Wearable Sensors in Health Monitoring Systems

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Abstract

Recent years have perceived an increase in the progress of wearable sensors for health monitoring systems. This increase has been due to several issues such as development in sensor technology as well as focused efforts on political and investor levels to promote projects which address the need for providing new methods for care given increasing challenges with an aging population. In this system is about study of how the data is treated and processed. This paper provides latest methods and algorithms used to analyze data from wearable sensors used for physiological monitoring of vital symbols in healthcare services. This paper outlines the data mining tasks that have been applied such as prediction, anomaly detection and decision making when considering in particular continuous time series measurements and detailed about the suitability of particular data mining and machine learning methods used to process the physiological data and provides an overview of the properties of the data sets used in experimental support.

Keywords:

Introduction ;Data mining for wearable sensors; Data mining Approach; ; Machine learning technique; Datasets and its properties;

1. Introduction

With the increase of healthcare services to implement the health monitoring system continuously without hospitalization using wearable sensors, the need to mine and process the physiological measurements is growing significantly. Advances in data mining for health monitoring systems have led to provide proactive information However, as the field progresses and more works consider utilization in real settings, data mining techniques that consider the specific challenges which develop from data coming from wearable sensors is of ever growing significance. It includes not only traditional pattern recognition and anomaly detection but also must consider decision based systems which can handle context awareness, and subject specific models and personalization.

Data mining reviews for healthcare and sensors most of them are related to general studies for healthcare *i.e.*, well known problems in healthcare with simple and routine data mining approaches categorized the main challenges of sensor data mining in five following stages: acquisition, preprocessing, transformation, modelling and evaluation.

Data mining algorithms mainly classified in two categories
(1) Descriptive or unsupervised learning (*i.e.*, clustering, association, and summarization) and
(2) Predictive or supervised learning (*i.e.*, classification, regression).

However, they are needing deeper insight into the appropriateness of the algorithms for handling the special characteristics of the sensor data in health monitoring systems.

2. Data Mining for Wearable Sensors

Research area of health monitoring systems has moved from simple reasoning of wearable sensor readings (like calculating the sleep hours) to the higher level of data processing in order to give more information that is valued to the end users, i.e. healthcare services have been converging on deeper data mining tasks to have deeper knowledge discovery. Three types of data mining tasks are predominant. They are:

i) Prediction,

ii) Anomaly detection

iii) Diagnosis

In Figure – 1 the first dimension involves in which the monitoring occurs. The most monitoring applications which consider home settings or remote monitoring deal primarily with prediction and anomaly detection whereas the applications in clinical settings are typically focused on diagnosis. This fact is explained by the growing need to have a more precautionary approach (prediction) via wearable sensors and to consider the chance to enable living in home environments by increasing the sense of security (alarm). Similarly, in clinical settings information is available in order to provide diagnosis and assist in decision making.

A second dimension in the Figure shows the main data mining tasks in wearable sensors with respect to the type of issues used. For patients with known medical records, both diagnosis and specifically the possibility to raise alarms are key tasks. For health monitoring which include healthy individuals who want to ensure the maintenance of good health, prediction and anomaly detection are used .The final dimension depicted in the Figure considers the three main data mining tasks in relation to how the data is processed. For all three tasks data has been addressed both in an online and offline manner.

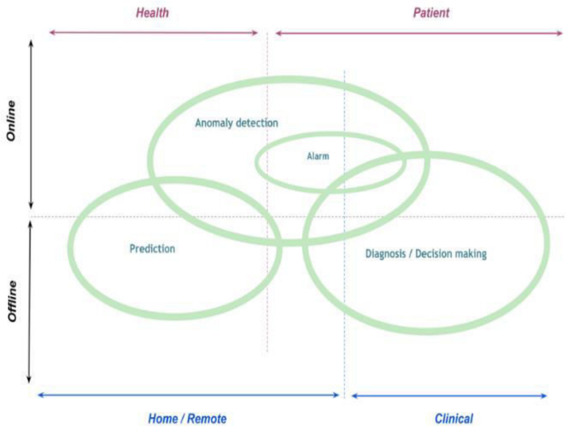

Figure 1. A graphical view of the position of the main data mining tasks (anomaly detection, prediction, and diagnosis/decision making) to the different aspects of wearable sensing in the health monitoring systems.

Figure - 2 delivers an outline of the three data mining tasks in relation to the symbols that can be measured by wearable sensors. ECG, which provides mostly the rich data, is mostly used for all tasks in comparison to the other types of sensors. Equal importance is placed on anomaly detection and diagnosis and less attention put on prediction. Generally, this relates to the majority of the symbol parameters in the Figure.

Health parameters such as heart rate and blood glucose, the percentage of the tasks dedicated to predication is higher. These parameters are associated with monitoring of specific diseases e.g., diabetes whereby prediction is an important component.

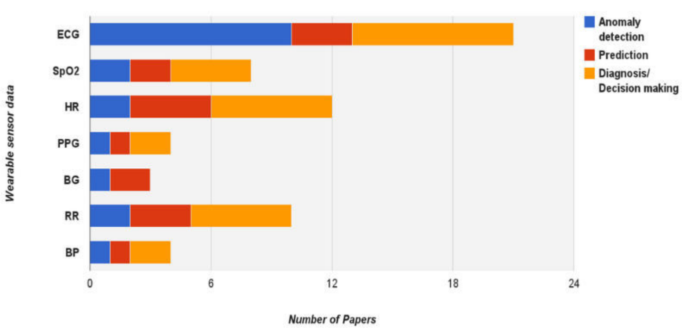

Figure 2. Outline of the data mining tasks in relation to the vital signs measured by wearable sensors.

2.1. Anomaly Detection

In data mining, **anomaly detection** (also **outlier detection**) is the identification of items, events or observations which do not conform to an expected pattern or other items in a dataset. Typically the anomalous items will translate to some kind of problem such as bank fraud, a structural defect, medical problems or errors in a text. . Detected unusual patterns in health parameters, especially for home monitoring systems, enables the clinicians to make accurate decisions in short time. Anomaly detection techniques are based on a classification methods to distinguish the data set into normal class and outliers. Support vector machines, Markov models and Wavelet analysis are used in health monitoring systems for anomaly detection. The anomaly detection approach usually deal with short term and multivariate data sets in order to characterize the entire the data to find conflicts, finding irregular patterns in vital signs time series such as abnormal episodes in ECG pulses and blood glucose level, which mostly notice unusual temporal patterns in continuous data. Somebodies used domain knowledge and predefined information to detect anomalies for decision making in sleep episodes, and finding risky stress levels. In online health monitoring systems, raising alarm as soon as detecting any difference in signs will be triggered to have immediate reaction and such alarm system are usually designed for monitoring patients in clinical units. In offline techniques in order to detect abnormal reading for each individual based on the historical measurements for the person.

2.2. Prediction

Prediction is an approach that is widely used in data mining field that Predicting the identity of one thing based purely on the description of another, related thing. It is getting more interest for the healthcare providers in the medical domain and it helps to inhibit further chronic problems and could lead to a decision about diagnosis. The part of the predictive data mining considering wearable sensors is nontrivial due to necessity of modeling sequential patterns developed from medical symbols. It is also known as supervised learning models where it includes extraction, training and testing steps while carrying the prediction of the data actions. Examples of the predictive models, a method which predicts the further stress levels of a subject. A related example of using predictive models in healthcare are: mortality prediction by clustering electronic health data, blood glucose level prediction, and a predictive decision making system for dialysis patients. For the sake of the unexpected situations and conditions in environmental health monitoring (in Home), the strain of using predictive models is higher than controlled positions such as clinical units. There are several new prediction works which have used experimental wearable sensor data to perform non clinical health monitoring.

2.3. Diagnosis/Decision Making

Decision making in diagnosis is one of the main tasks of proven monitoring systems which is often based on retrieved knowledge using medical symbols, and also other information such as electronic health records and metadata. The decision making is related to the anomaly detection in data mining in order to extract useful information of sensor data such as outliers, events and alarms which are meaningful for decision. Diagnosis systems are not necessarily using abnormal patterns in vital signs to make decisions. Moreover, the complication of the conditions, especially about patient's situations, needs more healthy and global information rather than sensor's abnormal patterns only. Decision making is considered as a task in processing physiological data. Examples of works in this area involve estimating the severity of health episodes of patients suffering chronic disease, sleep issues such as polysomnography and apnea, estimation and classification of health conditions and emotion recognition. We have used online databases with annotated episodes in order to have necessary and trustable real-world disease to evaluate the decision making process. The complexity of the data to deduce diagnosis, some researchers frequently used classification methods on short term clinical data such as Neural Network (NN) and decision trees.

2.4. Data Mining Tasks for Wearable Sensors

The main role of data mining in healthcare monitoring systems is extracting information and there are several tasks considering wearable sensors that data mining methods are able to carry out. They are dealing with the following issues:

(1) Data acquisition using the adequate sensor set
(2) Transmission of data from subject to clinician
(3) Integration of data with other descriptive data
(4) Data storage.

These issues leads to investigate some data mining tasks such as data cleaning, noise removing, data filtering and compressing as a part of any physiological data monitoring. Several data mining techniques are applied such as wavelet analysis for artifact reduction and data compression, rule-based methods for data summarizing and transmitting, and Gaussian process for secure authentication. These kinds of tasks are usually dealing with unlabeled and continuous data.

3. Data Mining Approach

The role of data analysis in health monitoring systems is to extract information from the low level sensor data and bond them to the high level knowledge representation. This reason recent health monitoring systems have given more consideration to the data processing phase in order to catch more valued information based on the expert user requirements and it is also not uncommon that several techniques are used within the same design.

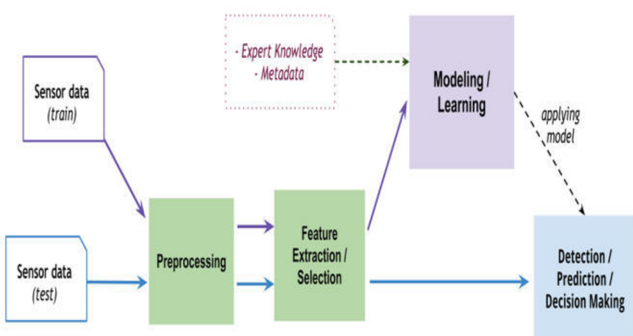

Figure 3. A generic architecture of the main data mining approach for wearable sensor data.

In the figure, the raw sensor data is usually used as a starting point of the data mining approach. Here, the sensor data is provided for both training data and helps in order to learn the system, make a model of features, as well as testing data for real-world usage designed model and make the result and also suggested as a general flow for both supervised and unsupervised data mining solutions in order to provide any kind of data mining task as result. Steps of the data mining approach is

(1) Data preprocessing
(2) Feature extraction and selection
(3) Modelling data learning the input features

Other parameters on data mining and machine learning methods are important such as expert knowledge, historical data measurements, electronic health records, and stable parameters. Metadata provides related analysis and improves the process of knowledge extraction. An instance is every healthcare system using HR sensor data needs to investigate the effect of metadata such as weight, and medicine in order to have meaningful reasoning to find (basic abnormal heart rates or to personalize the critical pulses based on the mentioned metadata).

3.1. Preprocessing

Data Preprocessing is often neglected but important step in the data mining process .Data preprocessing in the healthcare domain involves

(1) Filter unusual data to remove artifacts

(2) Remove high frequency noise

Filtering artifacts, designed modules have applied threshold-based methods to filter sensor data or used statistical tools to include the missing data points. In ECG data, several works have been done to improve the quality of signals for exact analysis.

To remove frequency noise, the other methods in frequency domain is low-pass/high-pass filtering tools and power spectral density (PSD) fast Fourier transforms (FFT are common to remove the fluctuations in sensor signals. The data is gathered from various wearable sensors, normalization and synchronization of sensor data is mandatory. Preprocessing phase in healthcare systems includes data formatting, data normalization, and data synchronization. The gathered sensor data is often erratic and massive

3.2. Feature Extraction/Selection

Feature extraction is related to dimensionality reduction. The aim of feature extraction is to find out the main characteristics of a data set. In wearable sensor data feature extraction provides a meaningful representation of the sensor data which can frame the relation of raw data with the expected knowledge for decision making.

Wearable sensor data which provide monitoring of l sign parameters tend to be continuous time series readings, most of the considered features are related to the properties of time series signals. Two main aspects of analyzing signals are

(i) Time domain

(ii) spectral domain

In the time domain, the extracted features usually include the visible attributes in data stream such as mean, variance, pick counts.

Although most of the future frameworks in the healthcare domain contain feature extraction/selection phases, the main challenge is costs for the system. For instance, it would be costly to use feature selection in real time systems since the showing techniques can handle the raw extracted features.

3.3. Modeling and Learning Methods

In applications such as home monitoring, a huge amount of data can be produced. Multiple sensors are used, this data is multivariate with possible needs. This means that appropriate data processing techniques are essential. In this section we sketch the most common algorithms used with wearable sensor data. Each algorithm is given in practical detail with the most representative examples on how the algorithm has been applied in healthcare services.

3.3.1. Support Vector Machines

In Model learning methods first we see a support vector machine (SVM) is one of the main statistical learning methods which is able to classify hidden information by developing selected features and making a high dimensional hyperactive plane to separate the data points into two classes in order to make a decision model. As the SVM has the competence to handle high dimensional data using minimal training set of features, it is recently very popular for mining physiological data in medical applications.

Health parameters considered by SVM methods are HR, ECG, and SpO_2 which are mostly used in the short term and marked form. SVM method for detecting the arrhythmia and seizure episodes while ECG signals. It is showed that the SVM method with polynomial kernel leads to better result rather than other kernels. Revealing of the patient's condition all SVMs method in order to handle multi-label classification. Based on the labels on data episodes (4 levels of the severity), several binary SVMs with different kernels such as polynomial, RBF and sigmoid are combined to model the input data from multi sensor features. This work identified the bad indentation in the subjects of chronic gastritis and ache with binary classifications of normal and abnormal radial pulses of ECG using the SVM algorithm. The performance of the method is evaluated with the specificity, sensitivity and correctness of the results.

SVM techniques are often suggested for anomaly detection and decision making tasks in healthcare services. SVM is not suitable method to integrate domain knowledge in order to use metadata or emblematic knowledge effortlessly with the measurements from the sensors.

3.3.2. Neural Networks

A Neural Network (NN) is an artificial intellectual approach which is widely used for classification and prediction. This method models the train data by learning the known classification of the records and relating with predicted classes of the records in order to modify the network weights for the next iterations of learning. Due to the admissible predictive performance of NN, it is the most popular data modeling method used in the medical domain. The ability of the NN is to model highly nonlinear systems such as physiological records where the association of the input parameters is not easily visible.

The multi-layer perceptron (MLP) neural network has been applied in to estimate the quality of the pulses in PPG. This network puts several individual signal quality metrics as input and then improves the number of nodes (2–20) hidden layer in validation iterations. A framework to recognize Heart Rate Variability (HRV) patterns using ECG and accelerometer sensors. It is used a three layer neural network to incrementally learn the extracted patterns and classify them. Three nodes in the output layer identified three classifications of data for activity, location, and heart status.

Replicator Neural Network (RNN) is another type of NN which is generally used for anomaly and outlier detection. RNN to predict blood glucose levels. They designed the network with 11 input variables, one node as predicted BG level and three hidden layers each with 8 neurons. Online classification of sleep/awake states is another research based on a feedforward neural network on ECG and RR features in the frequency domain. NN is a black box progress, NN method needs to justify for each input data.

3.3.3. Decision Trees

The decision tree method is one of the significant learning a technique which provides an effective representation of rule classification. In this method, the strongest features have been detected for initial splitting the input data by creating a tree-like model. Decision tree is a reliable technique to use in medical domain in order to make a right decision. Dealing with complex and noisy data, the C4.5 algorithm is used which is estimating the error rate of initial nodes and pruning the tree to make a more efficient sub-tree.

It used C4.5 decision tree algorithm based on the Mahalanobis distance to divide positive or negative emotions of subject while observing affective pictures. The tree is designed using the features of biosensor data in two layers of emotion perceptions.

Prediction of heat anxiety risk is another classification task which is considered with decision trees. And used the input parameters such as cooling actuation, mean skin temperature, and ambient temperature and with applying some rules in order to make a C4.5 tree. The output of the tree is a label of risk or safe with 95% accuracy.

For the structure of each tree of the forest, a new subset of the features was picked. For selecting the best tree, the method used threshold-based rules and the accuracy of the system has been checked with some predefined targets.

Decision tree methods are limited to the space of the built features as the inputs of the model. So, finding hidden information out of limited features would not be recognizable. Decision tree models are not usually applied to big and complex physiological data.

3.3.4. Hidden Markov Models

A hidden Markov model (HMM) is a numerical Markov model in which the system being modeled is supposed to be a Markov process with unobserved (*hidden*) states. The probability of each state's occurrence by calculating a histogram of the probabilities of successive states. Using this model the hidden states can be inferred from the other observations in sequence of data. HMM model to detect the abnormal values in measured blood glucose level. The state transition diagram of the HMM includes fasting, sleep, and meal states which are connected with the probability of the BG level for each transition.

HMM focused on detecting salient segments in the discovered ideas of wearable sensor time series. The performance of this model was calculated by ECG and accelerometer sensor data.

3.3.5. Rule-Based Methods

Rules are just patterns and an inference engines for patterns in the rules that match patterns in the data. Rule-based reasoning (RBR) is a simple method to identify patterns, anomaly and specific events based on the predefined and stored rules and conditions. The healthcare monitoring which is to find the obvious problem in physiological data, the RBR phase is essential to apply on any wearable sensor framework. A domain-specific expert system is a common rule-based method that defines and applies the knowledgeable conditions during data analysis. A rule-based method is designed by to notice different types of arrhythmias using ECG sensor data. A set of threshold-based rules is provided to apply to the ECG features in order to separate different arrhythmias such as Tachycardia, Bradycardia, Premature Atrial Contraction (PAC) and Sleep Apnea Premature Ventricular Contraction (PVC). The definitions of the conditions for various features in ECG signal are developed from expert system. Dealing with the general anesthetic problem is the subject of another research which it has an online query processing algorithm which maintenances data stream queries tested by the expert of the system. The detection of the trends such as up, down, and flat in the time sequence data is based on the logical rules. The aim of this work is to directly observe various requested trends by clinicians.

These methods are biased to the predefined rules in order to learn the features and performance of the data itself. The rule-based methods are not suitable for decision making and prediction tasks as well as the personalized system with context aware targets.

4. Data Sets and their Properties

In health monitoring system, consuming a healthy data processing stage needs suitable information about the data itself. Dealing with the type of input data and its properties is the precondition of any data processing system in order to handle the major issues such as: selecting the correct data mining approach, designing new methods and features, and regulating the parameters of data analysis. This information gives the opportunity for the readers and knows about how to distinguish the applied data processing methods based on the type of sensor data. It is based on type of data that has been collected using wearable sensors with considering two aspects: data acquisition approaches and data set properties.

4.1. Data Acquisition

Three major data gathering approaches have been identified such as experimental wearable sensor data, clinical or online databases of sensor data, and simulated sensor data.

Experimental characterizations of the wearable sensor: The health monitoring systems have mostly used their own data collecting experimentations to design, model and test the data analysis step. The gathered data are usually extended based on the predefined states due to the test and estimate the performed results, but usually these studies do not provide the accurate explanations.

Clinical or online databases of sensor data: Data from critical care clinical settings that may include demographics, vital sign measurements made at the bedside, laboratory test results, procedures, medications, caregiver notes, images and imaging reports, and mortality (both in and out of hospital). Data mining methods is designed for wearable health monitoring systems, evaluate quantitatively and test the performance of the framework, the most of the works used categorized and complex multivariate data sets with proper definitions and observations by domain expert. Very common example of online databases is PhysioNet database which consists an extensive range of physiological data sets with characterized and robust annotations for complex clinical signals.

Simulated sensor data: For the sake of having a wide controlled analysis system, few works have designed and tested their data mining methods through attractive simulated physiological data. Data model would be useful when the more focus of data processing method is on the efficiency and robustness of information extraction rather than handling real-world data including the artifact, errors, conditions of data gathering environment,

4.2. Data Properties

This section describes the examined the common properties of data sets such as time horizon, scale, labeling, continuous/discrete, and single sensor/multi sensors data.

Time Horizon (long term/short term): The length of time for allowing for data set measurements is a particular challenge for wearable sensor data in order to adjust the data mining techniques and the method of data interpretation. The time horizon of considered sensor data is categorized to short term and long term data. Some data analysis systems in healthcare were designed to process short signals such as few minutes of ECG data, a few hours of heart rate or oxygen saturation and the measurement of blood pressures for a day. On the other hand, dealing with long term data is the significant portion of some data mining methods for handling and processing lengthy period of sensor data. This period could be more than a number of days or a year of measurements. Blood glucose monitoring is an example of long term data analysis for the sake of right decision making.

Scale (large/small): Depending on the design of sensor network, data gathering, and the goal of decision making, the scale of subjects in the frameworks would differ. The aim of these works is in addition to process the stream of data individually, they can handle the same data modelling for large scale of monitoring. Due to the type of data mining tools, small scale of subjects (maybe one or at most 10 persons) in order to investigate the accuracy and correctness of results in proposed model.

Labeling (annotated/unlabeled): Health monitoring systems need to evaluate their results in order to show the correctness of the decision making process. Due to have significant data analysis step, attention of the most research is given to annotated data. By considering the behavior of vital signs the domain expert would able to mark the data with several annotations such as arrhythmia disease, sleep discords, severity of health, stress levels, and abnormal pulse in ECG. These annotations also acquired using another source of knowledge like electronic health record (EHR), coronary syndromes, and also history of vital signs. Notice that these annotations are not necessarily marked on sensor data episodes, such some final decisions for the scenarios may be applied to the data set as labels]. On the other hand, working with unlabeled data leads to have unsupervised learning methods in order to extract unseen knowledge among raw sensor data.

Continuous/Discrete: Based on the design and architecture of wearable sensors the continuity of sensor data would be continuous or discrete. From the data mining point of view, the continuity of physiological data is important, since dealing with streams of sensor data has its own problems and challenges as well as analyzing sporadic measurements. Due to the nature of vital signs, some of them are essentially counted as continuous such as ECG, heart rate and respiration rate or discrete like blood glucose level. Blood pressure data is an example which has been appeared in the literature in both continuous and discrete format.

Single Sensor/Multi Sensors: Due to have decision making in health monitoring system, the number of considered vital signs has an important role to improve the results. Single sensor data have been used for specific analysis on individual physiological data such as blood glucose monitoring or ECG signal analysis. Several wearable sensors in health monitoring frameworks are common and they have really performed the multivariate data analysis in order to extract effective information through multi sensor data.

Data properties with the relation to the data set acquisition approaches have been shown in Figures 5 and 6. From Figure 5, more devotion has been given to short term data sets which can be easily recorded and analyzed in both experimental and clinical conditions. Beside, large scale data is typically more available in clinical settings and online databases where more resources are available.

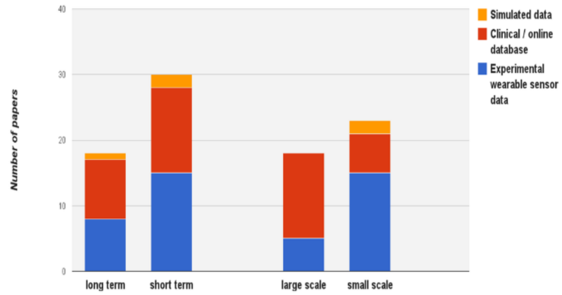

Figure 5. The distribution of works on two sensor data properties (time horizon and scale), with the relation to three types of data acquisition.

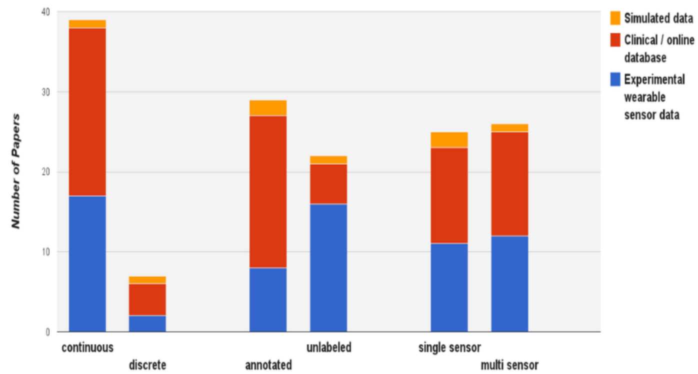

Figure 6. The distribution of works on three sensor data properties (continuous/discrete, labeling, single sensor/multi sensors), with the relation to three types of data acquisition.

Figure 6 shows the distribution of works on the other data properties. In a clinical setting and online databases, data is mostly categorized as continuous and labelled (as access to the experts and other health profiles is readily available). Wearable sensor data collected in other contexts are rather unlabeled.

On considering time horizon, since the short term data sets are easily developed and processed, they have been more used than long term for the most of the health parameters excluding BG, BP which need naturally long term data to analyze. For the scale property, the large scale data sets are more popular than the small scale for most of the health parameters, except ECG and BG due to the fact that they contain the high frequency of available data sets in online databases. Most of the health parameters are used the annotated data sets rather than the unlabeled measurements excluding BG and RR.

5. Conclusion

The goal of this study was to provide an overview of recent data mining techniques applied to wearable sensor data in the healthcare domain and to clarify how certain data mining methods have been applied. It also has exposed trends in the selection of the data processing methods in order to monitor health parameters such as RR, HR, ECG, BP and BG. Finally, particular attention was given to produce the current challenges of using data processing approaches in the health monitoring systems and analyses solutions provided by healthcare services by considering well-known aspects. This paper includes (1) data mining tasks for wearable sensors (2) data mining approach and (3) data sets and their properties and outlined the more common data mining tasks that have been applied such as anomaly detection, prediction and decision making when considering in particular continuous time series measurements. Moreover, further details of the suitability of particular data mining methods used to process the wearable sensor data such as SVM, NN and RBR has been described. Further study in this paper focused on the sensors data sets features and properties such as time horizon, scale and labeling. Finally, the paper addressed future challenges of data mining while analyzing the wearable sensors in healthcare.

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