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Reliability Metric based Patient Centred Activity Recognition for Smart Healthcare Monitoring

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Abstract

In recent years, increasing attention has been given towards reliability metrics in the healthcare systems. This reliability metric helps to evaluate the impact on healthcare monitoring systems redesign. Healthcare KPIs or metrics are the special key indicators that optimize the healthcare process by monitoring and analyzing healthcare data, which promotes a reliable measurement with the increase patient's satisfaction. These metrics are reliable key indicators and attained a huge impact with the healthcare monitoring system as they play a significant role with IoT based effective and non-effective healthcare monitoring system classification. But,there is room for improvements in analytical methodologies, data collection, and activity recognition with reliability measurement implementation. This could enhance the reliability of the healthcare monitoring system that promotes major opportunities to the policy makers with the reliable measurement. The proposed reliability-driven activity recognition solves the challenges of the real-life scenario of patient monitoring.

Keywords: *Semantic IoT applications, Activity recognition, Reliability metric, Healthcare monitoring system*

1. Introduction

Policy makers gain major opportunities with the reliable healthcare data measurement thereby promoting the security of these systems. The actors of the system include the governments, patients, managers and practitioners at all levels with the financial supporters (citizens) and the decision made by these actors will be improved[1]. Technological enhancement had been made in the field of healthcare reliability system due to the advancement in the information technology and also rising demands in the patient's choice with the healthcare systems. Still the healthcare systems are relatively in their development stage and improvements should be made with the analytical measurement, policy developments and data collection methodologies[2].

Health outcomes from the treatment, population growth and quality clinic are all the other aspects concerning with the reliability of the system that yields productivity, equity, appropriate care and responsiveness[3]. These different progressive aspects make variation with the data collection and reliability measurement techniques. In certain areas like population health, primary care and hospitality, progress has been generated in a considerable range but in certain fields like financial protection, mental health and responsiveness of health systems, developments should be made from the earlier stage[4].

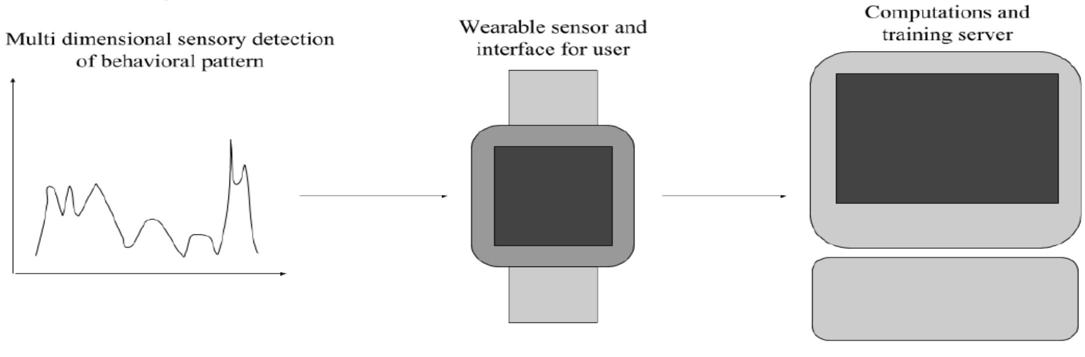

Figure 1: An example of wearable Healthcare sensor and its sensory detection

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For this, a robust conceptual framework should be formulated from which the measurements could be established as shown in figure 1. In recent years, stakeholders, payers, providers and healthcare consumers have demanded better business outcomes and patients care by achieving better reliable performances and organization status. This industry should catch with other consumer-based industries and invest with several efforts and resources that could maintain a solid track to get operated with the reliable organization model to enhance the patient's care outcomes and business result performance as shown in table 1,

Table 1. Reliability Metric based Principles for Healthcare

Important principles	**Care takers behaviour**	**Examples**
Failed preoccupations	Attitude	Physicians and other health care professionals marking the correct surgical site
Operational sensitivity	System based value practices	Maintaining a good record of the team with the incoming and outgoing information and their present situation status to enhance the accuracy of the team
Simplification disinclination	Meta-cognitive skills	Patients admitted at the critical situation and the fellow residents should know their roles and responsibilities
Determination for the organization	Emotional Intelligence and assertion	Nurses have the right to promote their advice to the physician regarding their allergies or any other physical information, which they might have known before
Respect the relevant and the qualified experts	Competency skills and leadership	Patient's healthcare should be monitored at the regular basis by the nurse who had been promoted to monitor their regular activities.

Activity Recognition has gained major attention due to its enormous potential that can enhance healthcare monitoring systems[5]. The main focus of activity recognition systems is to process realistic noisy data and applicable for several patients who needs healthcare monitoring as shown in

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figure 2.

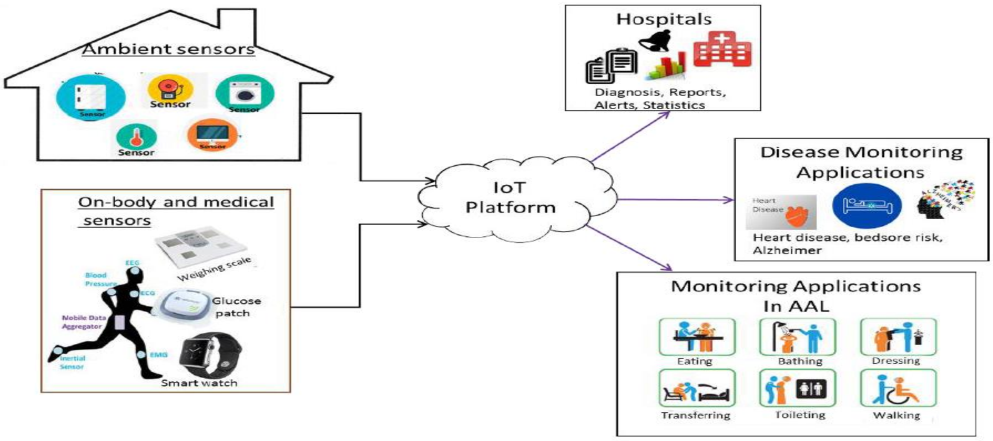

Figure 2 : An example of Healthcare activity monitoring

The proposed patient centered activity recognition can enhance reliability for smart healthcare monitoring[6]. Most activity recognition systems generate information about patients that will be analysed by doctors and then entered into the database through various tools in own proprietary data formats. In such cases, if any flawed patient input is entered which leads to imperfect healthcare database design that causes data inconsistency as well as redundancy. In order to preclude data redundancy, inconsistency problems and less expenditure, effective database structures should be deployed. But in some cases, healthcare database which does not have effective data structures can suffer from these problems, a process known as database normalization should be implemented. The purpose of database normalization is to re-modify tables such a way that the relations among them are logical, so that healthcare database is scalable without any anomalies and avoid data redundancy, inconsistency problems and less expenditure. It is recommendable to design the healthcare database in the OLTP format which are highly normalized which avoids data duplication errors.

In healthcare monitoring database, a central semantic store approach can be deployed which concentrates on logging as well as storing all the rules employed by the database integration process in a single centralized repository. The reason for this approach is that data sources are updated and new ones which are included do not fall outside data integration rules.

2. Related Work

Patient Monitoring systems are considered the most crucial diagnostic systems in the critical care units, these monitoring systems provide continuous display and interpretation of the patient's vital functions. The patient monitoring system is made up of combination of technologies such as sensors, telecommunication for the purpose of medical diagnosis, treatment as well as patient care. Patient monitoring system consists of real-time mode where the patient data will be accessible at remote terminal; store-and-forward mode can access only store data. Most patient centered systems are built with measurement techniques as well as low level signal processing algorithms. After the advent of monitoring systems, a number of techniques to identifying activity recognition algorithms have been developed.

Based on the sensor type, activity recognition recognition can be further classified into video sensor based, wearable sensor based, and even embedded sensor based. A. Ignatov presented a convolutional network that employs an accelerometer for activity recognition [7]. The downside of developing such accelerometer attached to patient bodies will lead to discomfort, moreover, activity recognition totally depends on certain parameters such as localization of the sensor. However, this problem can be solved by embedded sensors and it further secures the patient's personal privacy and independent from external environmental factors and patients does not need to carry sensors which is evident from the work of S. K. Guo et al [8-10].

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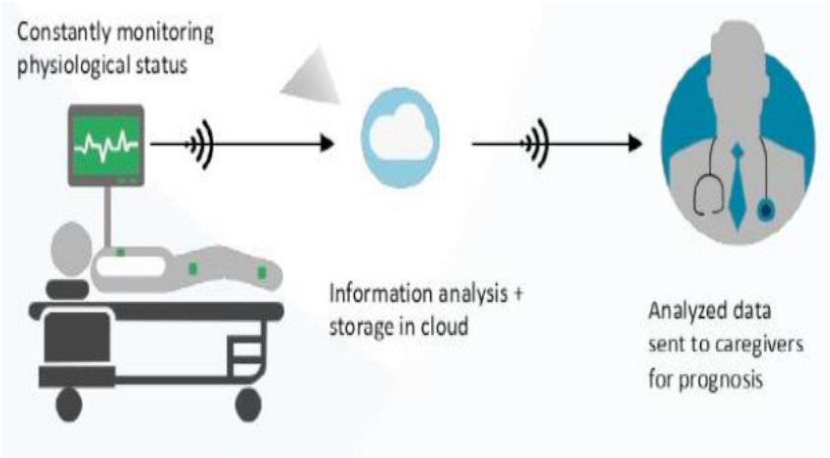

Figure 3: Activity recognition for home monitoring system

In the perspective of activity recognition for home monitoring systems as shown in figure 3, it can classified into data-driven as well as knowledge-driven [11-12]. Salguero et al. presented an ADL classifier that ontology automatically produces important features for the purpose of behavior recognition [13]. The ontology-based approach is clear and easy to understand. Knowledge-driven is therefore called a top-down approach, but it is poor in dealing with uncertainty and time information. One such network is Deep Belief Network proposed by M. M. Hassan et al for effective patient activity recognition.

3. Patient Centered Activity Recognition for Smart Healthcare Monitoring

Linear chain Conditional Random Fields (CRF) model had been used, which utilizes the labeled training data to make classifications with the use of posterior feature data sequences. This algorithm is therefore considered to be an indirect and discriminate probabilistic graphical model. This model is also compatible with the Markov Random Field (MRF), but with the coterie potentials on the input features.

CRF model bring out the structured output and is known to be the extended version of logistic regression. This linear chain structure is associated with the logistic regression and the assumed log-linear. Hidden Markov Model is also considered. This model is considered to be adversary with the CRF model but they have a very clear differences, which could be ostensible. A refined approach could be obtained by reversing the HMM arrows pointing from the point x to the output. This is known as the Maximum Markov Entropy and the input features are conditioned around the state transition probabilities representing the Markov chain. This special case of input-output HMM . By employing, gradient based approach, the scaled log-likelihood can be represented in the form:

$$l(w) \triangleq \frac{1}{N}\sum \log p(y_i|x_i, w) = \frac{1}{N}\sum_i [\sum_c w_c^T \emptyset_c(y_i, x_i) - logZ(w, x_i)]$$

and the gradient becomes,

$$\frac{\partial l}{\partial w_c} = \frac{1}{N}\sum_i \left[\emptyset_c(y_i, x_i) - \frac{\partial}{\partial w_c} logZ(w, x_i)\right]$$

$$= \frac{1}{N}\sum_i [\emptyset_c(y_i, x_i) - E[\emptyset_c(y, x_i)]]$$

Based on the pairwise case of x and y , the equation becomes,

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$$p(y|x,w) = \frac{1}{Z(w,x)} \exp\left(w^T \emptyset(y,x)\right)$$

The problem here arises due to label bias as the local features at time t will not impact the states before time t. The main frame of the work is to generalize long sequence of data obtained from the sensor and the model could also manage the context better with the high prophetic capacity.

The raw sensor events for the activity, “Walking”, when the patient starts to commence a daily activity, the sensors will be activated orderly in a time series manner as long as the activity instance stops. As soon as the sensor is activated, the data, time, name as well as the value of the sensor will be saved as shown in figure 4.

2011-06-15 03:38:13.877151 MA020
2011-06-15 03:38:14. 924765 MA020
2011-06-15 03:38:17. 750829 M021 ON
2011-06-15 03:38:17. 814393 MA020
2011-06-15 03:38:22. 584179 M021 OFF
2011-06-15 03:38:29. 213955 MA020
2011-06-15 03:38:29. 32819 M021
Walking=’’end’’

BATV015 9520
2011-06-15 03:37:46. 585185 M021
ON
2011-06-15 03:37:47. 706265 M021
OFF
2011-06-15 03:38:11. 211961 M021
ON

Figure 4: Activity Sensor Stream for activity “Walking”

The feature vectors are sporadic and the use of that makes the computation to be stored in a short space for reuse. The particular combination of labels could be chosen with the indicator function, which is utilized by the features for potential observations that out-turns as a feature vectors with values strictly equivalent to zero. The inadequacy of feature vectors promotes rapid operations on the features.

The dependent features are all combined in the CRF model and due to the evidence over count, the model does not have any problem in dealing with the penalty and also cope up with the rich class of features.After obtaining the labelled traces from the various patient activities, the trace contains successive readings obtained from the axes of the accelerometer sensor.

Consider, t represents a matrix trace with columns as well as four rows. In-order to represent the acceleration data from x,z and y directions, the first rows are employed while the remaining last row represents sampling time which corresponds the number of recording of the accelerometer present in the column.

The point value is asynchronous for different traces derived from the same activities. For instance, in single axis, a walking distance may arise from the positive acceleration and at the same time, another walking distance may commence from the negative value. The proposed method processes the traces from every activity produced from the time series of probability distributions model, the features are constructed from this model parameters.

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Assuming the features P1 , ..., Pn a probabilistic model consisting of associated class (C) could be F (C |P1 , ..., Pn). The label for a specific group of features can be obtained for a class which possess maximum conditional probability:

argmax C = F (C |P1 , ..., Pn)

According to the Bayes' theorem:

F (C |P1 , ..., Pn) = F (C)F (P1 , ..., Pn |C) / F (P1 , ..., Pn)

Instead of obtaining the class with maximum F (C |P1 , ..., Pn), the greatest class
F (C)F (P1 , ..., Pn |C) is selected.

CRF could be implemented in numerous ways. The feature vectors are sporadic and the use of that makes the computation to be stored in a short space for reuse.

4. Experimentation and Evaluation

The dimensions X,Y and Z are considered as features and the total set of input consists of X,Y,Z , total acceleration magnitude. The dimensions of the features are represented as X,Y,Z. The features were extracted and evaluated based on leave-one-out approach that can predict accuracy in the dataset.

The evaluation on the features were carried out based on the following convention:
- Frequency-based method for all features
- Percentiles that was below 25 and over 75 are determined and its square of sums in magnitude, for all features are determined.

Statistical features was employed in terms of time as well as frequency domain data of labeled sequences. The features consists of Mean amplitude of window, Variance of window , Sum of difference between consecutive measurements ,Square of sum, below 25th percentile in magnitude of feature, Square of sum greater than 75th percentile in magnitude of feature. The time and frequency domain signal provided the features from the monitoring sensor dimension. The database consists of various orientations in gathering each activity as provided by Zhang et al. [14]. A 3-axis accelerometer was employed and attached to the subjects front right hip. The accelerometer sampling frequency as well as length of the traces accounts to 100Hz and 23 seconds. The classes includes Walking, Walking Upstairs, Walking Downstairs, and Standing Up collected from 14 subjects. In order to recognize each activity, Conditional random fields for sequential classification was performed which provided a reliable accuracy between 87% and as low as 83%, along with variation in seed for randomized sub-sampling.

Table 2. CRF results, run 1

LABEL	PRECISION	RECALL	f1 SCORE	SUPPORT
0	0.779	0.851	0.813	10467
1	0.880	0.819	0.848	13950
Avg/total	0.837	0.833	0.833	24417

Table 3. CRF results, run 2

LABEL	PRECISION	RECALL	f1 SCORE	SUPPORT

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0	0.853	0.897	0.874	14283
1	0.888	0.841	0.864	13851
Avg/total	0.870	0.869	0.869	28134

Detecting Walking, Walking Upstairs, Walking Downstairs, as well as Standing Up are considered which proved to work at around 85% accuracy for few test as well as with various seeds as presented in table 2 and 3. Activity recognition considers inputs that are known labels i.e. activities and results in a system that can obtain the label for a fresh trace. These activities are collected by motion sensors and time series can be influenced by the activity performed. Monitoring sensors are fixed on the patient's body and these sensing devices offer their own specific accuracy, cost, prediction and privacy. Most healthcare based AR systems integrate more than one sensing technologies to achieve their goals.

Conclusion

In order to successfully maintain and make healthcare monitoring systems, new sustainable software architecture should be built that makes the deployment easy with the existing ones. Automation is rapidly applied in healthcare information systems all over the world. Application of automation and artificial intelligence applications in health sector has increased phenomenally in almost all healthcare organizations that includes benefits such as labor saving, enhanced monitoring of functioning of patients as well as hospitals with improved patient care and better planning. In developing an effective automated healthcare information should possess methods to manage the medical data processed by doctors, optimize the medical activities as well as medical-patient interaction.

Health care monitoring systems could enhance their characteristics by adapting their methodologies with other industries. By offering commitment with the resiliency, the patient safety culture is offered by eradicating the failures. In this research paper, the need for high reliability for healthcare monitoring is addressed and it is evident from the results that the proposed approach achieved reliable performance.

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