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Smart assisted diagnosis solution with multi-sensor Holter

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ABSTRACT

Cardiovascular disease has become an increasingly serious threat to human health. Holter monitoring is essential in the prevention and treatment of cardiovascular disease. When combined with a variety of sensors, a traditional Holter becomes a mobile health device. Based on Holter data and sensor data, this paper proposes a supplementary diagnosis and treatment program. The solution consists of three main steps: I. Perform segmentation of ECG (Electrocardiography) data and conduct feature extraction. Build the personalized ECG templates, apply factor graph and max-sum algorithm for precise template matching, and realize the feature extraction and representation of ECG data. II. Use the action sensor data for action classification and identification. As an important factor of health monitoring, body movements are categorized as resting, walking, going upstairs and downstairs, flipping and sudden change. The improved classification algorithm achieves high accuracy identification. III. Combine ECG data and action data for clustering analysis. The proposed solution improves the affinity propagation algorithm and allow doctors to supervise the clustering procedure. A knowledge matrix is introduced accordingly, thus achieving an iterable clustering optimization. With the help of these components, the innovative approach is able to integrate the Holter data and sensor data, meanwhile, doctors are encouraged to participate in the process of clustering algorithm. Our system is capable of not only assisting doctors in quickly determining the most valuable information, but also of building a personalized private repository for patients. The experimental results indicate that the proposed system is an efficient, accurate, and interactive auxiliary diagnostic and a therapeutic support tool.

1. Introduction

Cardiovascular and cerebrovascular diseases are threatening human health. In China, one in every five adults has cardiovascular disease and the morbidity rate continues to rise. It is difficult to cure cardiovascular disease and continuous monitoring of the patient is necessary. Electrocardiography, which is also called ECG, is the most popular monitoring method for cardiovascular disease [1].

ECG entails recording the electrical activity of the heart. Traditionally, this involves a transthoracic (across the thorax or chest) interpretation of the electrical activity of the heart over a period of time, as detected by electrodes attached to the surface of the skin and recorded or displayed by a device external to the body [2]. It is possible to record ECG invasively using an implantable loop recorder.

Based on the traditional ECG recorder, a new dynamic monitoring apparatus called Holter, was invented and is now widely used. In medicine, a Holter monitor (often simply referred to as Holter or occasionally ambulatory electrocardiography device) is a portable device for continuously monitoring of various electrical activity of the cardiovascular system for at least 24 h (often for 2 weeks at a time). Holter is constantly being improved with the developing of new technologies, as seen in Fig. 1. From Fig. 1, it is clear that the most classic Holter only recorded ECG signals. Later, other signal acquisition devices, such as the finger-trip sensor for monitoring of blood oxygen saturation (SpO_2) and the acceleration/orientation sensor, can be used to monitor the movement, and so on. The scheme proposed in this paper assumes that Holter comes with acceleration/orientation sensor.

Dynamic electrocardiography was originated by the "Holter Company" in the USA and is also called Holter ECG. In 1961, Del Mar brought the Holter into clinical applications. Initially, Holter

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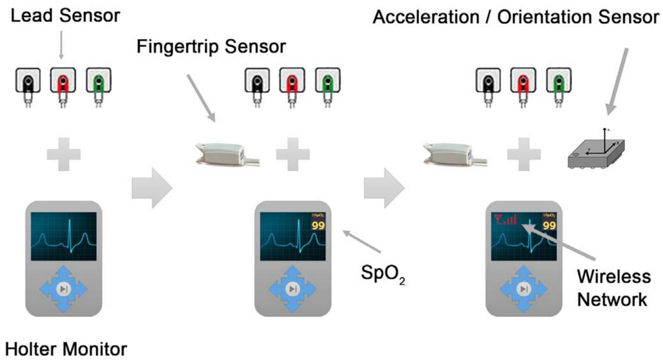

Fig. 1. The development of Holter.

consisted of a core monitor and 1, 2, or 12 lead sensors. Then, other sensors were added to entail more functions, such as a fingertip pulse oximeter and hygrothermograph. With the development of the Internet of Things and mobile networks, some conceptual Holter systems are using the GPS, acceleration or orientation sensors, and the wireless network to improve the ability of emergency services in the context of tele-medicine [3–5]. In fact, acceleration and orientation sensor data can reflect the patient's motion and actions, which is very valuable for ECG signal analysis. For example, body action can affect heart activity and appear in the ECG signals. The patient's action or activity may increase the risk of a heart attack. Therefore, the Holter data mixed with ECG and multi-sensor signals are valuable for assisted diagnosis [6].

There are many types of noise that occur in the Holter. Among them, action artifact is one of the most common noise type and particularly challenging to handle. Currently, action artifact is one of the major factors affecting the interpretation accuracy and diagnosis efficiency of dynamic electrocardiography. To handle the action artifact, previous computational efforts have largely relied on action artifact removal, but little attention has been paid to action artifact identification up to now [7].

ECG signals vary across different people or even for the same person at different times. These complex differences hinder feature extraction and classification. Some existing systems can realize the heart rate and the scatter-plot analysis, which is useful but not sufficiently insightful for all applications. According to a recent survey, some new research work focuses on the classification of certain heart diseases, based on open repository such as MIT-BIH database [8]. However, the majority of studies mainly focus on theoretical innovation that is not feasible in practical use [9–11].

As mentioned above, finding the unique and general solution in ECG analysis is an idealistic endeavor. In fact, there are many risks in providing unique and universal results to a doctor. In this paper, we propose a smart assisted diagnosis solution for a multi-sensor Holter monitor system which involves doctor participation in the procedure. This solution provides doctor with the most noteworthy ECG signals to increase efficiency. Then, the results can be updated automatically according to the doctor's professional knowledge.

The proposed solution consists of three key technologies: ECG signal segment identification, action and activity identification by multiple sensors, and the optimizable clustering algorithm based on the sensor data and doctor's knowledge.

2. Related works

2.1. ECG segment recognition

Segment recognition is the foundation of ECG signals analysis. The typical ECG is usually divided into several bands; each band corresponds to a class of electrical activity. For example, P wave (atrial depolarization), RR interval (atrioventricular conduction time), QRS wave (ventricular depolarization), ST wave (ventricular depolarization complete) and T wave (ventricular repolarization) and QT interval (ventricular depolarization to complete repolarization time and so on). R wave has salient features and is often used to divide the heartbeat cycle. A RR interval (RR period, or RR) can be regarded as a heart-beat. As typical time series signals, ECG data are usually segmented in two steps: 1) segment recognition using “ECG heart beats”, which is also called “rough segmentation”; 2) further segment recognition within one beat period using the “P-Q-R-S-T” standard, which is called “fine segmentation” [12–16]. A conventional method of rough segmentation is to find the crest of the R wave and then divide the ECG signals into many RR intervals [17,18]. In this paper, the wavelet transform and multi-threshold filtering are used to obtain the RR segments. In contrast, fine segmentation is much more difficult. Many publications have focused on the QRS wave group, whose results are stable and effective [19]. However, other waves, such as the P-wave, are also important for diagnosis. The P wave is not very notable with respect to the whole signals, but its variability is quite significant. Thus, P waves can be submerged easily. Recently [20], proposed a new method to identify the P wave with fairly high precision.

There are various research articles on segment recognition for ECG signals from the perspective of medical science or computer science. Some of the experiment results are very promising but experts have noted that some methods are not ideal in clinical practice.

2.2. Action recognition using sensors

Human action recognition has been a key research field in human-computer interaction, mobile computing, and ubiquitous computing over the last 20 years. Traditional human action recognition methods focus on the recovery of human poses from an image or video sequences, i.e., the vision-based method. Because images or videos are usually captured in dynamic environments, the recognition performance is susceptible to changes in lighting conditions or the occlusion of a moving target. The typical experimental equipment for such approaches are expensive and their application environments are constrained [21]. With the development of wireless sensor networks and mobile computing, mobile devices with various sensors (e.g. GPS sensors, light sensors, temperature sensors, direction sensors, and acceleration sensors) are becoming increasingly popular [22–24]. Human action recognition research has been shifting towards the use of body-worn sensors; thereby extending the potential applications of action recognition beyond instrumented rooms [25]. Some of the earliest work in sensor-based action recognition mainly used multiple accelerometers distributed over the human body [26]. In [27], researchers used multiple biaxial accelerometers fixed to 20 users' thighs, lower legs, wrists, arms, sternum, and waist to collect data and compared several classification algorithms to recognize 20 daily activities. Their research results indicated that just two accelerometers on a person's thigh and wrist can facilitate sufficiently accurate recognition performance.

Other researchers have used a combination of accelerometers and other sensors such as GPS in action recognition. Using 22 types of sensors to recognize 27 daily activities in eight scenarios (e.g. sitting at home, eating in a restaurant) [28], developed a system to collect signals and sensors data. Data from various sensors expand the action recognition range and improve the recognition performance compared with the use of only accelerometer data. However, these complex systems are only feasible for scientific research because too many types of body-worn

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