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An approach for predicting health status in IoT health care

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Abstract

Monitoring the vital signs of patients and thus predicting the health status of a patient in the Internet of Things (IoT) healthcare applications is the primary goal of healthcare systems. One common approach in these works is the detection of the activity of the patient (activity recognition) based on sensors in the environment. However, this method requires many sensors to record the patient's condition, which can be costly and inconvenient. These methods cannot predict the health status of a patient, and can only detect current abnormal behavior. In this paper, we propose for the first time a method for predicting both ECG sensor data and the most likely health status of the patient, which does not need a common activity recognition method to predict the health situation of the patient. The proposed approach predicts future mobile sensor data and the overall health status of the patient using a hidden semi-Markov model (HSMM) with two outputs. We achieve an accuracy of 83% on average in predicting the health status of the patient. Furthermore, Our approach does not need to deploy many sensors to monitor behavior of the patient, and it is more convenient for patients.

Keywords: IoT healthcare, MHealth status prediction, Hidden Markov Model, ECG sensors, Health-care

1. Introduction

Healthcare is among the most well-known and popular IoT applications and aims to monitor a patient's vital signs on a 24/7 basis, eliminating the need for the patient to be hospitalized. Although electronic health (e-health) systems were introduced before the emergence of IoT, in traditional healthcare applications two-way communication between sensors and a remote server is not possible, and a gateway/remote server cannot directly communicate with the sensor nodes. The IoT makes this possible by leveraging existing Internet protocols such as IPv6, which enable the direct addressing of various devices and sensors through the Internet [1].

In a healthcare system, various sensors are deployed to monitor the vital signals of the patient(s),

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including environmental monitoring sensors, and these tend to be inconvenient for the patient and costly.

There are two ways to detect and predict a patient's health status: either with or without activity recognition methods. Non-activity-based recognition methods can be further categorized into two groups, namely conventional and IoT-based methods. In conventional methods, the health data of a given patient are stored and further analyzed by different learning methods, to detect the most significant factors in diseases [2]. This is done using learning methods such as ANN or fuzzy logic. Srinivas et al. applied different classifiers including rule-based approaches, a decision tree, naive Bayes and an artificial neural network to a massive healthcare dataset containing attributes relevant to heart attacks. Their study showed that the naive Bayes approach outperformed other methods. In the current paper, our model is capable of online health status prediction per user, based on the temporal and spatial data of the patient [3]. Fuster-Parra et al. considered 23 attributes to increase the accuracy of offline cardiovascular risk assessment. They used multiple classifiers and found that a Bayesian network generated the best accuracy [4]. These solutions do not use the characteristics of the IoT in recognizing an abnormal status. Furthermore, they cannot predict (and can only detect) an abnormal status, and do not update their constructed models according to new data.

IoT solutions that are not based on activity recognition methods can only detect the status of the patient. They are inaccurate [5] and unable to predict the abnormal status of the patient. Some recent studies [6, 7] have focused on using support vector machines (SVM) to classify anomalous behavior using a data set based on door sensors within a home, but these are manually annotated. Moreno et al. [5] proposed a solution for detecting abnormal situations in home environments, oriented mainly towards elderly people and those living alone. This study is the most closely related to our work. The main hypothesis of this paper is to demonstrate that by merely analyzing the different locations of the inhabitants within a house, it is possible to teach an automatic system the patterns of these users, and thus to determine whether there is something strange in these behaviors. However, our solution is more accurate, since we consider ECG data over time and the location of the patient. The above authors use sensors to collect patient movement, whereas our solution uses a HSMM with two outputs, which can predict the subsequent location of the patient, and using ECG data can predict a normal/abnormal status more accurately. Kumara et al. [8] have proposed an abstract schema for an IoT healthcare system in which the monitored data of a patient are transformed into a social system that clusters patients with similar behaviors for symptom analysis. Their schema includes a prediction system for predicting anomalies; however, this is an abstract schema and is not implemented. The related works either propose only an abstract schema or are not sufficiently accurate; they also need a great deal of historical data to detect an abnormal status for the patient.

There are several studies which examine the feasibility of identifying abnormal behavior by finding behavior patterns that are dissimilar to learned normal patterns [9, 10]. Many studies have demonstrated the feasibility of training a classifier to detect a specific event, especially falls [11, 12, 13, 13, 14, 14, 15, 16]. Clustering algorithms have also been used to identify abnormal behavior patterns [17, 18].

Meng et al. propose an online daily habit modeling and anomaly detection (ODHMAD) model, which can perform daily activity recognition, habit modeling and anomaly detection for solitary older adults within their living spaces. ODHMAD consists of an online activity recognition (OAR) model and a dynamic daily habit modeling (DDHM) component. OAR performs online processing of sensor data to identify daily activities and urgent events for the elderly [19]. However, this method cannot predict anomalous behavior and also requires extra sensors to detect the behavior of the patient. However, these prediction methods are important, as they can predict an abnormal status for patients and help them survive.

Suryadevara et al. define wellness to monitor the activity of older adults. They carry out real-time activity recognition in elderly patients and determine the wellness function for these patients using appliance-based activities. Six types of sensors must be deployed in the monitoring environment. Based on the data accumulated from the environment and the use of wellness function, they detect abnormal behavior, although they achieve low accuracy. In our study, we use only two sensor types, ECG and static sensors at the middle of a predetermined cell and we predict both the next location and the ECG signal [20, 21].

Dohr et al. [22] introduced MobiCare, an architecture for a healthcare system that provides a broad range of health-related services for the efficient health care of mobile patients. These services include: (1) health-related services in medical devices and sensors for remote installation, self-activation, reconfiguration or even self-repair with new health services and applications; (2) secure and reliable dynamic software upgrade or update services, applied to the native code of a clinical device; and (3) remote registration and (re)configuration of body sensors and remote health data services, such as patient health report downloads and diagnosis data uploads with provider servers. However, this system focuses solely on web services and does not have a predictive capability.

Gayathri et al. [23] detect an abnormal status for the patient by hierarchically applying a Markovian logic network. They assume there are different sensors within different objects in the house. The goal of their method is to identify the status of the patient by considering: 1) the objects used by the patient; 2) the time of arrival in a room; 3) the duration of stay in a room; 4) the activity of the patient; and 5) the possibility of doing concurrent activities. To this end, they apply two learning methods: one for detecting and classifying the activity, and another for extracting rules that indicate the relationship between these factors and the abnormality of the status. Thus, the overhead in this method is considerable. Furthermore, they do not use ECG data, which is used in IoT healthcare systems .

Shaji et al. [24] collect body movement activity data, classify it and use it in conjunction with ECG data to detect an abnormal status of the patient. They claim that the activity of a patient reveals this status; however, their method requires that the patient wear four extra sensors for activity recognition, which may be annoying.

Although online prediction of a patient's health status can be achieved based on activity recognition techniques; it needs a considerable number of sensors to record the physical status [25, 26, 24, 27]. It is also inconvenient for patients, and especially elderly people, to wear a high number of sensors.

In our previous work, we introduced a schema using a customized HSMM to predict a patient's direction of mobility in healthcare applications to reduce the hand-off cost. We showed that prediction of the direction of movement helps in decreasing the hand-off cost in IP-based mobile sensor networks. In the current study, we use the same schema to predict the health status of the patient with the aid of ECG data [28, 29]. The contributions of this paper are as follows:

1. We predict the abnormal condition of a patient by modeling the ECG sensor data (wave signal) collected from mobile sensors attached to the patient's body, as well as the time, location and duration of stay within a cell, to increase the accuracy of ECG data.
2. Our solution does not require any extra sensors that are inconvenient for patients to wear.
3. Our proposed method can also recognize activity implicitly, without using extra sensors, and can also be also used in activity recognition applications
4. To our knowledge, this is the first time that a method and network scheme has been proposed to predict an abnormal status for a patient based on ECG sensors without using an activity recognition method.

Activity recognition approaches require numerous sensors to monitor the patient's physical status, as well as contextual information, making this a costly task. Furthermore, it is not convenient for a patient to wear five or six body sensors. Although previous works rely on activity recognition methods to increase the accuracy of mobile node data (such as ECG wave signals) and to detect a patient 's abnormal health status, their implementation is expensive due to the need for many different sensors, and they are not convenient for the patient [23].

To resolve these problems, an online health status prediction method is proposed in this paper that does not rely on the use of activity recognition sensors. The proposed IoT-based distributed health status prediction (DHSP) approach predicts future mobile sensor data using a customized version of an HSMM with two outputs. In this paper, a continuous ECG wave signal provides the mobile node data. To achieve a health status prediction capability, the monitoring area is modeled as cells of equal size with a static node at the center of each, as described in our previous work [30]. We have shown that each segment (composed of cells) in a time implicitly represents an activity. The network is built in such a way that we can extract the temporal pattern of the patient's ECG data in each cell, as well as the time of the patient's arrival and the probable duration of stay within that cell. A grid-based tree structure network has the following advantages:

1. It decreases the communication overhead during data collection in mobile nodes;
2. It facilitates distribution of the constructed model as relevant sub-models over deployed static nodes. It is also advantageous during the prediction steps, while the patient is remaining in and moving between the different locations within each monitoring area.

To build the prediction model, a log of the ECG data and the patient's location traces is collected by the static leaf nodes over a certain period. The leaves send their collected data to the gateway through the intermediate nodes of the network's tree [30]. Following this, a prediction model is constructed in the gateway and partitioned into appropriate sub-models, which are routed to their corresponding leaf nodes through the network schema. Therefore, each static leaf node holds the relevant data model in addition to the maximum and minimum thresholds for the mobile sensor node data.

It can be shown that the location of the patient, the duration spent within a given location and ECG data are correlated with each other. The constructed model is built such that it considers the relationship between these factors. In other words, the spatial and temporal information of a patient may have a direct impact on his or her vital parameters in environments such as a care home, where the patient has a scheduled daily routine. A normal ECG signal is related to the time of the day and the activity of the patient.

For example, between 11 p.m. and 7 a.m., when a patient is asleep in bed, the ECG signal is different from when the patient is walking to the kitchen to make breakfast, between 8 and 9 a.m. The activity of the patient is related to the location, especially in an elder care facility with predefined activity scheduling.

Obviously, a standard ECG signal during resting hours is not normal for physical afternoon activities. Thus, the determination of an abnormal status for the patient solely through the monitoring of ECG sensors is not accurate [24]. As an example, consider a scenario in which the duration of the presence of the patient in a given location in the house does not match the prediction model. For instance, Mary's presence in Cell 1 lasts more than three minutes, or Mary's presence in Cell 2 (the restroom) does not match her routine for 10:00 a.m. and her ECG data are not similar to her regular trained pattern at that time. In these situations, an alert is sent to the corresponding server indicating an abnormal behavior for the patient, and an appropriate response is awaited. Abnormal heart rate or any fall are considered as abnormal status. Abnormal behavior occurs by a combination of these factors:

1. The patient stays in a cell more than expected
2. The patient 's heart rate is above or below than expected one in that cell
3. The patient moves to an unexpected cell from the current cell

Our solution can also recognize patient activity with fewer sensors, lower cost and in a more convenient manner, and can also help to increase the accuracy of the patient's activity, as shown in the Evaluation section.

2. Proposed approach

In a monitoring area, such as an elder care facility, we consider an IP-based mobile WSN with n mobile nodes and m static sensors. The network schema is the same as that used in our previous work [30], in which we used the same schema to reduce the hand-off cost in an IoT healthcare application. The whole area is divided into $\frac{2*m}{3}$ equal sized regions (physical or imaginary cells), with a static node at the center of each cell. These nodes serve as the leaves of the proposed tree schema. The other static nodes are deployed between the cells and behave as the intermediate nodes. Each static node communicates only with its parent and children. Each mobile node sends its data through the nearest static node, known as the candidate node, to the gateway, which is the root of the tree. The candidate node periodically checks the mobile node to obtain information about its movement. The first goal of DHSP is to predict the mobile node data (ECG signal) in case of failure. The second and most important goal is prediction of the health status of the patient with the aid of the patient's spatial and temporal data, according to the presented network schema, thus enabling online prediction.

Fig. 1 shows the overall scenario of the proposed approach. In the initial setup of the system, some threshold for determining the abnormal health status is calculated and will be sent to each cell. Upon the patient movement, the sensors send the tracking info to the gateway. Thus, when the patient moves from one to another cell, time, duration of staying within a cell and ECG data is sent to the gateway. The model is constructed in the gateway and the relevant analysis result will be sent to the static node at the center of each cell via intermediate nodes in the path. We consider every four cells

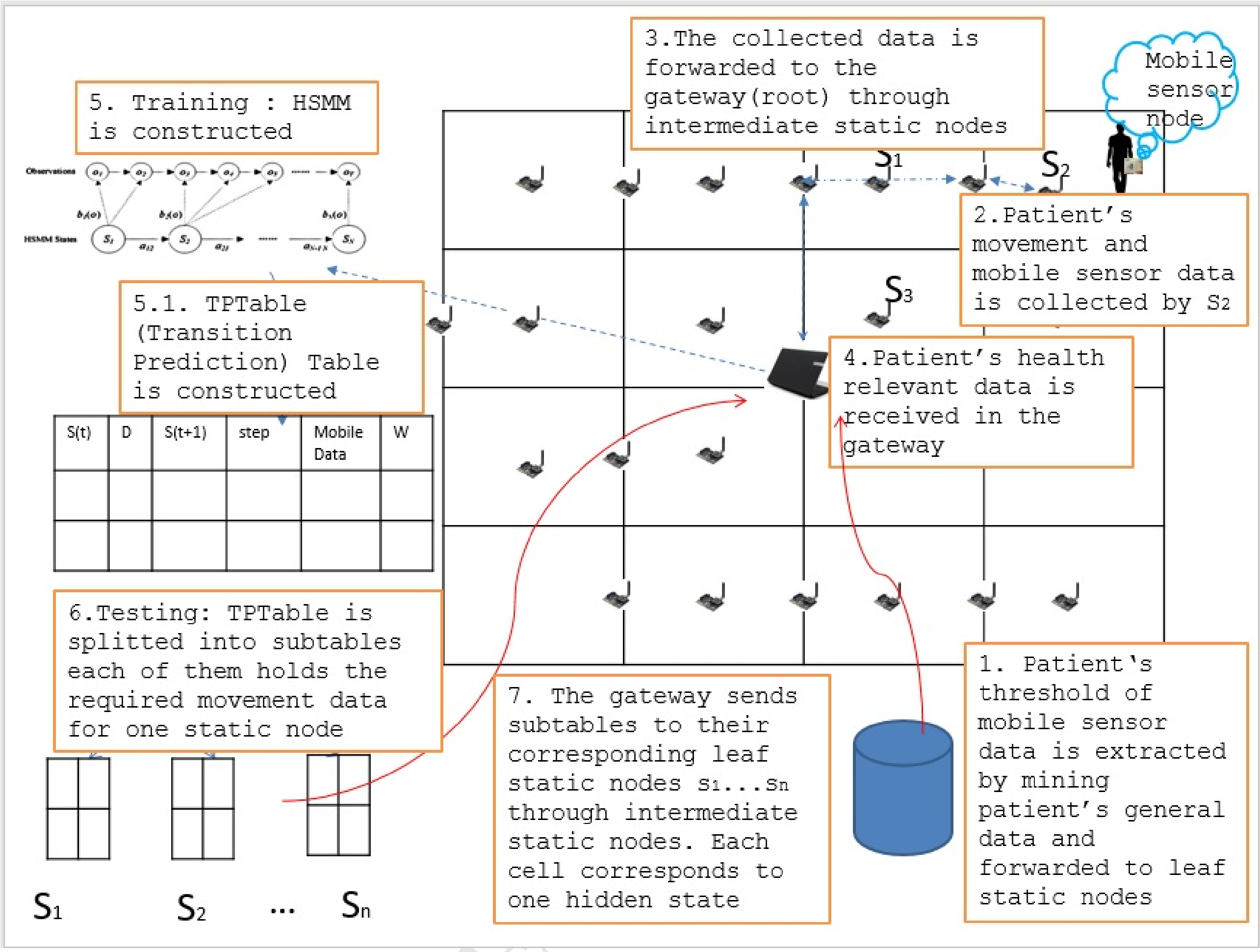

Figure 1: The proposed DHSP approach in the network scheme

(a sub-tree with four leaves) as a single hidden state, based on the fact that in an elder care facility, each part of the building is related to the individual activity of the residents, and this has a direct impact on the mobile node data. Our experiments are conducted on cells of different sizes, to find an optimum hidden state, and we observe that a sub-tree with four leaves gives the best accuracy. In HSMM, a hidden state can have two outputs. The first output is the next cell that the patient will go (next predicted cell). The second output is the next (predicted) ECG data. In an elder care facility, each part of the monitoring area is related to an activity affecting the ECG data.

As shown in Fig. 2, the primary functions of the DHSP are the initial network setup [30], mobile sensor data and location prediction. Initial network setup consists of static nodes placement and constructing the tree of static nodes. Then, we begin to collect data (tracking, time, duration and ECG data from the network). The data set in our approach consists of tracking data, general info of the patients and mobile ECG data. At the next stage, the prediction is done at the gateway by constructing data model. Then the prediction result is distributed over the entire networks via intermediate nodes. The health status and mobile node data prediction are provided by modeling the mobile node data collected from static sensors during the training step. Based on the received data, the total duration

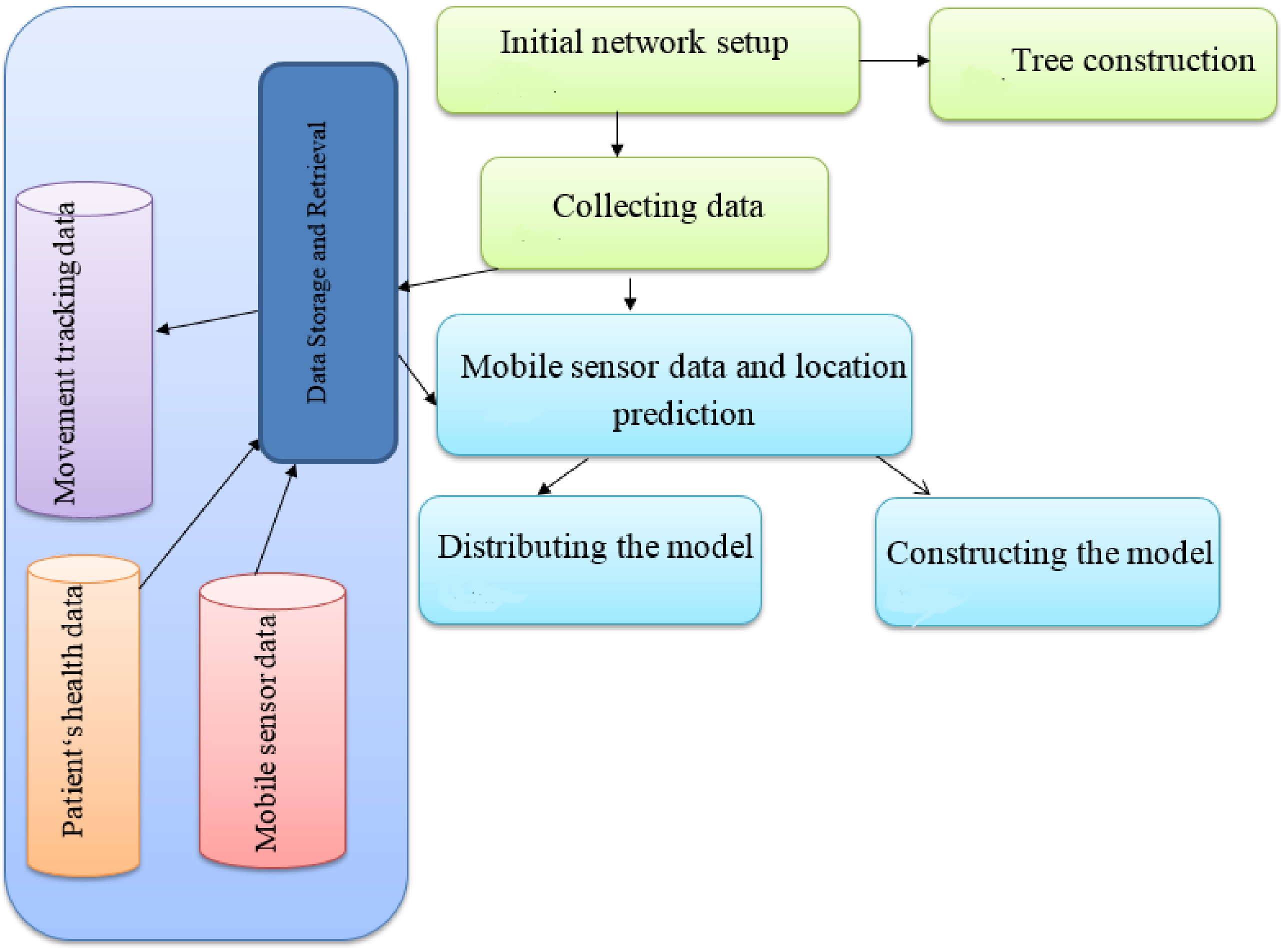

Figure 2: The proposed DHSP architecture

of a patient's stay in each location is determined, which is helpful in predicting abnormal situations. For example, at the prediction stage, if a static leaf node corresponding to the room in which the patient is located finds that the value of the patient's mobile sensor data is abnormal or the duration of the patient's stay is above or below a specified threshold, the static node sends an appropriate alert to the gateway. The static node will, in turn, send notifications to authorized users (e.g., doctors, nurses, relatives, experts, etc.)

In section 2.1, the initial network setup is described [30]. In Section 2.2, we explain how the prediction model is constructed and distributed over the static leaf nodes.

2.1. *Initial network setup*

2.1.1. *DHSP-Tree construction*

We need a schema which helps us to collect patient data in a distributed and efficient manner. This schema should collect patient data continuously and forward these data in a distributed way. Thus, a tree-like structure is a good solution. We place one static node at the center of each cell. We call them candidate node. There are other static nodes (intermediate nodes) that are placed at the intersection point of four neighboring cells. Table 1 shows static and mobile node's address structure. Each mobile

Table 1: IPV6 address structure

80 bits	16 bits	16 bits	8 bits	8 bits
Global Routing Prefix	Sub PANID	Tree	CandidateNodeID	NodeID

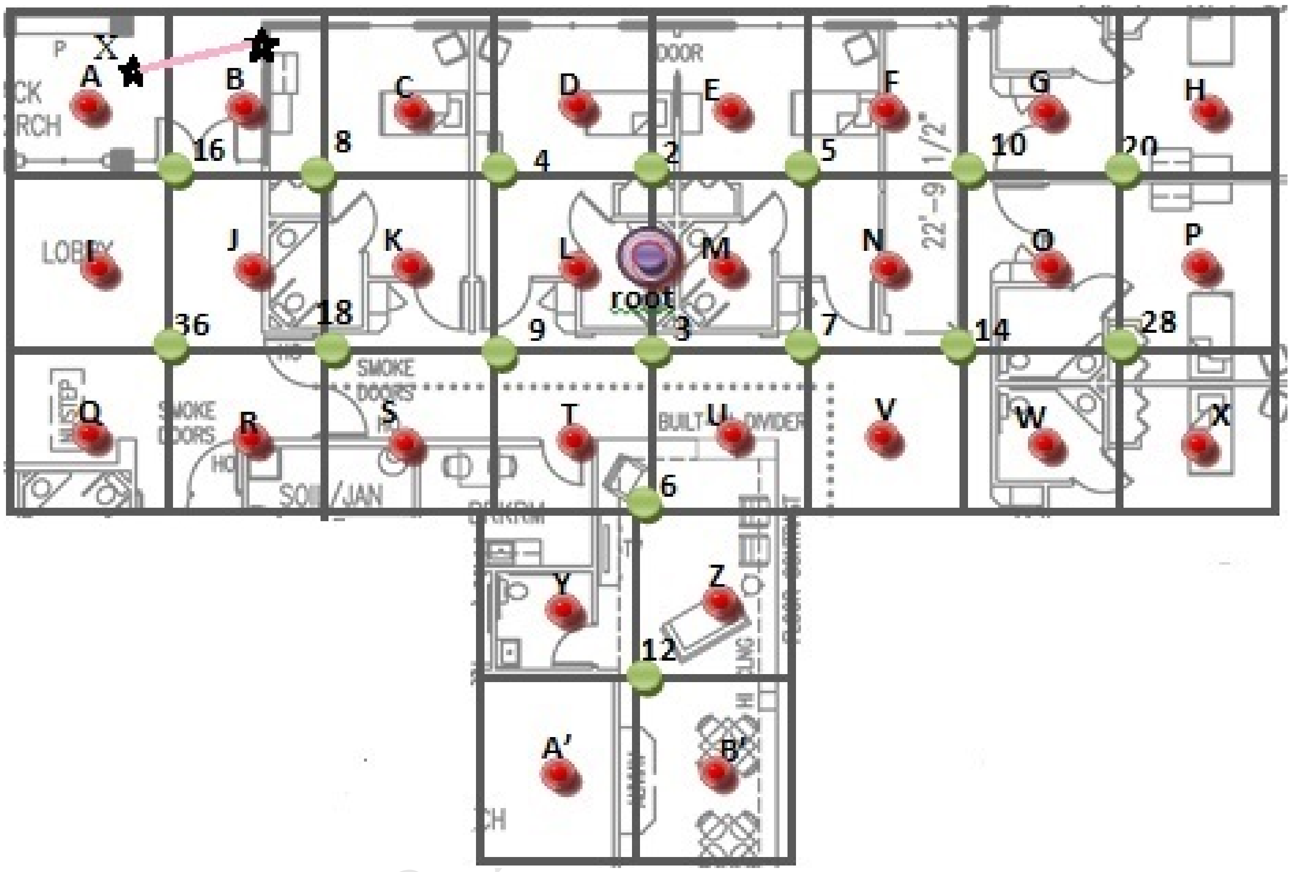

Figure 3: Initial setup: tree construction [30]

node has one IPV6 address that is not changed even when the mobile node moves between PANs. A mobile node address is set once at the initial setup of the network. The address of the mobile node consists of the address of its nearest intermediate node (tree part of the address in Table 1) which is the parent of its first candidate node followed by its candidate node ID followed by unique ID in the cell (NodeID part of the address in Table 1) [30].

In Fig. 3 when the mobile node is in cell A, the static node A forwards the mobile node data to node 16, which in turn sends it to node 8; it is then forwarded to node 4, which forwards it to node 2, and it is then sent to the root of the tree. The DHSP-Tree of Fig. 3 is depicted in Fig. 4.

The collected data contains the following: data from a mobile sensor attached to the patient; time of day; day of the week; duration of patient's presence in a cell; and the ID of the static sensor located at the center of the cell in which the patient is located. It is worth noting that based on the type of mobile sensor, the mobile node data are sent within specific time periods. Each sensor monitors

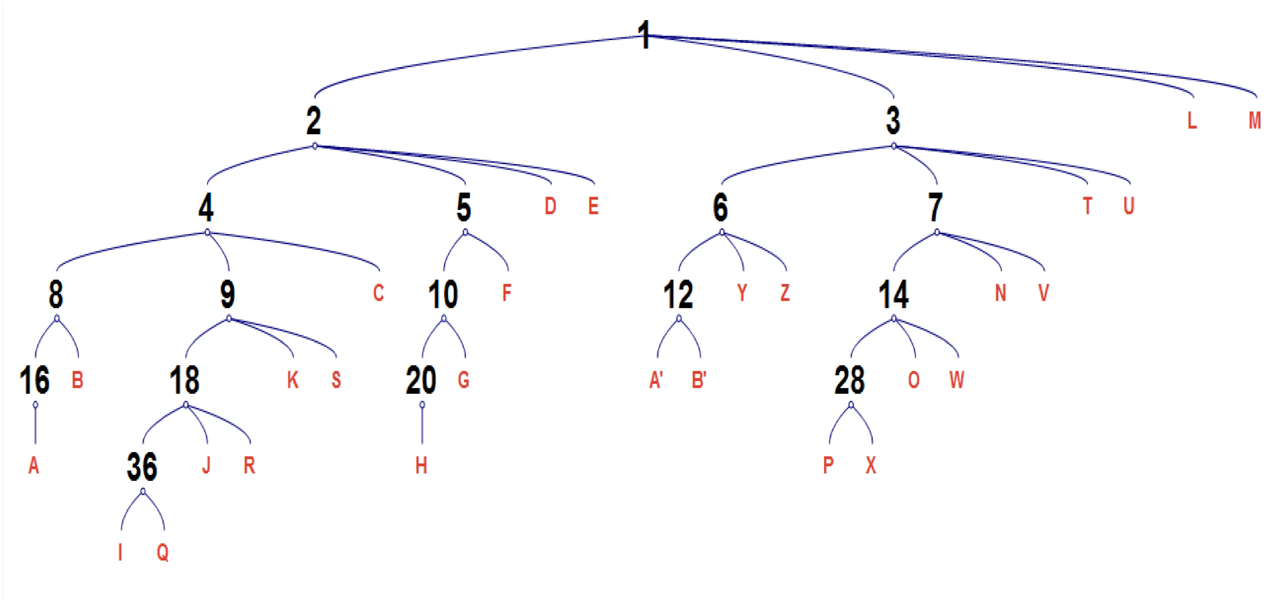

Figure 4: DHSP-Tree for the monitoring area of Fig. 4 [30]

a particular parameter of the patient's body. Based on the type of the parameter that is monitored and the patient's general health status, the monitoring process must be repeated at different intervals. For example, ECG data may be checked every fifteen minutes, while sensor scanning temperature is repeated every thirty minutes. As mentioned earlier, every four cells are considered to be a single hidden state in the constructed HSMM model.

2.2. mobile node data and location prediction

The model for health status prediction is constructed as explained in the first part. In the second part, we describe how the generated models are distributed over the tree's leaves.

2.2.1. Constructing health status prediction model

An HSMM with two outputs is defined by allowing the underlying process to be a semi-Markov chain [31]. Each state has a variable duration that is associated with the number of outputs that are produced. The duration d of a given state is explicitly defined for the HSMM; this is not present in HMM. The state duration is a random variable and is assumed to be an integer value in the set $d = 1$, 2,..., D. The number of observations produced during a patient's presence in state i is determined by the length of time elapsed in state i, i.e., the duration d. In the following section, the customization of the HSMM according to our proposed network schema is explained.

At the end of the training step, the following likelihoods are determined: 1) the most probable duration of each hidden state; 2) the most likely transition from each hidden state, and 3) the most probable sequence of both types of observations in each hidden state. Thus, the direction of movement from each cell can be predicted based on the current state, the previous mobile node data and the

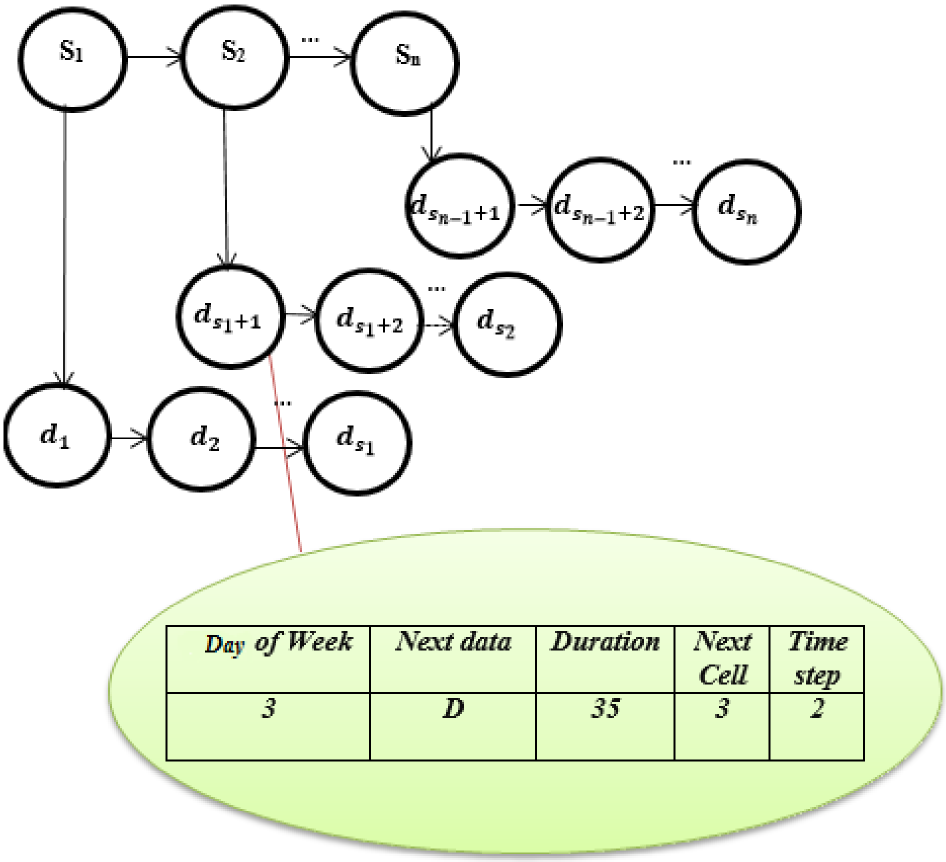

Figure 5: Abstract view of our HSMM model

time elapsed since the patient was in this state. After the training step, the most likely mobile node data in each state and the next cell can be determined fast.

Fig. 5 shows part of the constructed model as a table held by $sensor_2$ to predict the mobile node data when the patient is in the corresponding cell. As shown in the figure, the model has n hidden states. The *Duration* is the total allowable duration of the patient's presence in the cell, which is extracted from the model based on the patient's health status in the training dataset. For each time slot t, S_n is the nth hidden state (cell) and d_{S_n} is the mobile node data (output) that is read in S_n. In Fig. 5, if the patient is in the cell with static leaf node $Sensor_2$, the cell number is 2. The patient's mobile node data will be D at the next time step, the $DayOfWeek = 3$, and the next cell will be $Sensor_3$. The next mobile node data are those of the corresponding mobile sensor in the next period. As mentioned above, each sensor attached to the patient's body sends its data at different intervals, depending on the type of the sensor and the patient's condition.

Using the Baum-Welch algorithm, also known as the forward-backward algorithm, the parameters of an HSMM are estimated. This starts with initial probability estimates (π), computes expectations of how often each transition/emission is used, and finally re-estimates the probabilities based on these expectations (according to α and β). These steps are repeated until convergence is reached [32]. The aim is to achieve an accurate model with a precise emission probability which can best predict the future data of a mobile node. π_m in Equation 1 is the initial probability of being in each cell with $sensorID = m$. $Node_t$ is the ID of the leaf static node located at the center of the cell where the patient was at time t. As mentioned above, we consider every sub-tree with four leaves as a hidden state. Thus, if the grandparents of two nodes are not equal, it means they belong to two different hidden states. The grandparent addresses of two nodes are equal if the tree part of their address has $n2$ equal bits.

$$\pi_m = pr(s_0 = m), m = grandParent(Node_0) \tag{1}$$

Equation 2 determines the transition probability from $Cell(m)$ to $Cell(n)$ at time t. $Cell(Node_t)$ is the cell containing the static leaf node $Node_t$.

$$\begin{aligned} a_{mn} = pr(s_t = n|s_{t-1} = m, m \neq n \; and \; Neighbor(n) = m, \\ grandparent(m) <> grandparent(n) \end{aligned} \tag{2}$$

The probability that the value of the mobile node data (μ at time t) is l, and the probability that the patient being in a cell at time t + τ can be determined by Equation 3. We assume that two outputs are observed with τ delay.

$$c_m(l) = pr(Data(\mu_t) = l|s_t = m), b_m = pr(Node_{t+\tau}|s_{t+\tau} = m) \tag{3}$$

The definition of a $Neighbor$ is given by Equation 4. Two nodes are neighbors when they within each other's range.

$$Neighbor(Cell(Node_t)) \quad = \quad Cell(Node_{t-1}), ((Node_t) \quad \in \quad Range(Node_{t-1}) \tag{4}$$

The complete HSMM model with two outputs is characterized in Equation 5:

$$\lambda = (A, B, C, P, \pi) \tag{5}$$

Here, $A = [a_{m'm}]_{M\times M}$ is the state transition probability. The parameter $C = [c_m(l) : m \in S]$ with $c_m(l)$ is the conditional probability of $Data(\mu_t) = l$ indicating that the mobile node data is l at time t. The parameter $B = [b_m(Node_t) : m \in S]$ with $b_m(Node_{t+\tau})$ is the conditional probability of $Node_t = l$ and indicates that the patient is located in a cell with central static sensor ID of l at time

$t+\tau$. $P = [p_m(d)]_{M\times D}$ and $\pi = [\pi_m]_{M\times 1}$ are the state duration and initial state probability matrices, respectively. The forward probability α is computed as in Equation 6. $P_m(d)$ is the probability that the patient is in state m for d time units.

$$\alpha_t(m,\tau) = pr[Data(\mu_t) = l, pr(Node_t) = l2|DurationEnd(m) = t] = \sum_d P_m(d)P(S_{t-d}|Data(\mu_{t-d}) = l', Node_{t-\tau-d} = l") \prod_{t=t-d+1}^{t} c_m(l')b_m(l") \tag{6}$$

The backward probability β is calculated by Equation 7. $DurationStart(m) = t$ indicates that the patient is in the cell with $sensorID = m$ at its center at time t.

$$\beta_T(m,\tau) = Pr[Data(\mu_t)_t^T Node_{t+\tau}|DurationStart(m) = t] = \sum_{d=1}^{D} Pr[(Data(\mu_{t+d}^T)pr(Node_{t+d+\tau}|DurationEnd(m) = t+d-1]p_m(d)) \prod_{i=t}^{t+d-1} c_m(Data(\mu_t))pr(Node_{t+\tau}) \tag{7}$$

Model parameters are re-estimated to update and improve the parameters of the model. Equation 8 is the initial probability of the patient's presence in each state. $\beta_1(m)$ is the initial probability of the output sequence.

$$\overline{\pi_m} = \frac{\pi_m\beta_1(m)}{\sum_m \pi_m\beta_1(m)} \tag{8}$$

$\overline{a_{mn}}$ in Equation 9 represents the probability of a transition from $Cell(S_i)$ to $Cell(S_j)$ where $grandparent(S_i) <> grandParent(S_j)$ divided by the expected number of transitions from $Cell(S_i)$ to any of its neighboring cells.

$$\overline{a_{mn}} = \frac{\sum_t \alpha_{t-1}(m)a_{mn}\beta t(n)}{\sum_t\sum_n \alpha_{t-1}(m)\beta_t(m)} \tag{9}$$

$$\overline{p_m(d)} = \frac{\sum_t \alpha_{t-1}(m)\beta_t(t)p_m(d)}{\sum_t \alpha_{t-1}(m)\beta_t(m)} \tag{10}$$

$p_m(d)$ in Equation 10 is the probability that the patient is in $Cell$(m) for exactly d times divided by the expected number of times that state m is visited.

The last parameter $c_m(Data(\mu_t))$ is the probability of being in $state = m$ and $Data(\mu_t)$ divided by

Table 2: Training Model Algorithm

Training Model Algorithm
1.C=0 (c is the number of current iteration)
2.Initialize $\lambda = (A, B, C, P, \pi)$
3.Compute $\pi, P_m(d), \alpha_t(m), \beta_t(m)$
4.Adjust the model: compute $\overline{A}, \overline{C}, \overline{B}, \overline{\pi}, P$
5.c=c+1
6.Check the convergence condition, if it is not met, then go to 3
7. Update min, max $Data(\mu_t)$ for each state

observing the sequence $Data(\mu_t)$ in all cells. It is computed by Equation 11. As mentioned above, each cell is considered to be a state.

$$\overline{c_m(Data(\mu_t))} = \frac{\sum\limits_{t=1, Data(\mu_t)=v_k}^{T} \alpha_t(i)\beta_t(i)}{\sum\limits_{t=1}^{T} \alpha_t(i)\beta_t(i)} \tag{11}$$

$\overline{c_m(Data(\mu_t))}$ is computed in Equation 12.

$$\overline{c_m(Data(\mu_t))} = \frac{\sum\limits_{t=1, Data(\mu_(t))=v_l}^{T} \alpha_t(i)\beta_t(i)}{\sum\limits_{t=1}^{T} \alpha_t(i)\beta_t(i)} \tag{12}$$

The prediction model is constructed based on sequences of the patient's movements in addition to the data from the mobile sensors worn by the patient. The mobile node data is logged at different times of the day within the nursing home. The mobile node data is forwarded to the nearest static node at pre-defined time intervals and continuously sent to the gateway. The total duration of stay within a cell, and the current and next sensor IDs of the corresponding cells are also logged. The minimum duration of stay within a cell can be obtained based on the record of movement. The minimum time between a stay in a cell and the interval for reading mobile data is selected as the time step in the training phase. The algorithms for training and testing the model are shown in Tables 2 and 3, respectively.

In Table 3, d_1 is the minimum duration of of stay in a state, obtained during the construction of the model. In Line 1, the most probable initial state is chosen. Then, in Lines 2 and 3, the duration of each state (cell) m and a sequence of mobile node data are extracted. In Line 4, the algorithm checks whether the maximum duration of staying in a cell has been reached. If so, in Lines 6-9, the next probable cell n is extracted from a_{mn}. Otherwise, in Line 5, the next mobile node data is captured and the iteration continues at the next time step.

Table 3: Testing algorithm

Testing Model Algorithm
d_1: MinDuration of all states
1. choose initial hidden state maximizing π: m
2. d: Duration for state m : $p_m(d)$
3. choose most probable $c_m(Data(\mu_t))$, $b_m(Node_t)$ at time t
4. if $t + d_1 < d$ Then
5. $t := t + d_1$ go to 2
6: else
7. choose state n maximizing a_{mn}
8. m:=n, $t := t + d_1$
9. if the process continues, go to 2

2.2.2. Distributing data model

In this part, the structure of the data model is described. Then, an explanation is given of how the data model is distributed. After training the model, *TPTable* is constructed, which holds the constructed model that maintains the predicted mobile node data based on the specific time and location.

$TPTable(TransitionPrediction)$ at the gateway has the following attributes: current sensorID, next sensor ID, next state, day of the week, time step, next mobile node data, health status, and duration.

Thus, for each patient, each static leaf node holds the data that it needs to determine the next probable cell to which the patient decides to move, and the next data for the mobile node. $Healthstatus$ is determined based on the logs of the patient's status during the training phase. This table is broken into sub-tables, each of which holds the relevant data for predicting the mobile node data and patient's health status. Each of the sub-tables has the following attributes.

$TPsubTable$ includes the time step, the day of the week, the next mobile node data, the next sensor ID, and duration. This table determines the next data of the mobile sensor worn by the patient. The maximum number of rows, $TPsubTable$ size (rows), in each sub-table is equal to the number of days in a week the max total times that a cell is visited duration.

Each static node at the center of a cell looks up its table and predicts the next mobile node data. First, for a given period (e.g. one month), the patient's tracking and mobile sensor data are forwarded to the gateway to train the model. After the model is constructed, the relevant part of *TPTable*, called $TPsubTable$, is sent to each leaf node. As shown in Equation 13, for each leaf node a, its sub table

Table 4: Experimentation Parameters

mobility model	Mobile node speed (m/s)	mobile node count	mobile node direction	static sensor communication range
Random	0.5-2.5	80	0-2π	20 m

Table 5: general simulation parameters

MAC Layer	CSMACA
Radio Duty Cycling Algorithm	Contiki MAC
Radio Model	Undirected Graph Model
MAC Layer Queue Size	8 Packets
Bit Rate	250 kbps

contains the rows of the *TPTable* for which the *currentSensorID* column value is a.

$$\begin{gathered}At\ Sensor_i : d_t[t, day\ Of\ Week, Next\ mobile\ node\ data,\\ current\ SensorID, next\ SensorID, next\ state] \in TPTable\\ where\ current\ SensorID = aofSensor_i\end{gathered} \tag{13}$$

3. Results

The simulation is carried out in the Cooja environment [33, 34]. There are various COTS operating systems implemented for low-power wireless networks, and of these, TinyOS and Contiki are the most popular, since they provide several functions [35]. The Contiki operating system was initially designed for IP-based networks and is well known as an IoT emulator [34]. It has adequate facilities and extensions for IP-based protocols. Cooja is a Java-based simulator that was developed for simulations of sensor nodes running the Contiki operating system. The assumptions used in the simulation are listed in Table 4.

In 6lowPAN standard, Carrier Sense Multiple Access/Collision Avoidance (CSMA/CA) [36] protocol is generally used to send data, and they can transmit up to 250 kbps at 2.4 GHz, which is sufficient data rate for typical wireless sensor applications [36, 37]. We consider indoor 's speed of patient which is typically up to 2.5 m/s. The radio duty cycling algorithm is Contiki-MAC [38]. With ContikiMAC, nodes can participate in network communication yet keep their radios turned off for roughly 99% of the time. We consider 2D random walk mobility model [39].

Table 5 shows general simulation parameters. Table 6 shows ECG parameters for simulation [40]. The

Table 6: ECG parameters for simulation

Data to transmit	Transmission Frequency (PGI)
max ECG frequency: 200 Hz, one-second data with a sampling frequency of 600 Hz	15 packets, PGI: 80 ms

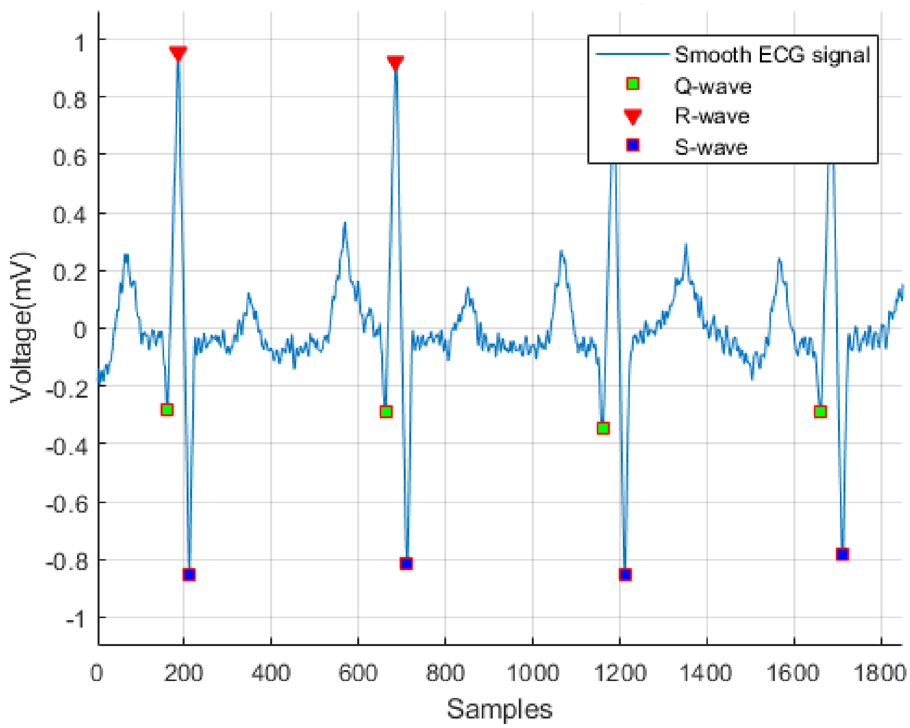

Figure 6: ECG sample

total area is 1740 m^2. The number of the static node is 40. The static sensor type is *Zolertia.*; and the rate of transmission for the ECG sensor is as follows: max ECG frequency: 200 Hz, one-second data with a sampling frequency of 600 Hz, packet generation interval (PGI) transmission frequency: 15 packets, PGI: 80 ms. A sample of ECG signals is shown in Fig. 6 .

Whenever the patient moves from one cell to another, or whenever ECG data is read (at a periodic interval of 15 minutes), the time, duration, current, and next sensor ID, and the latest ECG data is sent to the gateway via the tree nodes. The logs of the patient monitoring over a single month are simulated in Cooja as a training set. The anomalous behavior in this one-month period made up a total of 30%. The collected data was trained using an HSMM with two outputs. We tag the patient health status in the training phase. The data for patient health monitoring for another month was used as a test set and was also simulated in Cooja.

We constructed our dataset based on the MIMIC III data set provided by PhysioNet. It also contains the Arrhythmia data set. We used a Monte Carlo method, and a simulation was carried out

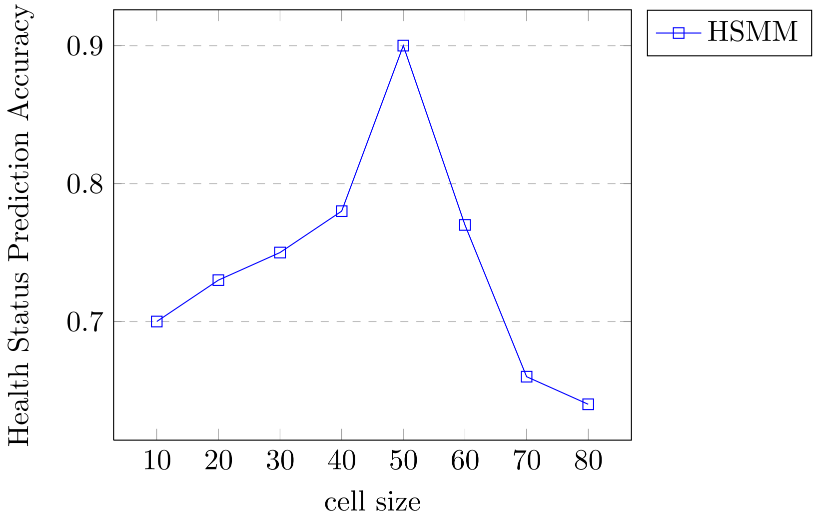

Figure 7: Accuracy of patient's health status versus cell size

for 10 patients. We relate these data to our scheme manually; in other words, the current and next cell are manually inserted, based on the data of the location in the data set [41].

To evaluate our proposed method, we first demonstrate the impact of each of the parameters of time, location, and duration on the accuracy of health status prediction. Fig. 7 shows the accuracy of health status prediction using different cell sizes, where the cell size shows the granularity of the states. As shown in Fig. 7, if the cell size is too small, the rate of false prediction increases. As can be seen from the figure, the accuracy of prediction is 89% on average. The size of a cell shows the approximate location of the patient. This approximation along with other factors help us in determining the health status of the patient. If the cell size is bigger or smaller than a threshold, this approximation is not useful and decrease the accuracy of the health status prediction as the cell could not represent the location that reflects the behavior of the patient. DHSP is scalable, so if the cell size grows, the accuracy is not significantly degraded. This result is better than the case where an HMM or neural network is used since our proposed method considers the duration, which helps in detecting an abnormal situation. It is noted that the cell is a logical division of the monitoring area, and is not necessarily a room. The accuracy of the health status means an accurate determination of a normal/abnormal condition.

Fig. 8 shows the prediction accuracy of the patient's ECG data regarding the accuracy of movement prediction. The better the accuracy of patient tracking, the higher the accuracy of the ECG sensor. This demonstrates that the patient follows a regular daily routine. As can be seen, DHSP-HSMM performs better than HMM and NN, since it considers the duration of stay in each cell when predicting the next cell that the patient will enter.

Fig. 9 shows health status prediction accuracy regarding movement prediction accuracy. When the

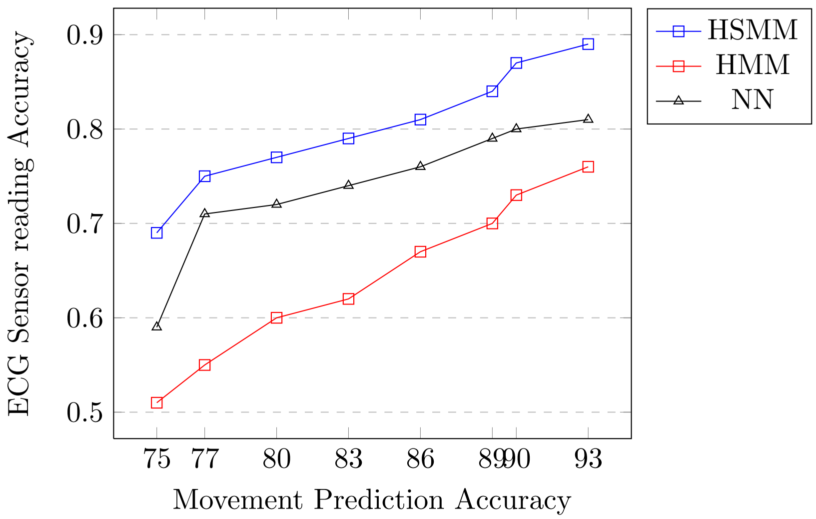

Figure 8: Total prediction accuracy of patient's ECG data vs. the accuracy of movement prediction

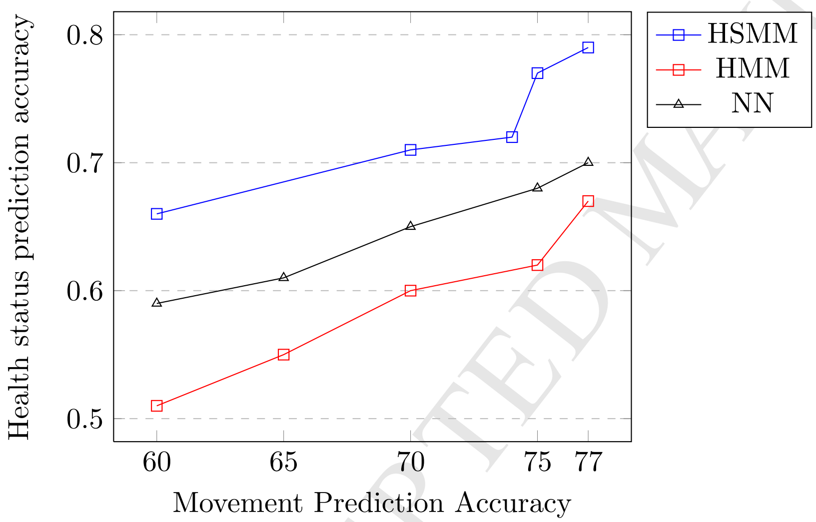

Figure 9: Health status prediction accuracy regarding the accuracy of movement prediction

lifestyle of the patient changes, movement prediction accuracy decreases. In other words, the system cannot predict the direction of patient movement correctly when the patient 's lifestyle changes.

Fig. 10 shows the prediction accuracy of the patient's health status in terms of the time interval for reading the ECG sensor, which considers factors including the duration of stay in a given state and the predicted ECG data (which takes into account spatial and temporal information). The prediction accuracy is 89%. As can be seen, when the time interval for reading ECG sensor is shorter, the accuracy is higher. Our result is better, since we consider the duration of stay within each location.

The accuracy of DHSP was evaluated using well-known metrics such as precision, recall, F-measure and specificity, as presented in Equations 14, 15, 16, and 17, respectively. A false positive means a wrong determination of the patient health status as normal, when it is not. A true negative means correctly defining the patient health status is abnormal. A true positive means determining the health status as normal when this is the case, and a false negative means wrongly determining the health

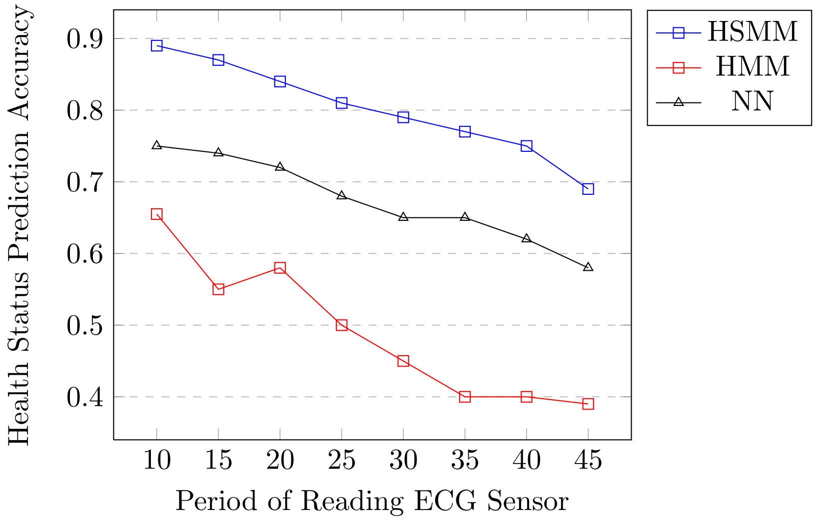

Figure 10: Total prediction accuracy of the patient's normal status regarding the period of reading ECG sensor

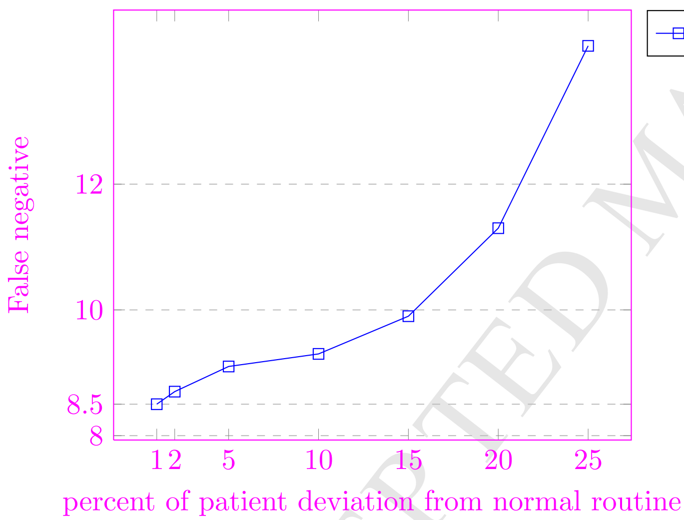

Figure 11: false negative regarding percent of patient deviation from normal routine

status as abnormal when it is not.

$$Precision = \frac{TP}{TP + FP} \tag{14}$$

$$Recall = \frac{TP}{TP + FN} \tag{15}$$

$$F - Measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{16}$$

$$specificity = \frac{TrueNegative}{TrueNegative + FalsePositive} \tag{17}$$

Fig. 11 shows false negative (in percent) regarding percent of patient deviation from normal routine. As it is shown, the false negative alarm increases slightly because deviation from normal routine implicitly means somethings wrong is happened. Fig. 12 shows false positive (in percent) regarding percent of patient deviation from normal routine. As it is shown, the false positive decreases slightly

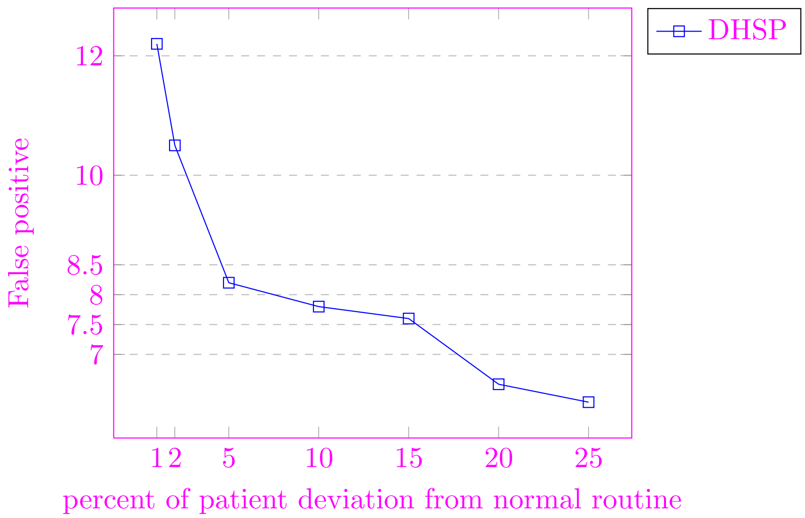

Figure 12: false positive regarding percent of patient deviation from normal routine

Table 7: Impact of time on precision, recall, F-measure and specificity

Method	Precision	Recall	F-Measure	specificity
With Time	84%	80%	81.95%	93.1%
Without Time	65%	61%	62%	60.5%

because when deviation from normal routine increases, it implicitly means somethings wrong has happened. Table 7 shows the impact of the time of arrival in each cell on the accuracy of the system, measured by the metrics of precision, recall and F-measure. As shown in the table, the time of arrival has a considerable impact on the accuracy. Since a resident in an elder care facility has a predictable, scheduled daily routine, based on the time and the day of the week, these different activities affect the interpretation of the ECG wave signal. Table 8 illustrates the considerable impact of the location of the patient on the accuracy. Considering that in an elder care facility, patients have a daily scheduled routine based on their location, it is expected that they will accomplish specific activities which affect the interpretation of the ECG data. Table 9 shows the impact of the duration of stay within each cell. As shown in the table, this parameter has the most significant impact on the accuracy in this approach. If the normal period is not used, it is most likely that the patient has an abnormal status.

We considered 3000 instances of the patient in the first part of the experiment, with the following features: time, duration, location, activity and ECG signal. The activity was labeled manually. These parameters form the log history of a single patient, for one month of training and one month of testing, from the MIMIC III database. Abnormal health status could be both fall, any abnormal increasing or

Table 8: Impact of location on precision, recall, F-measure and specificity

Method	Precision	Recall	F-Measure	specificity
With Location	85%	80%	84.26%	90.1%
Without Location	55%	50%	52.38%	63.2%

Table 9: Impact of duration on precision, recall, F-measure and specificity

Method	Precision	Recall	F-Measure	specificity
With Duration	89%	80%	84%	91.4%
Without Duration	75%	71%	72%	67.1%

Table 10: Activity count

Label	Count
Sleeping	104
Toileting	107
Showering	115
Breakfast	600
Spare time	1674
Lunch	500

decreasing of heart rate too. MIMIC III contains alarm records which could be red alarm and yellow alarm. Yellow alarm is used for notification of something abnormal, and a red alarm are used for notification of a critical or life-threatening event.Red alarms are due to asystole, extreme bradycardia, extreme tachycardia, ventricular tachycardia and ventricular fibrillation/tachycardia. The alarm are reviewed by expert. Thus, we consider only true positive red alarm as abnormal situation. The yellow alarm are also reviewed. Thus, any yellow alarm that are really abnormal, are considered too. The recall of normal health status means: all detected true positive alarms divided by total detected and undetected true positive alarms. A precision of normal means: all true positive alarm detected by our approach divided by total detected alarms detected by our approach.

We considered six activities from the UCI Machine Learning Activities database (sleeping, toileting, showering, breakfast, spare time, lunch). Table 10 shows the number of instances per activity, while Table 11 illustrates the number of instances per location and Table 12 shows the number of instances per duration. Table 13 shows the number of instances per time. Table 8 shows the number of activities per specific patient. Table 9 shows the number of times that each patient stays in each cell (showing with cell number) in all 3000 instances. For example, the patient stays 159 among 3000 times in cell 1. Table 10 shows the time of all 3000 instances. For example, 204 samples among all 3000 instances have occurred in 12-6 AM. Table 11 shows the duration of staying in a cell for all instances. For example, 109 among 3000 instances have the duration of staying below five minutes. This experiment was conducted using the Waikato Environment for Knowledge Analysis (WEKA) tool developed at the University of Waikato in New Zealand. The aim is to evaluate the efficiency of the proposed approach in recognizing an activity without using sensors to capture the behavior of the patient.

There is no online health status prediction model which considers time, duration and location

Table 11: Count of patient location

Label	Count
Cell 1	159
Cell 2	154
Cell 3	200
...	...
Cell 20	142

Table 12: Count of time of arrival to cell

Label	Count
12-6 AM	204
6-10 AM	725
10-2 PM	702
2-6 PM	210
6-8 PM	801
8-12 PM	358

using only ECG sensors for us to compare our approach with. Therefore, to show the effectiveness of our solution in implicitly recognizing activity, we compare our model with the system reported by Gayathari et al. [23] called MLN. In their paper, these authors use time, location and environmental/body sensors to recognize activities. We tag our data manually by activity and show that we can also predict more accurately. Fig. 13 shows the F1 measure of both solutions based on different activities. As shown in the figure, our solution performs better with less overhead and using no additional hardware. Although our goal is to detect abnormal behavior, Fig. 13 shows that we can not only predict an abnormal status for the patient but can also detect the activity of the patient more accurately.

Another related work to which we compare our result is the study reported by Moreno et al. [5]. This is the only health status detection method that uses the spatial and temporal information of a patient rather than environmental/body sensors. We implemented their methods using only spatial and temporal data, without ECG data. We considered different numbers of records and the results are compared in Fig. 14. As can be seen, our solution results in greater accuracy. This superior

Table 13: Count of duration of stay in a location (cell)

Label	Count
< 5 Min	109
5-10 min	310
10-30 min	563
30 60 min	140
1-2 hour	874
2-3 hour	800
< 3 hours	204

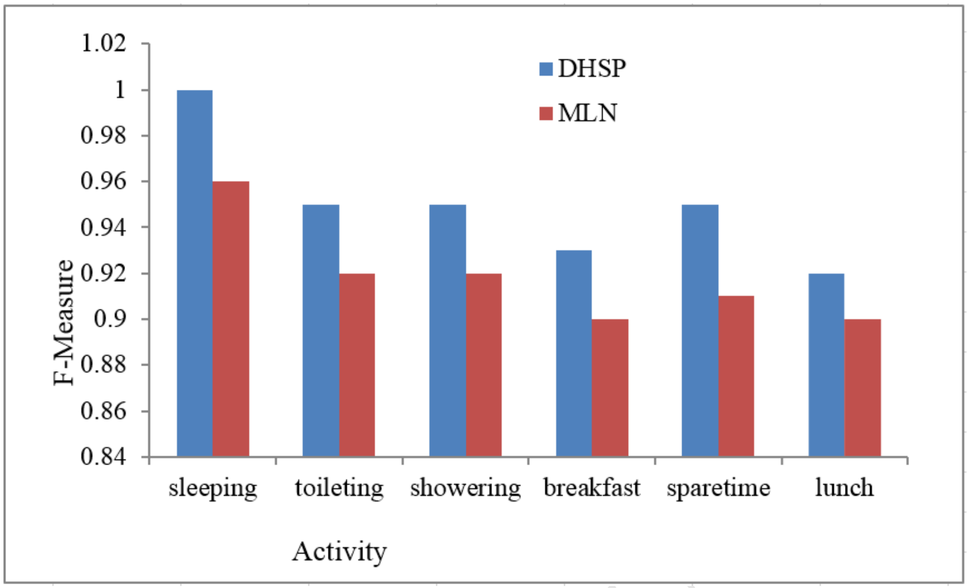

Figure 13: F-measure vs. activity

performance can be expected, since the other study did not consider the patient's body sensor data, resulting in less accuracy, while also requiring large numbers of data records to converge to an acceptable accuracy. We use only the ECG sensor data, which helps to give a higher accuracy without needing a large amount of recording data.

To demonstrate the effectiveness of our approach, we compare our method with another approach proposed by Suryadevara et al. [21, 42]. These authors use a wellness function to define the normal behavior of the patient, and the main goal of their paper is recognizing the activity of the patient. Their method requires numerous features, and a great deal of data related to various lifestyle parameters.

Our solution is suitable for an environment such as an elder care facility, where the lifestyle is routine. If the lifestyle changes considerably every week, our solution may be less effective. As shown in Fig. 14, our solution performs better incorrectly determining normal/abnormal conditions.

4. Discussion

There is no approach similar to us that we can not directly compare to. At the first part of the simulation section, we compare DHSP with methods that consider temporal and location information in detecting the health status of the patient [5, 23]. As it is shown in result section, our approach performs better because we consider ECG sensor reading too and our constructed model that considers the predicted location, predicted ECG reading and duration of staying at a cell, produce a more accurate result. To evaluate the efficiency of our approach, we also predict activity based on their

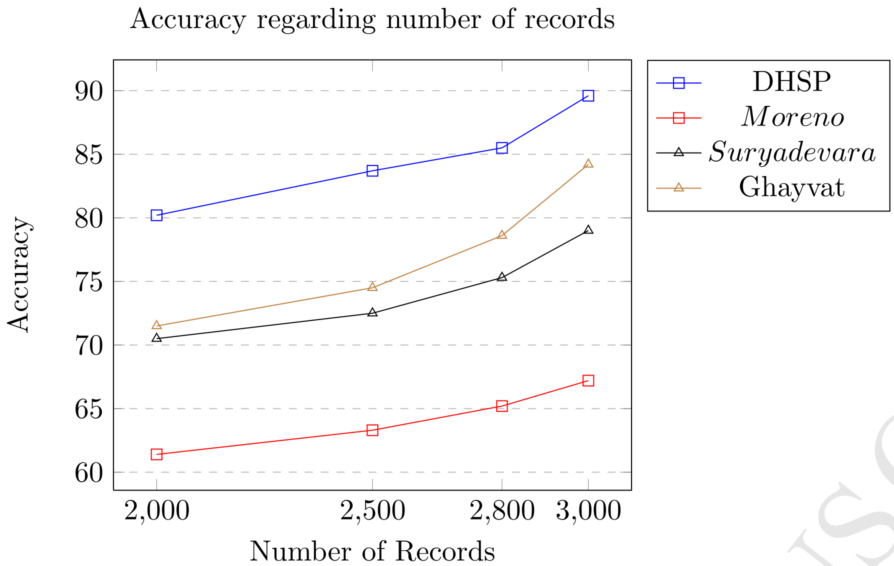

Figure 14: Accuracy vs. number of records

data, and it is seen that we can implicitly detect the patient 's activity more accurate than MLN as it does not consider the ECG sensor. The approaches that only consider patient 's tracking gain less accuracy.

In the second part of the simulation part, we compare our approach with some popular, high cited IoT health status methods that detect the abnormal status of the patient with activity recognition approaches [21, 42]. Our approach outperforms these solutions too. The reason is that they use wellness function and try to construct the normal model for the patient by deploying many environmental and body sensors. In our approach, we model the normal behavior of the patient based on the duration of staying cells, ECG reading, time and day of the week. We divide the region into cells. We believe that for an older adult with routine work, our model will be more accurate. As we log the person for a month, we model the abnormal situation too. Modeling the abnormality and also daily routine lead us to a more accurate result compared to the approaches that are based on constructing wellness function. Furthermore, our approach needs too many sensors which are not convenient for older adults. Our approach gains better result in a home care environment.

4.1. Analatical Verification

As mentioned earlier, our model is trained using the data from a patient's ECG sensor over a given period, and we obtained an accuracy of 89% on average (μ). To validate this accuracy, we aim to ensure that the ECG prediction does not fall below 89% if we increase the population size. Thus, the objective of this verification is to make sure that if the patient's mobile node data are collected over a longer period, for example, 365 days, the accuracy does not fall below this value. In other words, we want to show that our result is correct for the whole population, using null hypothesis testing. To this end, we determine two hypotheses, H_0 and H_1. The data is analyzed to determine whether the first stated prediction is unreasonable. We would like to know whether there is empirical evidence indicating that the speculation H_0 is probably incorrect. If we conclude that H_0 is wrong, then the alternate speculation H_1 is verified as the correct speculation [43]. We define H0 and H1 in Equation 18:

$$\begin{aligned} H_0 &: \mu \leq 89 \\ H_1 &: \mu > 89 \end{aligned} \tag{18}$$

Since we do not know the variance of the whole population, the distribution of our population is assumed to be a $t - Student$ distribution. We run the prediction for 30 days, i.e., n = 30. We assume the type I error, α, to be 0.01%, meaning that we tolerate a rejection of the null hypothesis when it is correct in only 0.01% of all the situations. According to the $t - Student$ distribution, with 29 degrees of freedom and 0.01 error, the value would be 2.462. The formula for the $t - Student$ distribution is shown in Equation 19.

$$t_{n-1} = \frac{\overline{X} - \mu}{\frac{S}{\sqrt{n}}} \tag{19}$$

The average accuracy and variance achieved for the health prediction of 30 patients were 91.1 and 3.9, respectively. According to Equation 19, the t value is 2.8, i.e. greater than 2.462. Hence, assumption H_0 is rejected, indicating that the prediction accuracy is more than 89%. The $t - Student$ distribution plot of accuracy is shown in Fig. 15.

5. Conclusions

Since ECG sensor data is not accurate, and a patient's health status cannot be determined accurately based only on data from this sensor, we propose for the first time an online health status prediction method based on an HSMM with two outputs. This model uses a tree structure network to predict the health status of residents in a nursing home. Since people in elderly households have a relatively scheduled daily routine, we implicitly recognize activities in each cell without using special sensors to record the patient's physical state, objects, or environmental conditions. The other contribution of this paper is the distributed online prediction of mobile node data in IoT healthcare applications, which has not been considered in previous works. Existing approaches which detect patient's health status using activity recognition methods are not cost-effective, due to their need for

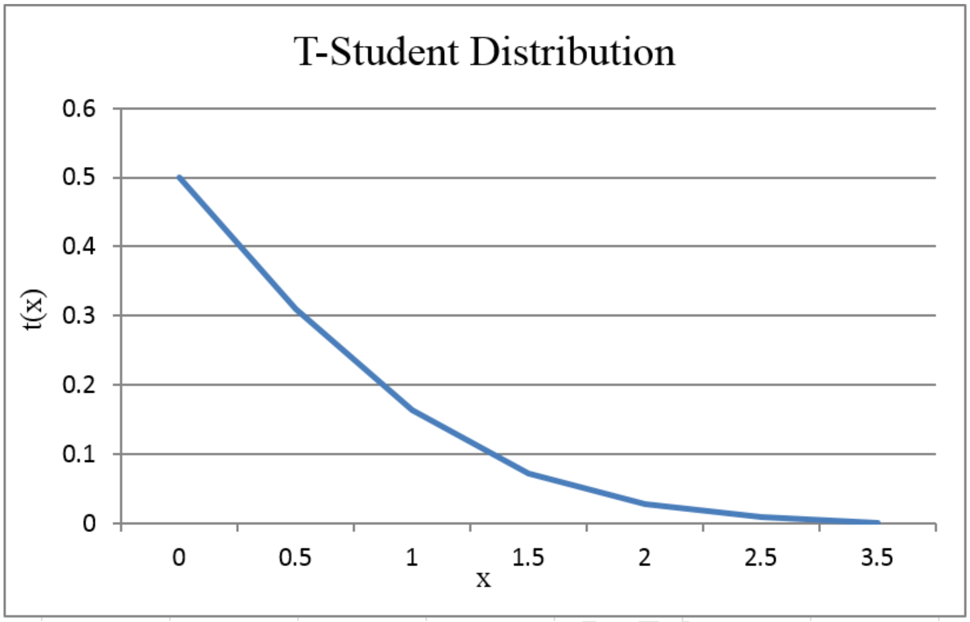

Figure 15: T-Student distribution of prediction accuracy

a significant number of sensors that are costly and inconvenient for patients to wear. Our simulation results show the effectiveness, using time of arrival within a cell, ECG signal, duration, and location in increasing the accuracy of our proposed method.

DHSP is designed to predict the movement of patients at different times of the day and to use data from mobile sensors connected to their bodies to foresee unusual health situations. DHSP involves a sophisticated tree structure network that simplifies the prediction on mobile node data, the patient's health status and the addressing/routing/forwarding of mobile sensor data to/from the gateway. Prediction is provided by a customized HSMM model with two outputs that is trained based on a patient's tracking data and mobile node data, in an elder care facility. HSMM takes into consideration the duration of each state, making the prediction more accurate. The results show the superiority of our method in accurately predicting the online health status of the patients, without using any extra sensors. Our solution can also be used for activity recognition, as we demonstrate in the Simulation section. In the future, we aim to increase the accuracy of our model by defining other factors and using a different learning method.

6. References

[1] Prajakta Kulkarni and Yusuf Öztürk. Requirements and design spaces of mobile medical care. *ACM SIGMOBILE Mobile Computing and Communications Review*, 11(3):12–30, 2007.

[2] Jesmin Nahar, Tasadduq Imam, Kevin S Tickle, and Yi-Ping Phoebe Chen. Association rule mining to detect factors which contribute to heart disease in males and females. *Expert Systems with Applications*, 40(4):1086–1093, 2013.

[3] K Srinivas, B Kavihta Rani, and A Govrdhan. Applications of data mining techniques in healthcare and prediction of heart attacks. *International Journal on Computer Science and Engineering (IJCSE)*, 2(02):250–255, 2010.

[4] P Fuster-Parra, P Tauler, M Bennasar-Veny, A Ligeza, AA Lopez-Gonzalez, and A Aguilo. Bayesian network modeling: A case study of an epidemiologic system analysis of cardiovascular risk. *Computer methods and programs in biomedicine*, 126:128–142, 2016.

[5] Aitor Moreno-Fernandez-de Leceta, Jose Manuel Lopez-Guede, Manuel Graña, and Juan Carlos Cantera. *Real Prediction of Elder People Abnormal Situations at Home*, pages 31–40. Springer International Publishing, Cham, 2017.

[6] Björn Gottfried, Hamid Aghajan, Kevin Bing-Yung Wong, Juan Carlos Augusto, Hans Werner Guesgen, Thomas Kirste, and Michael Lawo. Spatial health systems. In *Smart Health*, pages 41–69. Springer, 2015.

[7] Vikramaditya R Jakkula and Diane J Cook. Detecting anomalous sensor events in smart home data for enhancing the living experience. *Artificial intelligence and smarter living*, 11(201):1, 2011.

[8] Soundar Kumara, LiYing Cui, and Jie Zhang. Sensors, networks and internet of things: Research challenges in health care. In *Proceedings of the 8th International Workshop on Information Integration on the Web: In Conjunction with WWW 2011*, IIWeb '11, pages 2:1–2:4, New York, NY, USA, 2011. ACM.

[9] Shehroz S Khan, Michelle E Karg, Jesse Hoey, and Dana Kulic. Towards the detection of unusual temporal events during activities using hmms. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, pages 1075–1084. ACM, 2012.

[10] Fco Javier Ordóñez, Paula de Toledo, and Araceli Sanchis. Sensor-based bayesian detection of anomalous living patterns in a home setting. *Personal and Ubiquitous Computing*, 19(2):259–270, 2015.

[11] Jie Yin, Qiang Yang, and Jeffrey Junfeng Pan. Sensor-based abnormal human-activity detection. *IEEE Transactions on Knowledge and Data Engineering*, 20(8):1082–1090, 2008.

[12] Juan Cheng, Xiang Chen, and Minfen Shen. A framework for daily activity monitoring and fall detection based on surface electromyography and accelerometer signals. *IEEE journal of biomedical and health informatics*, 17(1):38–45, 2013.

[13] Behzad Mirmahboub, Shadrokh Samavi, Nader Karimi, and Shahram Shirani. Automatic monocular system for human fall detection based on variations in silhouette area. *IEEE Transactions on Biomedical Engineering*, 60(2):427–436, 2013.

[14] Sanjana Rakhecha and Kenneth Hsu. Reliable and secure body fall detection algorithm in a wireless mesh network. In *Proceedings of the 8th International Conference on Body Area Networks*, pages 420–426. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2013.

[15] Jay Chen, Karric Kwong, Dennis Chang, Jerry Luk, and Ruzena Bajcsy. Wearable sensors for reliable fall detection. In *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, pages 3551–3554. IEEE, 2006.

[16] Qiang Li, John A Stankovic, Mark A Hanson, Adam T Barth, John Lach, and Gang Zhou. Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information. In *Wearable and Implantable Body Sensor Networks, 2009. BSN 2009. Sixth International Workshop on*, pages 138–143. IEEE, 2009.

[17] Min-Seok Lee, Jong-Gwan Lim, Ki-Ru Park, and Dong-Soo Kwon. Unsupervised clustering for abnormality detection based on the tri-axial accelerometer. In *ICCAS-SICE, 2009*, pages 134–137. IEEE, 2009.

[18] Ahmad Lotfi, Caroline Langensiepen, Sawsan M Mahmoud, and Mohammad Javad Akhlaghinia. Smart homes for the elderly dementia sufferers: identification and prediction of abnormal behaviour. *Journal of ambient intelligence and humanized computing*, 3(3):205–218, 2012.

[19] Lei Meng, Chunyan Miao, and Cyril Leung. Towards online and personalized daily activity recognition, habit modeling, and anomaly detection for the solitary elderly through unobtrusive sensing. *Multimedia Tools and Applications*, 76(8):10779–10799, 2017.

[20] Nagender Kumar Suryadevara and Subhas Chandra Mukhopadhyay. Wireless sensor network based home monitoring system for wellness determination of elderly. *IEEE Sensors Journal*, 12(6):1965–1972, 2012.

[21] Nagender Kumar Suryadevara, Subhas C Mukhopadhyay, Ruili Wang, and RK Rayudu. Forecasting the behavior of an elderly using wireless sensors data in a smart home. *Engineering Applications of Artificial Intelligence*, 26(10):2641–2652, 2013.

[22] A. Dohr, R. Modre-Opsrian, M. Drobics, D. Hayn, and G. Schreier. The internet of things for ambient assisted living. In *Information Technology: New Generations (ITNG), 2010 Seventh International Conference on*, pages 804–809, 2010.

[23] KS Gayathri, Susan Elias, and Balaraman Ravindran. Hierarchical activity recognition for dementia care using markov logic network. *Personal and Ubiquitous Computing*, 19(2):271–285, 2015.

[24] Shereena Shaji, Maneesha Vinodini Ramesh, and Vrindha N Menon. Real-time processing and analysis for activity classification to enhance wearable wireless ecg. In *Proceedings of the Second International Conference on Computer and Communication Technologies*, pages 21–35. Springer, 2016.

[25] A. Avci, S. Bosch, M. Marin-Perianu, R. Marin-Perianu, and P. Havinga. Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey. In *Architecture of Computing Systems (ARCS), 2010 23rd International Conference on*, pages 1–10, Feb 2010.

[26] Tonmoy Choudhury, Sunny Consolvo, Brent Harrison, Jeffrey Hightower, Antonio Lamarca, Louis LeGrand, Azar Rahimi, Adam Rea, G Bordello, Bruce Hemingway, et al. The mobile sensing platform: An embedded activity recognition system. *Pervasive Computing, IEEE*, 7(2):32–41, 2008.

[27] Daniele Peri. *Body Area Networks and Healthcare*, pages 301–310. Springer International Publishing, Cham, 2014.

[28] Azadeh Zamanifar, Eslam Nazemi, and Mojtaba Vahidi-Asl. Dshmp-iot: A distributed self healing movement prediction scheme for internet of things applications. *Applied Intelligence*, pages 1–21, 2016.

[29] Azadeh Zamanifar, Eslam Nazemi, and Mojtaba Vahidi-Asl. Dmp-iot: A distributed movement prediction scheme for iot health-care applications. *Computers & Electrical Engineering*, 58:310–326, 2017.

[30] Azadeh Zamanifar, Eslam Nazemi, and Mojtaba Vahidi-Asl. A mobility solution for hazardous areas based on 6lowpan. *Mobile Networks and Applications*, pages 1–16, 2017.

[31] Kevin P Murphy. Hidden semi-markov models (hsmms). *unpublished notes*, 2, 2002, 2002.

[32] Xuedong D Huang, Yasuo Ariki, and Mervyn A Jack. *Hidden Markov models for speech recognition*, volume 2004. Edinburgh university press Edinburgh, 1990.

[33] Joakim Eriksson, Fredrik Österlind, Niclas Finne, Nicolas Tsiftes, Adam Dunkels, Thiemo Voigt, Robert Sauter, and Pedro José Marrón. Cooja/mspsim: Interoperability testing for wireless sensor networks. In *Proceedings of the 2Nd International Conference on Simulation Tools and Techniques*, pages 1–7, 2009.

[34] F. Osterlind, A. Dunkels, J. Eriksson, N. Finne, and T. Voigt. Cross-level sensor network simulation with cooja. In *Local Computer Networks, Proceedings 2006 31st IEEE Conference on*, pages 641–648, 2006.

[35] A. Dunkels, B. Gronvall, and T. Voigt. Contiki - a lightweight and flexible operating system for tiny networked sensors. In *Local Computer Networks, 2004. 29th Annual IEEE International Conference on*, pages 455–462, 2004.

[36] Carles Gomez and Josep Paradells. Wireless home automation networks: A survey of architectures and technologies. *IEEE Communications Magazine*, 48(6), 2010.

[37] Farid Touati, Adel Ben Mnaouer, Ochirkhand Erdene-Ochir, Waiser Mehmood, Ammad Hassan, and Brahim Gaabab. Feasibility and performance evaluation of a 6lowpan-enabled platform for ubiquitous healthcare monitoring. *Wireless Communications and Mobile Computing*, 16(10):1271–1281, 2016.

[38] Adam Dunkels. The contikimac radio duty cycling protocol. 2011.

[39] Kuo-Hsing Chiang and Nirmala Shenoy. A 2-d random-walk mobility model for location-management studies in wireless networks. *IEEE Transactions on Vehicular Technology*, 53(2):413–424, 2004.

[40] Waiser Mehmood, Ammad Hassan, Rohan Tabish, Farid Touati, Adel Ben Mnaouer, and Brahim Gaabab. Performance evaluation of 6lowpan based networks for ubiquitous health monitoring system. In *Proceedings of the International Conference on Wireless Networks (ICWN)*, page 1. The Steering Committee of The World Congress in Computer Science, Computer , 2014.

[41] Alistair EW Johnson, Tom J Pollard, Lu Shen, Li-wei H Lehman, Mengling Feng, Mohammad Ghassemi, Benjamin Moody, Peter Szolovits, Leo Anthony Celi, and Roger G Mark. Mimic-iii, a freely accessible critical care database. *Scientific data*, 3, 2016.

[42] Hemant Ghayvat, Jie Liu, Subhas Chandra Mukhopadhyay, and Xiang Gui. Wellness sensor networks: A proposal and implementation for smart home for assisted living. *IEEE Sensors Journal*, 15(12):7341–7348, 2015.

[43] Rand R Wilcox. *Basic statistics: understanding conventional methods and modern insights*. Oxford Univ Pr, 2009.

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