Chapter 1. Introduction

1.1 Research background

1.1.1 Home telehealth and telehealthcare

Most developed countries are facing the problem of increasing number of elderly. In an aging society, it is highly desirable to reduce the need for medical services by maintaining the health of the population. The need of health care and management for the elderly is an urgent issue. Home has become the centerpiece of health delivery system today. Intensive monitoring of health parameters in the home environment is necessary for health care and management. Telehomecare, or the more modern term home telehealth, can be defined as the use of information and communication technologies to enable effective delivery and management of health services at a patient’s residence [1]. Home telehealth allows the patient the dignity of remaining in their own home for as long as possible by providing care that is equal or superior to approaches that rely solely on health providers coming into the home for scheduled visits [2]. Home telehealth systems can provide access to the users’ monitored data for users themselves, contributing to health self-management and reduction in in-person home visits [3, 4]. Home telehealth differs from telemedicine in the sense that people who transmit and receive medical information are not necessarily medical doctors but the patients themselves and their families, nurses, care-givers, home-helpers and medical technical experts, etc [5].

Figure 1 shows a typical structure of home telehealth system. In a typical home telehealth scenario, users subscribe service with the telehealthcare service provider. Care-receivers (or patients) measure their vital sign parameters, such as blood pressure, heart rate, blood glucose, body temperature, body weight, and ECG/EKG, regularly and
deliver the measurements to the service provider. Data were transmitted to the service provider via the Internet or POTS (Plain old telephone service, usually called “telephone line”) by the telehealth home gateway devices, personal computer, PDA, or mobile phone, etc. The care-givers, doctor experts who user trusted or the health care team which operated by the telehealthcare service provider can monitor the health status of care-receivers from vital sign measurements for health care and management purpose and take necessary actions. The telehealthcare service provider corporates with the medical institution to provide health care service and acts the major role [6].

![Figure 1-1. A typical structure of a home telehealth system](image)

The usefulness of the home telehealth systems has been recognized in many studies [7, 8, 9], and all technologies required are readily available, more and more home telehealth systems and applications were adopted worldwide.

The main technical functions of a home telehealth system is to collect biomedical data measured at home, to classify these data, and to create alerts for further actions. As the development of telehealthcare service and its applications, there are demands of data analysis and classification. The most important thing is the analysis and classification of biomedical data in the telehealthcare for various purposes (e.g. events detection, diseases classification). However, biomedical data have many different types and forms in the different telehealthcare applications. In the next section, this research will introduce the biomedical data in details.

### 1.1.2 Biomedical data and data classification

From the Merriam-Webster dictionary, the English definition of ‘biomedical data’ can be defined as data related to biological, physiological, clinical and medical science. Categories of common biomedical data are trying to be defined in this research. Figure 2 illustrates the diagram of four categories of common biomedical data. The common
biomedical data in telehealthcare applications can be categorized as single-valued vital sign measurements, vital sign time series, human motions & behaviors and subjective observations.

Figure 1-2. The diagram of four categories of common biomedical data

Single-valued vital sign measurements are referring to the vital sign measurement with one time measurement and output single value, such as the blood pressure, heart rate, blood glucose, body temperate and body weight. Vital sign time series are referring to the vital sign measurement with long time measurement and output continuous values, such as ECG/EKG time series (the heart beats time series may extract from ECG/EKG time series). Human motions & behaviors are referring to the measurement of body motions (such as gaits data, COP, body movements during sleep, etc.) and recording of activities (such as activity of daily living, medication compliance, etc.). Subjective observations are referring to the symptoms data from observations & perceptions, such as pain, swollen and wound fluid.

Each category of biomedical data has different forms and meanings and is used in different scenario or application in telehealthcare. Thus, there exists a need of developing a framework of biomedical data classification methodologies for telehealthcare applications.

1.2 Purpose of this research

The purpose of this research is to develop a framework of biomedical data classification methodologies for telehealthcare applications. Various biomedical data measured in home telehealth applications are studied. Each category of biomedical data is demonstrated a corresponding classification methodology within an application scenario in this framework.
The need for single-valued vital sign measurements is to generate real-time alerts. Thus, the methodology for classification cannot be complicated. Single-valued vital sign measurements are demonstrated with the rule-based expert system - Telehealthcare Expert System (TES). Classification rules are composed by boundaries / thresholds of the vital sign measurement. Customizations of the rules are based on individual clinical history. Malfunction of hardware devices (vital sign meters and home gateway) are also detected and alerted by TES.

The need for vital sign time series is to extract features representing the characteristic of the time series. Several previous studies also described time series analysis and clustering of the biomedical data [11][12]. Vital sign time series (e.g. heart beats time series) are demonstrated with the specific designed time series characteristic analysis & classification method - Adaptive Interbeat Interval Analysis (AIIA) method. It uses algorithms to extract features to represent the characteristic of the time series. Classification is based on the comparison from extracted features among disease group and health young groups.

The need for human motions & behaviors is to extract indices representing the characteristic of the data. Classification is based on comparing indices with long-term data or a big volume of samples. Several previous studies also described statistical methods for analysis the biomedical data [13][14]. Human motions & behaviors (e.g. the assessment of abnormal gaits) are demonstrated with the statistical estimation method – lower confidence limit. It uses algorithms to extract features of the data. Classification is based on comparison with long-term data or a great volume of samples. Statistical method is established for the estimation of abnormal human movements for patients.

The need for subjective observations is to derive clinical suggestions from subjective observation. Classification based on human heuristics and machine learning models. A previous study also described machine learning methods for the biomedical data classification [15]. Subjective observations are demonstrated with a telehealthcare decision support system (TDSS) to provide indication of the need of revisiting a doctor from symptoms and clinical histories for patients discharged from hospital. It uses machine learning algorithm to build and update the predictive model.

In the following sections, this research will introduce previous studies of these demonstrated methods for each biomedical data category respectively.
1.2.1 Expert systems and its telehealthcare applications

Expert systems have been widely used in medical and healthcare practice for various purposes [16]. The first large-scale medical expert system, MYCIN, was developed in 1975. It was an interactive computer program that used the clinical decision criteria of experts to help physicians who request advice regarding selection of appropriate antimicrobial therapy for hospital patients with bacterial infections [17, 18]. The medical expert system CASNET/Glaucoma was developed in the early 1980s. It drew on the clinical expertise of a network of glaucoma specialists and was eventually able to help with even complex cases [19]. A system called PUFF, also developed in the early 1980s, interpreted lung function test data and became a working tool in the pulmonary physiology lab of a large hospital [20].

In telehealthcare, the use of expert systems to generate automated alerts to patients and clinicians and instructions to patients based on telemonitoring data could increase self-care and improve clinical management [21]. Ulieru et al. [22] presented a web-based expert system for glaucoma that can convey diagnosis alerts or emergencies to registered users, doctors, or patients, thereby allowing them to take immediate actions. Medina et al. [23] presented an expert system that is able to suggest diagnoses, interventions, and outcomes based on the valuation for the patient and vital signs. Seto et al. [21] developed a rule-based expert system for telemonitoring of heart failure. This mobile phone-based system generated alerts and instructions based on the patient’s weight, blood pressure, heart rate, and symptoms.

In addition to vital sign data, important concerns in telehealthcare include the compliance with the measurement prescription, accuracy of vital sign measurements, and the functioning of vital sign meters and home gateways. However, few expert system applications are found in the telehealthcare domain to address these issues. Christensen et al. [24] developed an Internet-based expert system for the control of oral anticoagulation therapy. Weekly measurement and dosing at an international normalized ratio at home using the expert system was shown to be superior to conventional computer-assisted monitoring and treatment in an anticoagulation clinic.

From the studies review of expert systems above, expert systems were effective solutions for each specific healthcare application. But there were need to develop an expert system for the telehealthcare application which satisfies several concerns mention before for the commercialized practice.
1.2.2 Biological signals analysis for heart beats classification

However, most of expert systems in healthcare were based on existing knowledge and collected clinical data. Classification of abnormal events of vital sign measurements (e.g. blood pressure, blood glucose and body temperature) were well developed for a long while. But another type of biomedical data (e.g. biological time series & sequences) is not easy to classify. For this type of data, researchers are still attempted to develop analysis methods in recent years.

Heart beats time series data are biological time series & sequences of biomedical data. The abnormality is not easy to distinguish and classify in the time series data. Studies to the time series data were trying to find out characteristics hidden in the sequence for data classification. In this section, previous studies are discussed for the analysis of heart beats classification.

Biological signals may carry specific characteristics that reflect basic dynamics of the body. In many studies, biological signals are mapped into symbolic sequences for further analysis. For example, the DNA-sequence, which is composed of adenine (A), cytosine (C), guanine (G) and thymine (T), is a well-known biological symbolic sequence. When mapping to symbolic sequences, the essential information of the original signals must be preserved.

The human heart beat time series is another well-studied example. Human cardiac autonomic activity is affected by two different interactions: sympathetic activity increases heart rate, and parasympathetic activity decreases heart rate. Since these opposite effects are stimulated by many different kinds of stimuli, human heart beat time series is highly variable and complex. Cysarz et al. [25] demonstrated that even regular heartbeat dynamics may be associated with cardiac health. They found that in healthy subjects, continuous adaptation to different activities occurs during daytime, but there was erratic behavior in Congestive Heart Failure (CHF) patients.

Regular heart beat dynamics contains distinct alternation of acceleration and deceleration. Some early traditional linear methods could reliably describe partial actions in autonomic regulation, such as respiration [26, 27]. However, non-linear methods are needed to analyze highly variable data, such as heartbeat signals [26, 28, 29]. In recent years, many researchers have shown that representations which used non-linear symbolic sequences can often reveal much hidden dynamic information. This kind of symbolization proved to be useful for predicting life-threatening cardiac diseases [30-35].
At present, there are three different approaches for using non-linear symbolic sequences to represent heart beat time series. The first approach is based on the deviation of the heart rate time series from the local mean, and a symbol is assigned to each heartbeat. For example, if the momentary heart rate is close to the mean value, it is assigned a “1”; if the heart rate is lower than the mean value, it is assigned a “2”; others are assigned a “3”. Voss et al. [30] found that there were some specific patterns in patients after suffering myocardial infarction using the symbolization based on deviation from the mean value. They later improved this method to identify patients with other high risk cardiac diseases [36].

The second approach is to symbolize the increase or decrease of the momentary heart rate by two different symbols. For example, Yang et al. [34] simplified the heartbeat dynamics via mapping the output to binary sequences, where the increases of the interbeat intervals were denoted by “1” and others were denoted by “0”. They presented a distance method based on rank order statistics to calculate the dissimilarity between two symbolic sequences. According to the results, this method can robustly recognize the difference between healthy people and patients with heart diseases. Peng et al. [35] of the same research team, combined the distance method with a weighting function, resulting in less overlap between groups, and more clearly distinguished classes corresponding to the level of subjects in the CHF group. Van et al. [37] also found that symbolization can be applied to quantify the fetal heart rate, demonstrating that development of the autonomic nervous system and emergence of behavioral states lead to increase in both irregular and regular heart rate patterns.

The third approach is to divide the range between minimum and maximum heart rate into a few equidistant intervals, or to map a time series onto a symbolic sequences of permutation rank [30-40]. Entropy and entropy rate were used to evaluate the complexity of heart variability. Porta et al. [30] used the pattern classification method to automatically identify different physiological conditions by the activation of different mechanisms responsible for cardiovascular regulation. Permutation entropy and modified permutation entropy analysis have also been studied, which maps a time series onto a symbolic sequence of permutation rank [39-40].

The second approach described above for symbolization does not need any parameter settings (e.g., the mean heart rate is required in the first approach), and it is independent of any other features of heart rate variations. In contrast to the third approach described above, it does not need to adjust the range of intervals which might affect the results of classification. However, the second approach used only binary symbols (e.g., 0 and 1) to represent acceleration and deceleration of interbeat intervals, which might not be able to represent the degree of variations. For example, the difference between two interbeat
intervals such as $+250$ and $+100$ may both be represented as acceleration and assigned “1”, but actually they are not the same in a detailed interpretation, and the degree information of acceleration is lost in this binary representation.

From the review of previous studies above, there were already many studies tried to find out the features in the sequence of time series and categorize them. In order to improve the result of classification of heart beats time series, this research proposes another approach – adaptive interbeat interval analysis (AIIA) method for the classification of heart beats in the framework of this research.

1.2.3 Gait monitoring and assessment of abnormal gaits

Human motions and behaviors, such as gaits data, are not easy to collect and assess. For this type of data, researchers have attempted to develop sensing and analysis technologies in recent years.

Individuals with degenerative mobility, e.g., Parkinson's disease (PD) patients or older adults usually have gait disorders such as reduced walking speeds with increased cadences, reduced step/stride lengths, and increased inter-stride variability [41]. PD is a progressive neurological condition characterized by hypokinesia (reduced movement), akinesia (absent movement), tremors, rigidity and postural instability. These movement disorders are associated with a slow short-stepped, shuffling gait pattern [42]. PD patients in the advanced stage may encounter episodic gait disturbances, like festinating or even freezing of gaits which can lead to falling and adverse health outcomes [43, 44].

Falling is a frequent complication for patients with PD. Falling will lead to an incapacitating fear of falling again, because the patient fears additional complications such as severe fractures. Therefore, it is important to develop a system designed for preventing PD patients from falling. In order to achieve this aim, the normal and abnormal gaits of PD patients should be defined and distinguished. If a PD patient is walking normally and then develop an abnormal gait, a warning signal can be issued in real-time to remind the patient to adjust his or her stride. For this purpose, gait cycle parameters, which can quantify and describe the characteristic of each gait, need to be defined first. In related studies, cadence, regularity, rhythm and symmetry are important gait cycle parameters which can apparently be altered in walking patterns among patients with varied mobility [44-45].

Gait monitoring and analysis techniques for measuring the above gait cycle parameters have been widely developed and studied. For example, gait dynamics can be accurately measured using optical motion capture systems which use high-speed infrared cameras to record the three-dimensional positions of reflective markers attached to the
joints and segments of the human body [46]. Gait detection techniques using pressure sensors embedded in a walkway have also been used [47]. These techniques can detect foot contact (heel strike and toe-off) and evenness of foot pressure distribution in an effort to investigate temporal gait parameters. However, these systems are expensive and require sophisticated instrumentation and specialized personnel. So, the uses of such systems are usually limited to laboratory or clinical environments. Simpler systems based on pressure detection, such as a portable in-shoe pressure measurement system have also been introduced [46, 48]. The systems using in-shoe pressure detection can only provide simple temporal gait measures while video-based systems can provide temporal and spatial gait measures, even including accurate measurement of the motion of lower limbs and body.

In recent years, accelerometers have been widely accepted as useful and practical sensors used as wearable devices to measure gait. For example, Yang et al. [49] provided a cost-effective approach to real-time gait monitoring. They developed a wearable accelerometry system for real-time gait cycle parameters recognition. A waist-mounted wearable motion detector (WMD) was designed to measure trunk accelerations during walking. The autocorrelation procedure is implemented in the WMD for online calculating the real-time gait cycle parameters, including cadence, step regularity, stride regularly and step symmetry in real-time. These parameters can be sent out via Zigbee transmission for further recording, processing and/or reaction.

From the review of previous studies above, gait detection, monitoring and analysis techniques were well developed and matured for advanced analysis and applications in recent years. However abnormal gaits data are not easy to collect either in the experiment or the real environment due to the safety of patients. Therefore there is need to assess abnormal gaits by the statistical estimation method from normal gaits data.

1.2.4 Decision support system and its healthcare applications

Symptoms data are another type of biomedical data. Symptoms data are coming from patient themselves observations and perceptions of their body. Symptoms data are important keys to the diseases’ progress and recovery progress. However, these data are difficult to quantify, each patient case is different and each ones’ observations and perceptions is different. The diseases’ progress and recovery progress are mainly depending on doctors’ medical knowledge and clinical experience. However, the clinical decisions are very difficult in different cases and rapidly changed patient status especially in the doctors who lack of experience or in the telehealthcare applications. In this section, previous studies are discussed for the information systems which can aid doctor to make clinical decisions.
Decision support system (DSS) is a computer-based information system that supports business or organizational decision-making activities. DSSs serve the management, operations, and planning levels of an organization and help to make decisions, which may be rapidly changing and not easily specified in advance. DSSs include knowledge-based systems. A properly designed DSS is an interactive software-based system intended to help decision makers compile useful information from a combination of raw data, documents, and personal knowledge, or business models to identify and solve problems and make decisions [50].

Clinical decision support system (CDSS) is an application of DSS, which is designed to assist physicians and health professionals determining diagnosis of patient. CDSS links health observations with health knowledge to influence health choices by clinicians for improved health care. A clinical decision support system has been coined as an “active knowledge systems, which use two or more items of patient data to generate case-specific advice [51].

Research into the use of artificial intelligence in medicine started in the early 1970's and produced a number of experimental systems. The first well-known clinical decision support system, AAPHelp, was developed in 1972. It was a computer aided diagnosis system to support clinical assessment and decision-making for Acute Abdominal Pain (A.A.P.). It was based on the clinical evidence and best practices from the UK and Europe. It implemented the electronic data collection protocol and prompting clinicians to take a thorough and accurate clinical assessment. It provided definitions of clinical symptoms and signs, access to large databases of information about patients with A.A.P., display of real outcomes of patients with similar clinical presentation to new patient. [52]

DXplain and Quick Medical Reference were successful and commercialized systems originating in the 1980s. DXplain is another decision support system, developed by Laboratory of Computer Science, Massachusetts General Hospital, Harvard Medical School at 1987, which uses a set of clinical findings (signs, symptoms, laboratory data) to produce a ranked list of diagnoses which might explain (or be associated with) the clinical manifestations. DXplain provides justification for why each of these diseases might be considered, suggests what further clinical information would be useful to collect for each disease, and lists what clinical manifestations, if any, would be unusual or atypical for each of the specific diseases. DXplain includes 2,200 diseases and 5,000 symptoms in its knowledge base [53].

A system called Quick Medical Reference was developed in 1989. It is a diagnostic decision-support system with a knowledge base of diseases, diagnoses, findings, disease associations and lab information. It is design for 3 types of use: as an electronic textbook;
as an intermediate level spreadsheet for the combination and exploration of simple diagnostic concepts; as an expert consultant program with information from the primary medical literature on almost 700 diseases and more than 5,000 symptoms, signs, and labs [54].

From the review of previous studies above, there were already many studies tried to build up a clinical decision support system. However, none of studies were found for telehealthcare application and patients discharged from hospital. In order to provide a solution on this problem, this research proposes a TDSS in the framework of this research.

This dissertation is organized as follows. Chapter 2 describes the development and practice of a telehealthcare expert system – TES. Chapter 3 describes the uses of AIIA method to classify heartbeat signals. Chapter 4 describes the assessment of abnormal gaits of Parkinson disease patients using a wearable motion detector. The design and use clinical decision support system for telehealthcare application is further presented in Chapter 5, while Chapter 6 discusses biomedical data classification methodologies for telehealthcare applications and concludes this research.

References


