | 16 | 4 |
| 1.4 | 16 | 4 |
| 1.5 | 16 | 4 |
| 1.6 | 18 | 2 |
| 1.7 | 18 | 2 |
| 1.8 | 18 | 2 |
| 1.9 | 19 | 1 |
| 2 | 19 | 1 |

$\sigma_{S_O} = 1.12$. We performed 20 experiments of a person entering a room, and 20 more leaving the room, in the training process. The results of the algorithms evaluation for the events $I$ and $O$ are shown in Tables 8.1 and 8.2, respectively. It can be observed that the algorithm showed a good performance for $\lambda \geq 1.8$.

Next, we wanted to evaluate if our model was able to detect when a patient leaves a room without supervision. In order to do that, we conducted series of controlled experiments using diverse scenarios, recreating real situations of patients in a healthcare residence. The scenarios that we evaluated were: (a) the patient arrives alone to the room, and leaves the room by himself; (b) the patient is accompanied to the room and leaves it alone; (c) the patient enters the room alone, and leaves it with the help of an authorized person; and (d) the patient arrives and leaves the room accompanied by a person. We conducted 20 experiments of each scenario. In these experiments, we used $\lambda = 2$. Table 8.3 shows the obtained results from the experiments. As we can observe, the proposed algorithm showed a very good rate of detection of the events of interest. As we can observe from Table 8.3, scenario $d$ showed the worst

**Table 8.3** Evaluation of the second algorithm

| Scenario | Rate of detection (%) |
|---|---|
| a | 90 |
| b | 80 |
| c | 80 |
| d | 70 |

detection rate. This is because the parameters of the system were obtained from the training stage considering only one person, and in this scenario two people are involved: the patient and the caregiver. A change in the parameters (e.g., a larger $\lambda$) may provide a better detection rate.

## 8.6 Conclusions

The fast urban population growth and the aging of the world population are imposing a heavy burden in the government's healthcare and financial systems. One of the major health problems of the elderly is dementia. Dementia is the main cause of dependency in older people, since they need constant supervision. Alzheimer's disease and vascular dementia are the most common types of dementia. The use of sensors of networks to assist the elderly has been a subject of intensive research in recent years. In this chapter, we reviewed some of the most important proposals regarding the use of wireless sensor networks for target tracking. Also, we discussed some of the proposals published to date about human detection and tracking for healthcare applications.

We introduced a pervasive computing model, based on the use of a WSN, to support the activities of assistance and monitoring of patients with dementia. Using high-availability and low-cost binary sensors, the proposed model has been designed to detect in real-time when the patient enters a secure zone, and to emit alerts if he leaves it. Particularly, we proposed two algorithms to determine if a patient leaves a room without supervision, assuming the use of a WSN equipped with passive infrared sensors and magnetometers. The evaluation of the proposed algorithms showed that they are able to detect efficiently when a patient leaves a room without supervision. In addition, the proposed model can detect events in more complex scenarios with minor modifications and the addition of more sensors.

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