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Application on Pervasive Computing in Healthcare – A Review

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Abstract

Background/Objectives: Application of pervasive computation in healthcare is an interdisciplinary research domain for both the medical and computer domains. Such systems provide support to remote patients and to disaster affected people. **Methods/Statistical Analysis**: This paper calculates percentage of contribution of various methodologies which have been described in this whole paper. Along with this it has presented comparative analysis of the surveyed algorithms based on their important features. **Findings:** The literature studies in this field are found to concentrate on specific applications of pervasive healthcare, such as remote patient monitoring, fall detection, etc. In this paper, we exhibit a descriptive study of different features of pervasive healthcare in recent years. **Application/Improvements**: The pervasive healthcare has proved to be much useful in case of elderly people living alone or patients undergoing post-operative recovery phase. Finally, a comparative analysis table of the respective techniques has been presented.

Keywords: Access Control, Classification, Clustering, Daily Activities, Decision Making, Healthcare, Pervasive, Prediction, Remote Patient Monitoring

1. Introduction

The pervasive healthcare is gaining popularity day by day as it offers health support to patients irrespective of their location. In emergency medical situations, help can be sent quickly by using the pervasive health-support applications. In all pervasive healthcare systems, patients are benefited by receiving service of telemedicine and health related guidelines from caregivers, doctors. Researchers have been working in this domain to make the systems more effective and reliable. Till date, the surveys works in this area mostly concentrate on a specific technique or application like fall detection etc. The features of the Pervasive Computing in Healthcare such as: 1. Context aware, 2. Machine Intelligence, 3. Knowledge Discovery database and 4. Security. It is observed that in the context of reasoning, classification, real time prediction and decision making, various machine learning algorithms and data mining techniques[5.1,5.2] have been designed in remote and smart home healthcare systems. Clustering algorithms are designed by researchers to be used in Pervasive healthcare for providing intelligent location aware and ADL detecting services. Clustering is also being used for route navigation in remote monitoring of disabled people. We have also presented a brief discussion on the state of the art work with respect to security of confidential health data. The whole paper is organized with a comparative analysis in the following subsections as follows. Section 2 presents background study, subsection 2.1-2.3 present category wise reviews and Section 3 provides a comparative analysis of the reviews with a conclusion of the discussion in Section 4.

2. Review Work

Pervasive computing has evolved as an emerging future of the healthcare services. In recent years lots of research work and study[5.3] in the related field have been carried

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out. We have selected 60 research papers dealing with techniques, frameworks and modeling of pervasive healthcare applications. These papers were then categorized in a quantitative manner based on the underlying logic, such as decision making, data handling, ontology and security.

2.1 Purpose of the Review

Our aim is to identify different features of pervasive domain and analyze the basic research challenges in this field. We have provided a comprehensive list of existing research woks in this area and have included comparative analysis tables as well. This literature review provides a valuable resource in pervasive healthcare domain for researchers. Different methodologies that we studied for pervasive computing in health care field are described below:

2.2 Machine Learning

Several machine learning algorithms have being used in pervasive healthcare systems to provide great potential for extracting useful knowledge to achieve the appropriate care in health care for individuals.

3. Decision Making

Decision making in Machine Intelligence is described here by multiple learning and training methods. Multilayer Neural Network, Fuzzy Inference system and Decision Tree are the popular classifiers to train data. A real time ANN based medical decision support system[5.4] is proposed to take decision and provide suitable suggestion. On the other hand it has no predicting technique.

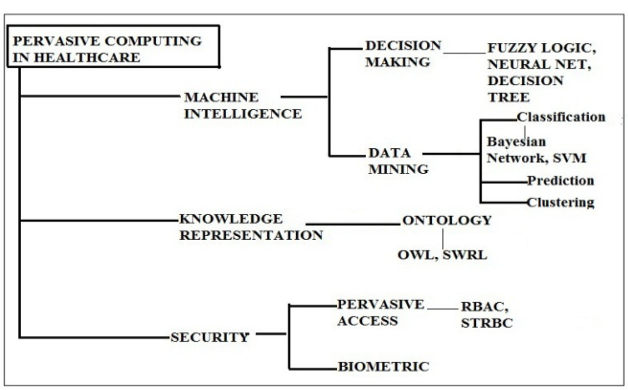


Figure 1. Different methodologies applied in pervasive computing in healthcare.

A prototype named Intelligent Heart Disease Prediction System (IHDPS)[5.5] for detecting heart diseases is proposed by applying different classifiers like Decision Trees, Naive Bayes and Neural Network to predict and identify the significant impact of attributes of Heart Diseases. Pervasive computing is implemented for recognition of Activity in Daily life (ADL) using many classifiers and decision making algorithms to provide better health and life style management. An ear worn device[5.6] is used for activity recognition in order to improve the daily life in a sensor based ambience. The common activities of daily living are being identified in those works. A two-stage Bayesian classifier is proposed for each feature using a multivariate density Gaussian model. It is used to model the posterior probability of each activity class. Another one[5.7] implements a real time algorithm to recognize the physical activities automatically among people and the intensities of various activities. This algorithm uses C4.5 Decision Tree and Naïve Bayes classifier. They show results for HR with low discriminate features like FFT, entropy of intensities. Automatic feature extraction method is also implemented in[5.8] for Activity Recognition. Restricted Boltzmann Machine learning model (RBM) and Nearest Neighbour classifier are implemented for analysis of training data. A method[5.9] for detecting ADL in elder people with offline and online stages. This method can be improved by covering more features in both supervised and unsupervised learning in papers[5.10] to propose a hybrid model and auto-generated Decision Tree. Heterogeneous sensors are made in fusion based on a Gaussian Bayes EM classifier[5.11] and training algorithms. Custom DT uses domain knowledge for self recognizing and concluding the activities from the signal information by the user annotation. The implementation of fall detection algorithm[5.12] uses Decision Tree model to detect a fall. The training of DT is done by radio signal of Wi-Fi network in online mode to predict user's location. Smart home[5.14] proposes a user centric economical prototype design. The system implements the Multilayer Neural Network's back propagation algorithm for Condition Diagnosis of patients. Similarly, Back Propagation algorithm[5.15] is used to compare with other optimization algorithms like Particle Swarm Optimization on unstructured patient data.

3.1 Fuzzy Reasoning

Previous papers are not concerned about the representation of vague and uncertain data in inference system. A fuzzy-logic based context aware system CARA[5.16,5.17] is presented in a personalized, flexible real-time framework to provide inference mechanisms. It supports remote patient monitoring and caregiver notification. The fuzzy rules are used in previous papers with Case based Reasoning method (CBR) to detect different conditional anomalies in order to automate the home environment by using K-NN classifiers. A fuzzy based data fusion model EMUTE[5.18] is proposed to monitor distress people at smart home where multimodal data of various sensors are classified by fuzzy-classifier and detected by Fuzzy Inference rules for each subsystem.

Table 1 provides information that are studied here about the major types of the systems used in the pervasive Healthcare services and their percentage of contribution in this review work.

Table 2 illustrates that the application of decision making methods in healthcare systems use supervised, semi-supervised and unsupervised learning techniques. The kind of the environment where decision and recognition are occurred may be dynamic also. Fuzzy CARA systems are shown here be more dynamic and robust in reasoning capability.

Table 1. System functionalities

System	Function	References	[n]%
ADL	Activity recognition, Fall detection	[5.6], [5.7], [5.8], [5.9], [5.10], [5.11], [5.12], [5.13], [5.22], [5.23], [5.3], [5.33], [5.34], [5.37]	23
Smart Home	Homecare treatment, continuous remote monitoring, decision making	[5.2], [5.14], [5.15], [5.16], [5.21], [5.35], [5.39], [5.42], [5.43], [5.44], [5.45], [5.46], [5.47], [5.48], [5.49], [5.50], [5.51]	30
Body Sensor Network	Ambient intelligence and remote monitoring	[5.6], [5.13], [5.24], [5.26], [5.30], [5.27], [5.28], [5.29], [5.32], [5.34], [5.35], [5.38]	16
Behaviour Modelling	Activity recognition	[5.1], [5.32], [5.39]	5
Biometric, access control	Secured real-time medical data transmission	[5.36], [5.53], [5.54], [5.55], [5.56]	8
Medical Decision support system	Disease monitoring, emergency response	[5.14], [5.17], [5.18], [5.19], [5.25], [5.26], [5.31], [5.40], [5.41], [5.39], [5.43], [5.44], [5.45], [5.46], [5.47], [5.48], [5.49], [5.50], [5.51]	32

3.2 Data Mining

Pervasive healthcare system requires a huge heterogeneous data which are poor in knowledge. That is why it is important to discover the hidden relationship among data and classify them accordingly for decision making in real time. To extract the hidden pattern in the large data set various data mining tools are available there. In this survey paper an intensive study has been presented as per following category:

- **Classification:** It is implemented in data mining for predicting analysis of pervasive healthcare. It involves discrete class attributes where the goal is to learn a concise model hypothesis from the training data and apply this model to predict a new feature for an unlabelled class (Andrea Zanda). Several probability based algorithms such as Hidden Markov Model, Conditional random field, Expectation Maximization are used for classification of activities in healthcare systems.
- **Activity Detection**: In[5.19] eight activities are recognized using combined classifiers with five base data classifiers and a meta classifiers as Boosting (AdaBoost)[5.20] for improving the classification to handle frequent occurrence of imbalanced data from a single accelerometer data. Bayesian Framework for Feature selection[5.30] is used to rank the relevance of features to different activity classes with Multivariate Gaussian Bayes classifier. Another pattern recognition methodology[5.22] is used to detect the activity by monitoring the action of chewing. It identifies the periods of food intake based on a non-invasive mechanism. Support Vector Machine is implemented as classifier for training the sensor data for automatic detection. A decision support system (DSHDPS)[5.23] is implemented using Naive Bayes classifier for classifying discriminate medical profiles such as different health parameters and age, sex, etc. It can predict the likelihood of patients getting a heart disease through DSHDPS. [5.24]proposes a generalized context aware model of continuous monitoring of activities in a smart pervasive space. Automatic recognition of ADL is performed in a smart space with mainly three classifiers as Naive Bayes, HMM and CRF to manage sequential data and generate probability distributions over the class labels.

Table 2. Decision making methods

Alg Algorithm and Function	Machine Learning			Co Context Modelling	En Environment
	Classifier	Learner	Reasoning		
Fo FOG freezing of Gait detection	C4. C.45, Random Forest(RF)	Weka API	×	√	Dy Dynamic
Mu Multi Appliance Recognition	Hy Hybrid SVM/GMM	Lib SVM	×	×	Dy Dynamic
Aut Automatic feature extraction (RBF) for activity recognition	Nea Nearest Neighbour	Ne Nearest Neighbour, PCA, ECDF	×	×	Dy Dynamic
Aut Automatic chewing pattern detection	S L Svm	Lib LibSvm	√	×	Dy Dynamic
Fu Fuzzy-CARA, EMUTEM for remote monitoring	Fuz Fuzzy classifier	××√×	√	√	Dy Dynamic
Ass Assisted living IH IHDPS, ANN Based decision support system	SV SVM, RBF,MLP, ANN, Decision Tree, Naïve Bayes	Bac Backpropagation uns Unsupervised	×	×	Dy Dynamic
Ge Generalized ADL Detection at smart home	NB NBC, HMM, CRF	Sup Supervised, semisupervised	×	×	Sta Static
Fall FallAlarm	Dec Decision Tree	sup Supervised	√	×	Static

- **Body Sensor Network**: For online application of BSN[5.26,5.28] implement machine learning to detect freezing of gaits on the smart phone from the wearable devices. Supervised machine learning algorithm like C4.5 and RF[5.26] are implemented offline at the base station and the FoG-detection classifier is trained at offline mode to classify a typical motion pattern serialized with Weka classifier at online. Online body acceleration sensors are used[5.28] to track the movements of patients for automatic detection FoG by analyzing frequency component.
- **Clustering:** In pervasive healthcare system clustering provides a couple of services for reducing the task of searching in the context of location, service etc. According to the study (Ed Colet), related records are grouped together through clustering on the basis of having similar values for attributes.
- **Remote Healthcare Monitoring:** For continuous care at nursing home, it is difficult to manually track, identify and label individuals and classify their body activities in different ambient. The clustering of motion frame[5.29] is proposed to label individual person-region in temporal duration for automated tracking and labelling the body actions in nursing home. Patient's behavior pattern is observed and inferred by a proposed HMM model[5.30] by representation of similarity spaces into clustering. The overlapped activities as cluster AALO[5.33] is proposed in the similar time duration to recognise each cluster of group of activities automatically using unsupervised training algorithm. [5.32]allows learning Activities of Daily Living (ADL) cluster models automatically implementing the proposed Flocking algorithm with supervised learning. Walking style of different of gait affected person is monitored remotely by cluster in the 2D feature space[5.33] of walking speed, heights. But for similar activities in different rooms at same time cannot be monitored here. The human activity pattern[5.35] is recognized by k-means temporal segmentation.
- **Privacy in Mobile Network:** The necessity of privacy preserving is described[5.34] in Location Based Service (LBS) of a mobile network. It introduces flocking algorithm instead of using fixed number of cluster to determine the various daily activities in designing a smart home environment. It proposes and implements three rules for measuring similarity and dissimilarity in flocking clustering method.
- Processing Data in Sensor Network: [5.36]presents a k-means data stream clustering algorithm (AG-KCDSC) to process data on sensor network using the k sets of centroid and average square error.

Table 3 provides the information about the type of clustering algorithm that is illustrated here towards the

Table 3. Clustering algorithms

Cluster Algorithm	Type	Number of cluster	Learning	Flexibility
Flocking based ADL	ADL	No predefined number.	Supervised	√
2Dfeature space	Gait Measure	2-height, speed	×	×
AALO	ADL	Overlapped cluster	Unsupervised	√
AG-KCDSC	Data stream	K sets of centroid	Unsupervised	
Cluster Cloak	Location Privacy	k-anonymity levels	×	√

classification and prediction of data. Most of the clustering methods can be applied in dynamic environment.

- **Prediction:** Prediction is a technique of data mining used for predictive analysis of unstructured data. In context of prediction of imbalanced data context alignment prediction algorithm[5.37] is discussed to represent the similarities between two pattern sequences of context data using Markov, ARMA, PCA and ICA (Independent Component Analysis) algorithm. A regression based data mining technique[5.38] is proposed to find the effectiveness of different types of diabetic treatment using predictive analysis for different age group. SVM and regression analysis are implemented for learning classification. [5.39]predicts the activity based on sensor reading in order to provide continuous monitoring in pervasive healthcare using Support Vector Regression (SVR). Bayesian statistical approach[5.25] is implemented in health management for prediction and detection. Bayesian linear regression[5.25] is used to estimate a predictive distribution on the values to predict the impact of accurate swimming velocity when the computational cost becomes lesser than the value of other model like Gaussian.

3.3 Knowledge Representation

To manage the huge data in cloud database for pervasive healthcare proper knowledge representation should be there. Ontology is the information about a context. It contains the relationships among the entities. It is based on the domain knowledge such as name, time, location, event or any description.

- **Ontology:** Ontology can be implemented in dynamic pervasive environment also. Ontologies are used in the aspect of knowledge representation to represent the relationship between various variables and symbols to enhance the modularity of the knowledge base.
- **Implementation of Ontology using OWL:** The architecture of the homecare system[5.40] is proposed for the treatment of a patient with dementia in pervasive homecare environments. In this paper Semantic Web Rule Language, Semantic Query-Web Enhanced Language[5.41] is implemented to bridge between the existing knowledge and the proposed ontology using the language OWL. In[5.42] dynamic homecare environment of a patient's context are handled as it constantly being changed. A cloud computing module is implemented to store the patients' health related data in EHR as well as the ontologies written in OWL and inference rules and queries in SWRL, SQWRL.
- **Dynamic Ontology:** To make the ontology dynamic[5.43] discusses the solution to the limitation of that problem using the architecture of the centralized pervasive context aware distributed system named as Context Broker Architecture (CoBrA) which is a collection of different ontology (COBRA-ONT). In this paper dynamic knowledge is shared among other ontologies.
- **Context aware ontology:** In[5.44] ontology based daily life activities are recognized and inferred by logical semantic reasoning. This paper studies about the different approaches of activity recognition like vision based, sensor based, ontology based. It finds the machine learning algorithm based on supervised and unsupervised learning to recognize activity. A fuzzy based ontology OWL 2[5.45] is used to model uncertain knowledge and to represent fuzzy concrete predicates by adopting NeOn ontology. In context aware system[5.46] proposes a quality assured and context aware data fusion and an ontological rule based semantic network for context delivery by Dynamic Bayesian network and mediated by ontological rules in a smart home. [5.47]evaluates the most appropriate context aware tools to build a hybrid context model for sophisticated reasoning using OWL standards by W3 and SWRL. Architecture for knowledge representation in large service oriented medical application is proposed in[5.48]. It supports automatic adaptation by triggering discovery services for satisfying timely need of user by using XML, RDF and RDF schema.

In Table 4 the various characteristics of different knowledge representation methods are represented.

Table 4. Knowledge representation

Onltology	Cloud computing	Privacy	language	Knowledge sharing	dynamic	cost-effective
CoBra-ONT	×	√	OWL, Flora 2	√	√	√
ADL Detection	×	×	OWL	×	×	×
Homecare	√	×	OWL, XML, SWRL, SQWRL	×	×	×
ACMA	×	×	Netica BN	√	√	×
Context adaptation	×	×	OWL, XML,XSD	×	×	√

Among all features it is seen that one of the important factors is cost effective. It is required to evaluate the feasibility of the faster assignment of appropriate caregivers to remote patients.

3.4 Security

In pervasive healthcare systems security plays a vital role in the corresponding network, data, underlying infrastructure, and related services. A few of them are described below.

- **Access Control:** Access control is given to every user to manage the security mechanism in pervasive healthcare computing. For sharing of patients' health information in pervasive healthcare systems we need access control schemes to fetch and implement the specific needs of each patient.
- **Role Based Access Control:** Role Based Access Control [5.19,5.20,5.24] is used in the pervasive healthcare as the most popular access control method. It offers control to role of a user rather than a specific user. The dynamic RBAC [5.49] is implemented by combining it with context awareness.
- **Dynamic Access Control:** To maintain privacy control in framework papers[5.50,5.51] design dynamic context aware application. [5.52]designs a semantic for context-aware policy model by adopting ontologies and rules to implement in contest aware models. STRBAC[5.53] model uses accessibility by user's time and location for supporting privilege delegation.

3.5 Biometric Security

An authentication method Markov model-directed key exchange method and [5.56,5.57] are proposed to strengthen the information in the central database and the access in various settings.

- **Threats in Cloud based Architecture:** Cloud computing and IoT[5.58] have been deployed in pervasive healthcare systems to provide secured and smart assisted care to many elder and disable people. This model enhances the agility, availability, scalability in the healthcare systems. Therefore it requires identifying the underlying vulnerabilities including various flaws in a system that could cause threat or attack. Most of the pervasive healthcare systems include cloud platforms to store and process the heterogeneous data and to assure remote access to the central information for continuous monitoring in a faster, simpler and safer way[5.59]. It is shown in literature review that the SPI (Saas, PaaS, IaS) model in cloud infrastructure uses prediction processor, alert generating processor for remote patients, doctors, caregivers. The challenge of security lies in SaaS with the cloud provider. The PaaS model presents a greater customer control in the cloud architecture. Due to the relatively lower degree of abstraction, IaaS has a greater customer control[5.60] over security than in other models in existing SPI.

Table 5 represents the security models used in the pervasive healthcare domain to allow role permission, role delegation and also authentication. Results show from the table that most of them are used to provide access control scheme in healthcare systems.

4. Results of Comparative Analysis

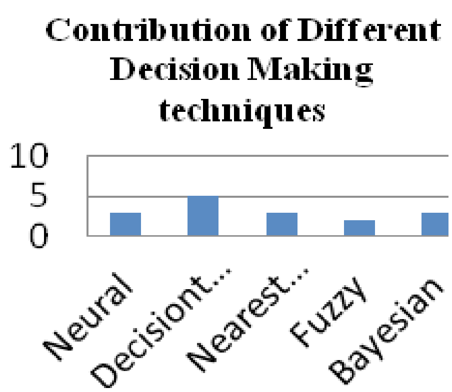
A result of the literature survey on various techniques of pervasive healthcare is shown in this Section. The first figure displays the contribution of the various research papers on the methodologies of Decision Making tools discussed in Section 2.2. Figure 2 displays the comparative growth of the other methodologies discussed in section Data Mining in Section 2.1 and in Section 2.2 and 2.3.

4.1 Research Challenges and Open Issue

From the study of earlier literature review, it can be observed that pervasive healthcare has become the next

Table 5. Security mechanism

Algorithm	Context aware access control	Authentication	Dynamic	Role Delegation	Cost effective
RBAC	√	×	√	√	×
Context guard mechanism	√	×	√	√	√
Tuning active role permission	√	×			√
Context policy model	√	×	√	×	×
Markov model	×	√	×	×	×
STRBAC	×	×	√	√	×
Cloud computing based architecture	√	√	√	√	√



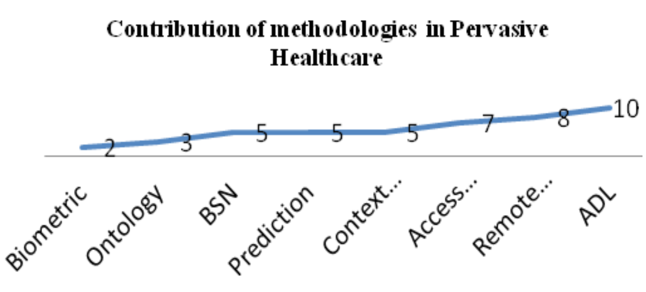


Figure 2. Number of papers studied using different decision making techniques and Methodologiesstudied in Section 2.1, 2.2, 2.3.

step of pervasive computing. However, there still remain a number of challenges and open issues that should be dealt by the research community. This section describes some of the existing research challenges in this domain.

- **Security, Privacy, Trust:** To ensure users that their confidential data are communicated to the authenticated persons only remains the most serious challenge. Proper user identification management, location based and trust value based security techniques are required to be integrated to the existing remote healthcare systems.
- **Context Management:** Existing semantic approaches discussed in the review section need to include various descriptors for providing support to end users in pervasive computing. These approaches include several characteristics in the corresponding ambience to facilitate the interoperability and compatibility among all the components.
- **Infrastructure Based Computing:** Due to lack of a proper infrastructure and maintenance of the base nodes, the link between the server and the user may be destroyed. Research issues are open as the performance analysis of the battery power of sensors, location of base station and other networking devices, addressing schemes of the network and to improve the strength of the signal for faster communication.
- **Data Management and Heterogeneity:** The challenge in pervasive healthcare lies in the proper management of the large heterogeneous data. We need to ensure the integrity and availability of the on-demand large data in cloud services. Data abstraction and data integration are used to maintain the accuracy and consistency of altered data efficiently during the exchange of data in large scale application.
- **Fault Tolerance:** The context data changes rapidly and with the heterogeneity in the pervasive healthcare applications. Therefore, reliability between different components is required to guarantee fault tolerance.

5. Conclusion

The research area in pervasive computing field is open for designing a complete emergency system in remote pervasive health care environment and to handle large database of complicated patients' profile and proper scheduling for emergency care. This paper includes a broad overview of the different aspects of pervasive healthcare applications, as well as detail study of existing works in those areas. The security and privacy aspects have also been studied.

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