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Multi-sensor fusion for body sensor network in medical human–robot interaction scenario☆

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ABSTRACT

With the development of sensor and communication technologies, body sensor networks(BSNs) have become an indispensable part of smart medical services by monitoring the real-time state of users. Due to introducing of smart medical robots, BSNs are not related to users, but also responsible for data acquisition and multi-sensor fusion in medical human–robot interaction scenarios. In this paper, a hybrid body sensor network architecture based on multi-sensor fusion(HBMF) is designed to support the most advanced smart medical services, which combines various sensor, communication, robot, and data processing technologies. The infrastructure and system functions are described in detail and compared with other architectures. Especially, A multi-sensor fusion method based on interpretable neural network(MFIN) for BSNs in medical human–robot interaction scenario is designed and analyzed to improve the performance of fusion decision-making. Compared with the current multi-sensor fusion methods, our design guarantees both the flexibility and reliability of the service in the medical human–robot interaction scenario.

1. Introduction

In recent years, body sensor networks(BSNs) has been gradually promoted in the field of intelligent healthcare and medical assistance. Depending on sensoring and communication technologies, BSNs can reliably collect a wide variety of physiological, psychological and activity information from users to make offline diagnosis or provide medical advice [1,2]. Although it can alleviate the shortage of medical resources, BSNs cannot provide real-time feedback online services for users. Fortunately, with the rapid development of intelligent robots, the mode of smart medical services has changed from “user-doctor” to “user-robot-doctor”. The introducing intelligent robots perform simple diagnosis and treatment, which handles emergencies more quickly and reduces the workload of medical staff. This requires BSNs to collect the real-time state of robots in addition to the state of users.

In medical human–robot interaction scenarios, it needs to comprehensively consider the interaction between human, robot and the environment. Before performing a task, the robot must accurately identify surrounding environment and the state of the served user. Therefore, multi-sensor fusion is used to obtain the real-time situation of human-robot-environment to ensure the efficiency and safety of medical services. It is widely used in BSNs and needs to be redesigned for medical human–robot interaction scenarios.

Due to the cost and technical constraints, sensors tend to have low acquisition accuracy and are susceptible to interference. Sensors data also has the characteristics of multi-source heterogeneity, which increases the difficulty of understanding the perceptual data. With the increasing complexity of medical applications, multi-sensor fusion becomes a nontrivial task that directly impact performance of the activity monitoring application[3]. Adam et al. [4] argued how the various processes of molecular interaction and fusion in the biological immune system can produce analogous behavior for the using of data in an artificial context, which provides a biologically inspired approach for multi-sensor fusion. Wen et al. [5] found that sensors exist latent structure influence mode in multi-sensor fusion. Carol et al. [6] proposed a biosensor data management framework including data collection and decision, which optimizes data transmission effectively and reduces the amount of collected data without destroying data integrity. Liu et al [7] designed a multi-data sensor fusion system combined with storm architecture to solve data loss problem in large-scale data processing. These studies have promoted the development of multi-sensor fusion in BSNs, but not focus on people and the environment while ignoring the factors of the robot.

☆ Fully documented templates are available in the elsarticle package on CTAN.

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In this paper, we focus on multi-sensor fusion for BSNs in medical human–robot interaction scenario. We first propose a hybrid medical human–robot interaction architecture for supporting stable, safe and efficient medical services. Then multi-sensor fusion for medical human–robot interaction is designed to meet the requirements of real-time healthcare based on three aspects: data correction, scene reconstruction, and fusion decision. The main contributions of this paper are summarized as follows.

1)We propose a hybrid body sensor network architecture based on multi-sensor fusion(HBMF), that combines current advanced human–robot interaction technologies and supports the most advanced intelligent medical services.

2)We use data correction, scene reconstruction, and fusion decision to design a unique multi-sensor fusion method for meeting the requirements of healthcare applications with human–robot interaction.

3)We compare our design with related works. The results reflect the advantages of our design on efficiency and safety in healthcare application with human–robot interaction.

The rest of paper is organized as follows: Section 2 presents some related works. Section 3 describes the infrastructure of HBMF architecture. A multi-sensor fusion framework for medical human–robot interaction is proposed in Section 4. Section 5 proposes a multi-sensor fusion method based on interpretable neural network. The functional comparison between several systems has been given in 6. Section 7 concludes the paper.

2. Related work

Intelligent robots are introduced to implement smart medical services with BSNs. The related researches can be classified into three categories: medical human–robot interaction, body sensor networks, and multi-sensor fusion.

2.1. Medical human–robot interaction

Human–robot interaction is a developed field based on artificial intelligence, robotics, natural language understanding, and social sciences. In resent years, the perception of human–robot interaction in medical scenarios can be roughly divided into two aspects: human–robot collaborative environment perception and human intention perception. For human–robot collaborative environment perception, Kuehn et al.[8] developed the concept of artificial Robot Nervous System(aRNS), which aims to unify different perception modes for allowing robots to react to perceived stimulus like humans. Zaraki et al. [9] presented a robotic social perception system that enables robots to achieve true perception of different surrounding environments. Lin et al. [10] proposed a human-robot-environment interactive reasoning mechanism and designed an object sorting robot system. Barbagallo et al. [11] developed a human–robot collaboration solution based on Kinect that combines body detection and voice commands to establish a safe moving space for the robotic arm. Truong et al. [12] presented a proactive social motion model that enables mobile service robots to perceive complex dynamic environments. Lin et al. [15] proposed a localization method (LNM) based on neighbor relative RSS (NR-RSS) and Markov-chain prediction algorithm for precise positioning in smart buildings. Rezaee et al. [13] designed a robot modeled by electric charge and proposed an obstacle avoidance technology based on behavioral structure. In terms of human intention perception, Ji et al. [14] designed a method of recognizing human motion based on three-dimensional convolutional neural networks, which realizes the recognition of human motion in surveillance video. Chen et al. [16] developed a cognitive information measurement theory for measuring dynamic information based on the mailbox principle. Liang et al. [17] proposed a locality-constrained affine subspace coding method to feature code on depth map, and realized the human motion recognition based on single depth feature. Du et al. [18] presented a human skeleton data recognition method based on hierarchical recurrent neural network to realize the classification and recognition of human motion. Francesco et al. [19] developed a computational model of action intention understanding, which uses motor prediction to transform the action intention understanding into the process of active inferential and hypothesis testing. Chen et al. [20] proposed a label-less learning for emotion cognition (LLEC) to achieve the utilization of a large amount of unlabeled data. Harish et al. [21] presented an adaptive-neural-intention estimator to reason the motion intention of human upper limb movement. Elisabeta et al. [22] designed a motion and emotion recognition system for robotic assisted treatment of autistic children. Ma et al. [23] proposed a deep weighted fusion method for audio-visual emotion recognition, which improved the accuracy of natural language understanding. Chen et al. [24] designed a wearable affective robot from perspective of hardware and algorithms. These studies enable robots to provide services to users in medical environment.

2.2. Body sensor networks

BSNs are responsible for collecting the real-time state of users. Ding et al. [25] proposed a body sensor network which based on tonoarteriography(TAG) for unobtrusive blood pressure measurement. Carlo et al. [26] developed a wireless unobtrusive monitoring system for continuous measurement of user's temperature. Hou et al. [27] presented a system for human gait analysis based on BSNs to reflect the body's physiological functions, mental state, and physical state. Yeh et al. [28] introduced an IoT-based healthcare system which uses BSNs to simultaneously achieve system efficiency and robustness. Wang et al. [29] presented a quantized compressed sensing(QCS) architecture to reduce the energy consumption of communication in BSNs, and proposed a rapid QCS(rapQCS) algorithm to combat the computational complexity of the configuration procedure in quantized compressed sensing architecture. Zhou et al. [30] proposed a mathematical optimization problem which commonly considers network topology design and cross-layer optimization in BSNs. Sasikala et al. [31] designed a routing protocol based on security aware trusted cluster to reduce the information misfortune in BSNs systems. Zhang et el. [32] proposed a random numbers generation method based on electromyogram to secure the data acquired from BSNs for rehabilitation. Shoaib et al. [33] designed a method of representing IMU data with deep neural networks to remove motion artifacts in free-mode BSNs. Chen et al. [34] proposed a medical AI framework based on data width evolution and self-learning for skin disease recognition. Although these studies have made progress of the development of BSNs, their objects are limited to humans.

2.3. Multi-sensor fusion

Multi-sensor fusion aims to fuse sensory data to achieve more accurate and comprehensive perception. Attiq et al. [35] proposed a multi-sensor image fusion strategy based on genetic algorithm. Fang et al. [36] presented a decision-making algorithm for uncertain fusion based on grey relation and DS evidence theory, which can solve the uncertainty problems caused by the inconsistency of sensors and complex monitoring environment. Ammar et al. [37] proposed a track-to-track fusion(T2TF) algorithm based on information filter framework to solve issues such as the correlation of the estimates, the transmission shortcomings, and the high complexity cost. Lin et al. [38] proposed an AI-driven data-analytics-based spectrum allocation(ADASA) algorithm to analyze high-dimensional data and improve the spectrum utilization in heterogeneous wireless networks. Shi et al. [39] designed an electronic health system based on multi-sensor fusion algorithms, which has good classification accuracy. Zeng et al. [40] developed a multi-sensor fusion algorithm based on factor graph to deal with complex data provided by different sensors asynchronously or non-linear output signals. Alberto et al. [41] proposed multi-sensor fusion algorithm based on adaptive fingerprint for accurate indoor tracking. Wei et al. [42] presented an algorithm based on the weighted sum of sensor outputs, which improves