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Modeling of Human Activity Prediction in Healthcare Internet of Things (Iot) System

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Abstract

The life of people can be improved simply and conveniently through the use of the Internet of Things (IoT). The healthcare sector is considered to be one of the most encouraging IoT applications. In the current paper, a predicted model of healthcare based on the Internet of Things (IoT) system that uses distinct Markov state-space models is proposed. Here, a real-time Received Signal Strength Indicator link quality assessment technique is followed by a way to identify people's movements and the probability of the next move, Experimental findings The results of the coverage tests internal environments are displayed of the probability of the system patient activity with the change of motion sensor rate of Received Signal Strength Indicator that can detect the human activity for each state in Markov model.

Keywords: IoT healthcare system, object detection, Markov model, a prediction system

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الكشف البشري والنمذجة في نظام إنترنت الأشياء (Iot) للرعاية الصحية

هالة مهند يوسف و ظاهر عبد الهادي عبد الله

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الخلاصة

يستخدم انترنت الاشياء (IoT) كوسيلة لتحسين حياة الناس وجعلها اكثر سهولة. يعد قطاع الرعاية الصحية واعدًا بكونه ضمن تطبيقات انترنت الاشياء. ان هذه الورقة البحثية تقترح استخدام نظام انترنت الاشياء والذي يعتمد على نموذج ماركوف المنفرد (distinct Markov state-space) لشرحه. حيث أقترح في هذا البحث نهج تحديد هوية بشري خالٍ من الاجهزة بعد تقنية تقييم جودة الرابط (RSSI) الفوري. باستخدام تقلب (RSSI) فقط، يحقق النهج المقترح نفس وظائف الحلول التقليدية التي تستخدم مجاميع مقعدة من مستشعرات الحركة (sensors). يعزى تذبذب (RSSI) الى البيئة وعوامل اخرى. تظهر النتائج غموض تغييرات (RSSI) عند حركة الاشخاص عبر منطقة الشبكة. وتدعم امكانية تطبيق نهج الاكتشاف.

الكلمات المفتاحية: نظام إنترنت الأشياء للرعاية الصحية ، كشف الأشياء ، نموذج ماركوف ، نظام التوقع.

Introduction

One of the most exciting IoT uses is in the medical field [1]. The Internet of Healthcare Things, created by networked medical equipment, aims to improve circumstances for patients who need ongoing medical supervision and/or preventative action via health monitoring and preventive treatment. However, the employment of new technology often entails dangers, including as infrastructural, device, and component failures that might have catastrophic effects on patients. Therefore, it is definitely worthwhile to research modeling, performance assessment, and performance improvement strategies for the health IoT systems in order to reduce such risks and provide the necessary system availability [2].

One of the hot topics in research is object detection. WSN-based detection analyzes and transmits object information from sensors to the control center, where it is analyzed to make the detection [3]. The collection of the sensor signal is crucial, and the kind of sensors affects the outcome of the detection.

Received Signal Strength Index (RSSI) refers to the movement of humans in wireless networks is one of major effects leading to significant received signal strength indicator (RSSI) variation. Using fluctuated RSSI on estimating the target position in the RSSI-based indoor localization system can give large error and poor decisions of the system

Many academics have shown a significant interest in the study on properly adopting acceptable control mechanisms to enhance network performance. One of the most important stages in the communication process between machines and people is data collecting.

Furthermore, research has shown that a variety of variables, including the functionality of WSN nodes and the environment's temperature and humidity, may have an impact on RSSI [5] [6]. Each individual has the ability to alter RSSI, which prevents RSSI from truly reflecting the caliber of the network connection. Hamida and Guillaum [7] discovered that individuals strolling about in the network area had a significant impact on RSSI and hypothesized that RSSI cannot effectively represent network connection quality when there is someone in the vicinity throughout the day.

Interpolation

The Internet of Things (IoT), which is expanding quickly, is delivering vast amounts of data via billions of linked smart gadgets. One of the most used methods for modulation and Media Access Control (MAC) in wireless IoT networks is IEEE 802.15.4. wireless sensor network (WSN) sensors and actuators are often installed in edge situations where multipath fading or high bit error rates may cause burst packet loss on wireless networks [4]. A significant element that lowers the resilience of WSNs is packet loss.

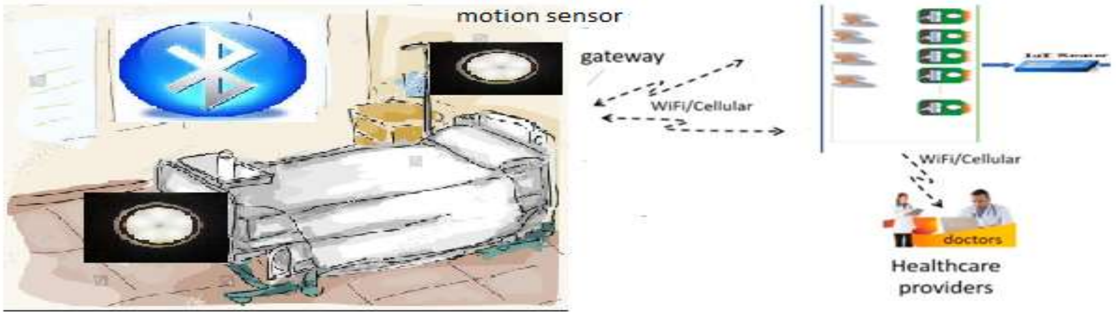

Figure 1: IoT healthcare system [1]

The gateway device and many motion sensors placed around the room make up the WSN. The sensors are used to collect physiological data and transmit it in the right format to the gateway device. Medical sensors and sensor devices come in a variety of forms, such as battery-free wearable sensors that sit just above the wearer's sternum. Due to the use of a passive sensor, the data is scarce and noisy[9], [10].

The gateway device is designed to gather data from motion sensors, deliver it to cloud servers, and update software in addition to keeping track of sensor condition. ZigBee or Bluetooth technology is used by the gateway to connect to the sensor nodes and WiFi or cellular wireless technology is used to connect to the cloud servers. The gateway is capable of simultaneous communication with several motions sensor nodes [10]. Data collected by motion sensors are transmitted to the portable gateway device using e.g., ZigBee [11] or Bluetooth technology network protocols. Due to its long battery life and low power consumption rate, ZigBee technology is used for the connection held between nodes of sensor and the gateway devices. ZigBee is a low-power wireless protocol that employs physical (PHY) and media access control (MAC) layers based on the IEEE 802.15.4 standard[12]. The 2.4 GHz ISM (industrial, scientific, and medical) bands are where ZigBee works. The protocol enables long-lasting battery life and communication between sensor nodes in a range of network topologies. WiFi/Cellular wireless technologies are used for communication between the gateway and servers, providing a greater connection range and more dependable communication connectivity. The wired technologies (e.g., fiber-optic or copper cables) or the wireless ones (e.g., WiFi or cellular) are used to communicate the healthcare providers [13].

Modeling of (IoT) healthcare system

IoT network performance modeling is difficult because each node behavior is unpredictable. For instance, how data is sent from source to destination affects how well each node along the selected path performs. The IoTs may use a variety of routing protocols that were developed for sensor networks. Stochastic techniques are a good match for estimating the act of the individual flows and the network to examine the effects of routing along the selected route. These techniques analyze the past to forecast the future by profiling previous occurrences. IoT applications are characterized by the connection between devices such as sensors, and that sensors have sensing limits to objects, which causes a problem in forecasting, in addition to the increasing size of Internet groups, which has led to the need to analyze, model and test the performance of devices' efficiency. Depending on the requirements of the applications, IoTs often have packets with variable inter-arrival rates. The performance of IoT applications is influenced by a variety of variables. Round trip durations and throughput are severely impacted by a large number of the gateways [10].

Markov chain Model

A Markov model is represented by the transition probability matrix P and the total number of states n. These states serve as a reflection of the model system's environment. For instance, the CPU may decide whether to remain in the computation-intensive Active mode or switch to the idle state after a certain amount of time. A system may have many states and transitions. The probability with which the system switches from one state to another represents how the system really behaves. When the future state of a system relies simply on the present state and the transition probability, this is referred to as the Markov property. A NxN matrix, where N is the total number of states, represents the transition probability. Each entry in the matrix represents the likelihood that state I will change into state j. Given the current value, the transition probability matrix is used to forecast the next series of data. Comparing the actual and projected situations allows us to determine how accurate the forecast is. Using the following equation, we are able to determine the subsequent state.

$S_1 = S_0 * P$ ....(1)

Where S0, S1, and P refer, respectively, to the initial state, the next state, and the transition probability matrix.

The equilibrium or steady state is a unique stationary matrix that is always approached by succeeding state matrices in a normal Markov chain. The following equation, where S and P stand for the stationary matrix and transition, may be used to calculate the steady state. And when the number of samples approaches three, the stationary distribution is the proportion of time the patient spends in each state (out of four states) [11].

Markov model approaches and Methods

Let S_i the current state and S_{i+1} is the next state, then the next state is only dependent on the current state, As the number of samples becomes closer and closer to infinity, the stationary distribution may be defined as the proportion of time that the patient spends in each of the four states

Human activity prediction model of IoT

The healthcare solution model considered in this paper is dynamic and time-varying. If the PRR is determined by the percentage of data receptions that are successful, the inaccuracy is significant, and the link quality cannot be predicted. The Markov model technique[14][15] , a popular strategy for forecasting future occurrences, is used in this research.

Proposed System

In this work, we developed a model based on the predictive model that can predict the patient's state, which recognizes the abnormal activity that indicates something wrong with the patient so we health workers can act. Figure (2) shows the main block diagram of proposed system. We present a predictive model for human activity in IoT system based on the Received Signal Strength Indicator (RSSI) that captures through motion sensors.

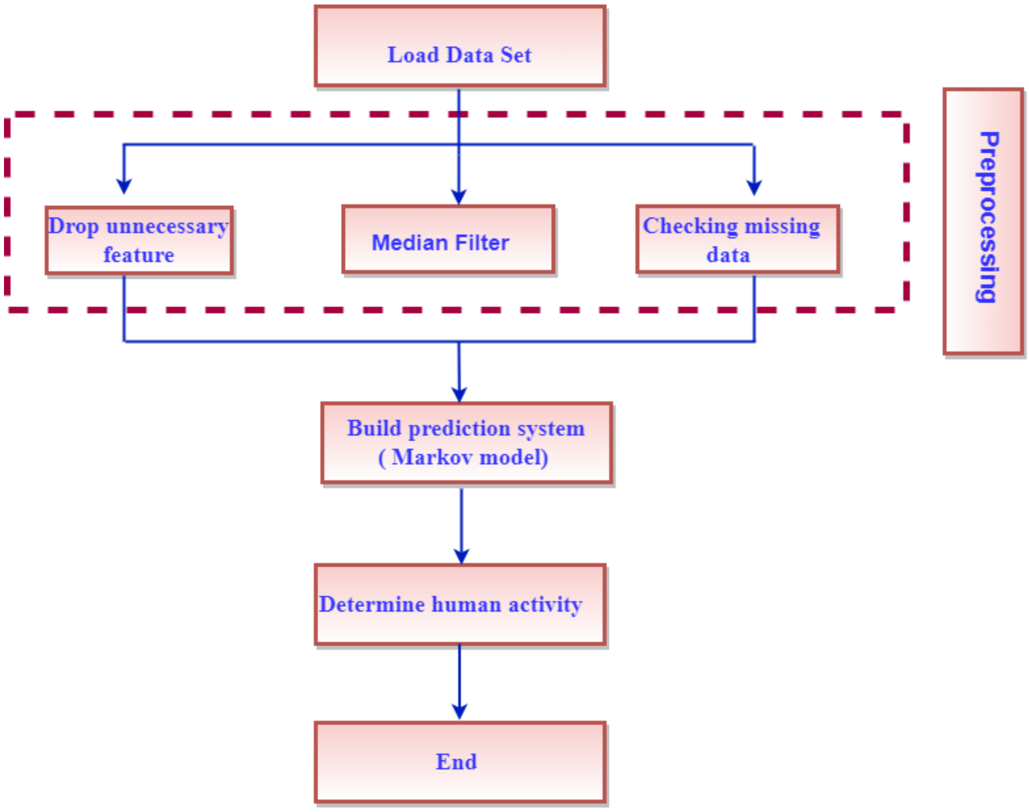

Figure 2: prediction model of human activity

Load data set

Since the system operates in accordance with the prior scenario, which represents the situation before all sensor data are collected. This dataset includes the mobility data of 14 healthy older adults, ages 66 to 86, who undertook widely prescribed activities while wearing a battery-free wearable sensor at the sternum level. Due to the use of a passive sensor, the data is scarce and noisy. Participants were divided across two clinical room environments (S1 and S2). While 3 RFID reader antennas are employed by S2 (Room 2) for collecting motion data (two on ceiling level and one at wall level), S1 (Room 1) uses four RFID reader antennas throughout the room—one on the ceiling level and three on wall level—to gather data. Going to the chair, sitting down, getting up from the chair, walking to the bed, laying down, getting up from the bed, and walking to the door were the actions carried out. Figure 3 shows the description of the dataset.

Data Set Characteristics:	Sequential	Number of Instances:	75128	Area:	Life
Attribute Characteristics:	Real	Number of Attributes:	9	Date Donated	2016-12-12
Associated Tasks:	Classification	Missing Values?	N/A	Number of Web Hits:	44636

Figure 3: Dataset description

Dataset preprocessing

The preprocessing of input data is a very important part of the modeling process. It entails evaluating the input data's quality and, in the end, enhancing the kinds of inputs, selected stages, and time constraints. It directly influences the dependability, accuracy, and outcomes of predictions.

1- Drop unnecessary features (cleaning)

Cleaning Dataset is the most fundamental step in big data collection Before we can run our data through a Machine Learning model, we will need to clean it up. the first step is dropping features, when going through our data cleaning process the first thing we'll do should remove any unrelated or irrelevant features.

2- Checking missing data

Since it contains at least some data support, this is often a highly favored phase. The remaining data was utilized to approximate the missing values in cases where a null cell was checked, and the column's mean value was used to make up the difference. The accuracy and dependability of prediction results are directly impacted by null cells.
After cleaning the data set, the missing values must be processed into the features we need, and the missing rows are compensated by calculating the mean value or the mean.

3- Median Filter

In certain rank-order filters, the median value is used to replace each source vector element, thereby "moving in" and "taking over" the neighborhood (mask) of the element being processed. These filters find extensive usage in signal and picture processing. In order to get rid of sudden noise, median filtering is used, and it does so with as little signal blurring as possible. The Al1 is the first pre-processing phase.

Build the Markov model

For clinical situations with continuing risk, the Markov model offers a far more practical method of modeling prognosis. The Markov model presupposes that the patient is constantly in one of a limited number of Markov states. Every important event is portrayed as a change from one state to another. A person's action is given to each state.

In this work, a Markov models were developed [18]. In a Markov-based dynamical method, the IoT device's emission probability is the likelihood of seeing an RSSI signal given its current state. For a given instance of the MM, the transition probabilities indicate the likelihood that a certain state change will take place. Figure 4 illustrates emission probability states and describes the link between the model's state and the observations as supplied by the input data.

The ultimate instruments for monitoring and making predictions about human behavior. These models' states correspond to phases of human activity. Transitions show how a person's activity is progressing.

Determine Human Activity

In this section, we identify human activity. Figure 4 displays an extract from one of Emission probability. In a dynamical method based on a Markov model, probability is the likelihood of seeing person event data conditional on the state of the motion sensor. The transition probabilities show the likelihood that a certain state transition will take place for a given pixel inside the Markov model . The link between the state in the model and the motion sensor observations via RSSI as supplied by the input data is referred to as the emission probability.

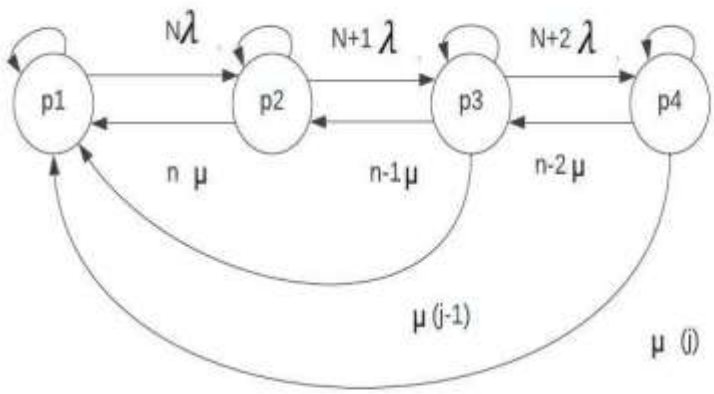

Figure 4: Markov State Model of RSSI

Assume that each state Si produces an RSSI observation XX. Then, the state emission probability is the probability of state Si given the RSSI value.

Em=Pr{RSSI|X}.. (2)

where X is the state, then we can calculate the probability of RSSI value for 'X' as follows:

$P(x)=\frac{\sum no\ of\ RSSI\ occurs}{total\ no\ of\ symbol}$ .... (3)

For each RSSI that is activated directly in time, a Markov model was built. This suggests that the duration of a person's activities will determine both short and lengthy intervals. To collect the data dynamically and obtain more reliable outcomes in the system ongoing behavior.

Experimental Results

This section presents the experimental results obtained with the method described in the previous parts. After determining the system's steady-state probability, we now extract certain transition metrics of relevance.

Let us define the following four events:

T1 = {(RSSI1, ACTIVITY 0)}

T2 = {(RSSI2, ACTIVITY1)}

T3 = {(RSSI3, ACTIVTY2)}

T4 = {RSSI4, ACTIVIT3}

Where T1 represents the transition probability that our model recognizes through ISSR, where activity 0 means the system is static; T2 states that the system is up partially (degraded transition), where activity 1 indicates that the patient is carrying out activity 1. T3 represents the event that the system can provide an activity due to the connection between all motion sensors and the gateway (which is referred to as move between state 2 and state 3), where (T1, T2) denotes that the T1 structure is in the Down state while the T 2 structure is in the Upstate; and T4 represents the event that the system is down due to the last activity while in the T 3 series structure including RSSI 4 structure directly causes the connection of the IoT system). Thus, RSSI for all states represents the likelihood that the IoT system offers complete service.

The likelihood of the system P(E1) providing complete RSSI service with a changed motion sensor transition rate λ . Table 1 refers to state activity belonging to state one and FA refers to Acceleration reading in G for the frontal axis, VA refers to the vertical axis, LA refers to the lateral axis, and RSSI refers to the Received signal strength indicator

Table 1: RSSI States Probabilities

No.	Time	FA	VA	LA	RSSI	Activity	Prob state
0	0.0	0.27203	1.00820	-0.082102	-63.5	1	0.288899
1	0.50	0.27203	1.00820	-0.082102	-63.0	1	0.288899
2	1.50	0.44791	0.91636	-0.013684	-63.5	1	0.288899
3	1.75	0.44791	0.91636	-0.013684	-63.0	1	0.288899
4	2.50	0.34238	0.96229	-0.059296	-63.5	1	0.288899

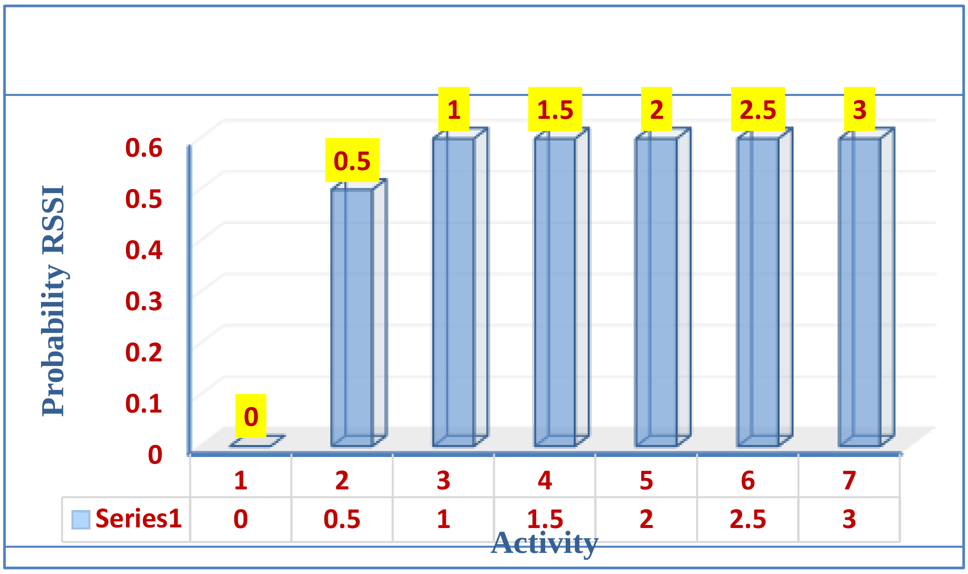

Figure 5: RSSI P(E1) vs. Human activity

Table 2: Median of RSSI

No.	Time	FA	VA	LA	RSSI	Activity	Prob state	Median RSSI
0	0.0	0.27203	1.00820	-0.082102	-63.5	1	0.288899	-58.5
1	0.50	0.27203	1.00820	-0.082102	-63.0	1	0.288899	-58.5
2	1.50	0.44791	0.91636	-0.013684	-63.5	1	0.288899	-58.5
3	1.75	0.44791	0.91636	-0.013684	-63.0	1	0.288899	-58.5
4	2.50	0.34238	0.96229	-0.059296	-63.5	1	0.288899	-58.5

As RSSI varies slightly and each state is assumed to have RSSI emission probability, the median filter of the RSSI is estimated for each state as displayed in Figure 6 to improve the quality of signals in transmission. Table 2 shows the probability of the system P(E1) patient activity with the change of motion sensor rate. As expected, when activity 1 increases, the probability P(E1) is also. As the rate at which sensors are being sampled rises, a greater proportion of sensors transition out of the active state. It is also clear that bigger activities result in greater increases in P (E1) for larger values of senores.

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Conclusions

A predictive model in this proposed approach achieves the same function as conventional solutions that use a complex set of motion sensors using only RSSI volatility. Under a given scenario, the human activity prediction put out to raise both the likelihood of current human activities and the probability of a system providing complete RSSI service to predict the next steps of human activities. The suggested system modeling improvement technique may be used as a helpful guide for the design and assessment of typical IoT systems.

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