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Human motion intent learning based motion assistance control for a wearable exoskeleton

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ABSTRACT

Human motion intent (HMI) acquiring by using physical human robot interaction (pHRI) information is one of the most crucial issues for lower extremity exoskeleton control. The mapping from the pHRI information to the HMI is complicated and nonlinear since the wearer is in the control loop, which is difficult to be modeled directly via mathematical tools. The nonlinear approximation can be learned by using machine learning approaches, e.g., Gaussian Process (GP) regression, which is suitable for high-dimensional and small-sample nonlinear regression problems. However, GP regression is restrictive for large scale datasets due to its computation complexity. In this paper, an online sparse GP algorithm is proposed to learn the HMI, where the input is the pHRI signal and the output is the angular increment of the active joints, i.e., the knee joints. The data of HRI is collected by the torque sensor and the angular position of the active joint is measured by the optical position sensor respectively. The pHRI signal is dealt with Kalman smoother to achieve the following functions, i.e., (1) eliminating noise and (2) predicting forward. The learned HMI via the online sparse GP regression algorithm is regarded as the reference trajectory of the lower extremity exoskeleton. A fuzzy-PID control strategy is designed to drive the robotic exoskeleton to follow the estimated HMI. Prototype experiments are performed on the subjects who wear the exoskeleton system to walk on different terrains without any transition. The experimental results validated the effectiveness of the proposed algorithm. The online sparse GP regression algorithm is capable of learning the HMI based on the pHRI and the fuzzy-PID can shadow the HMI quite well.

1. Introduction

Wearable robots are worn by operators to enhance the power to assist walking or carry heavy loads. This kind of robotic system has the similar mechanical structure parallel with human limbs. In recent years, many advances and progress have been made in the development of wearable exoskeletons. A program, Exoskeletons for Human Performance Augmentation (EHPA), was sponsored by the DARPA in 2000 and aimed at increasing and improving the soldiers' capabilities [1]. There are several important products in the process of EHPA, e.g., Berkeley Lower Extremity Exoskeleton (BLEEX) [2], ExoClimber, ExoHiker and HULC [3]. In the field of wearable robots, University of Tsukuba also developed a wearable exoskeleton, named Hybrid Assistive Limb (HAL), for performance augmentation and limb rehabilitation [4,5]. The wearable exoskeleton robot is in essence a human-robot cooperation system, where the human operator is located in the control loop. Many kinds of wearable exoskeletons are controlled based on the analysis of walking gait, e.g. Soft Exosuit [6], ReWalk [7], and Nurse Robot Suit [8]. However, they defined the desired trajectory beforehand and driven the exoskeleton to follow the predefined trajectory, i.e., the HMI estimation that represents the human natural movement is not included in those systems.

The HMI estimation is the foundation of the exoskeleton control. In general, control strategies can be classified according to the ways of the HMI estimation, i.e., biomedical signals measured directly from the user body, e.g., Electromyographic (EMG), physical HRI signals, e.g., force or torque signals generated at the interaction cuffs during movement, and mechanical signals only from exoskeletons themselves [9]. Indeed, the control procedure of assistive wearable exoskeletons can be followed by two steps, i.e., (1) estimating the HMI, and (2) following the HMI to achieve the motion coordination between users and exoskeletons. The HAL system uses an EMG-based system, i.e. skin-surface EMG electrodes placed on the wearer's body, to estimate the HMI and applies a closed loop control strategy based on reference walking patterns to drive the mechanical structure [10]. The BLEEX system uses the force

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sensor, placed on the end of cylinder rod, to estimate the HMI and design a control strategy called sensitivity amplification control (SAC) to drive the exoskeleton to react to human behaviors properly [11]. In this paper, physical HRI signals collected by torque sensors are proposed to estimate the HMI.

The HMI includes strictly three components, i.e., (1) walking phases to judge whether the leg is located in the swing or stance, (2) kinematics information of limbs, e.g., position, velocity and acceleration, (3) kinetic information, e.g., joint torque. In this paper, the HMI is defined as the angular position of the active joints, i.e., the knee joins. The walking phase is identified by the ground reaction forces. Indeed, acquiring and estimating the HMI by using physical HRI signals is an important hot research topic in human-robot collaborative control especially for assistive exoskeleton systems. If the HMI can be estimated online accurately, it is possible to improve the performance of exoskeletons [12]. Based on pHRI signals, collected by force or torque sensors (placed on the robot links not human body or human exoskeleton interface), the HMI can be estimated. Control strategies can be designed to drive the exoskeleton to shadow the estimated HMI [13]. However, due to the complex physical properties of human limbs and exoskeleton systems, the appropriate relationship between the pHRI and the HMI, e.g., the angular position of the joints cannot be clearly determined by using mathematical model. Some researchers reported the results of HMI estimation, e.g., joint kinematics or kinetics, can be attained by adopting RBFNN online [14], and using GP regression to search the desired actuating torque [15]. Those reported methods, however, hardly mentioned the problem of online computation complexity and the estimated HMI, indeed, lagging behind the real user's HMI. In our work, the Kalman filter is utilized to deal with the pHRI signal for two considerations, i.e., eliminating noises and providing prediction forward. Therefore the measured pHRI can be smoothed and predicted to compensate the time delay [16].

Since the relationship between the physical HRI and the HMI is complex and nonlinear, it is difficult to model it by using mathematical approaches. GP is a general supervised learning method which is widely implemented in robotics, e.g., system model learning [17], mobile robot localization [18], and interface model learning [19]. A GP is suitable for high-dimensional and small-sample nonlinear regression problems. A general GP regression is restrictive for large scale datasets due to its computation cost, which limits its application in control schemes. Two main approaches have been developed to deal with the problem, i.e., sparse GP [20] and the sparse pseudo-input GP (SPGP) [21,22]. The sparse GP, which needs to choose an appropriate subspace to essentially summarize the original input space, is the most effective method to reduce the computation complexity [23]. Sparse GPs can be expressed as exact inference under different modifications of the original GP prior for low-cost approximations.

As discussed previously, once the HMI is estimated and obtained, the control strategy should be designed to drive the exoskeleton to shadow the estimated HMI accurately, finally to achieve the human-exoskeleton motion coordination. Control strategies of the lower extremity exoskeleton can be divided into two categories, i.e., model-based and model-free. The model-based control strategy is applied based on the dynamic model of the exoskeleton system. In the BLEEX, the lower extremity exoskeleton is modeled with physical characteristics of the system. Based on the dynamic model, the control strategy named SAC is designed to aid the user's movement [24]. The dynamic model in the BLEEX is dependent on the walking phases, which has three different forms, i.e., the single support, the double support, and the double support with redundancy [25]. Since the exoskeleton is tightly coupled and highly nonlinear, it is difficult to attain an accurate and appropriate dynamic model using mathematical approaches. The model-free control strategy is not dependent on the dynamic model of the exoskeleton system. In general, model-free control strategies can be classified into the following modes, i.e., position control, torque/force control and interaction force control. The position control scheme is utilized to drive the exoskeleton to track the desired trajectory, e.g., RUPERT [26] and HAL [27]. The torque/force control is aimed at following the commanded torque/force trajectory while the primary goal of the interaction force control scheme is utilized to ensure the interaction force close to zero.

In this paper, we propose to choose a subspace of dataset for training to reduce computation cost by using Grey Relation Analysis (GRA). Through GRA, the training dataset stemming from the original dataset can be obtained. We propose to use torque sensors to measure the HRI signals that represent human-exoskeleton interaction information directly. The training dataset is collected when the human user wears the exoskeleton system to perform unconstraint motions. A subspace is selected to reduce the size of input space to eliminate the computation complexity. The sparse GP regression algorithm is designed to learn the HMI of the user. The learned HMI is the reference input of the controller which is an adaptive motion control strategy using fuzzy logic system. The model-free position control strategy is adopted to drive the lower extremity exoskeleton to shadow the estimated HMI. However, since the exoskeleton system is subject to load changes, friction and external disturbances, the conventional position control, e.g., proportion integral derivative (PID) is difficult to achieve the desired tracking performance. This kind of position control strategy is highly dependent on PID parameters. In this work, fuzzy inference system is adopted to update the parameters of PID in real time according to the real tracking performance, which means the input variables of the fuzzy system are the tracking error and its changing rate. To verify the proposed algorithms, experiments on different terrains are performed.

2. Exoskeleton system under studying

Exoskeletons are anthropomorphic devices that perform similar movement with the human body. The design of an exoskeleton is dependent on human motion analysis, i.e., Clinical Gait Analysis (CGA), which gives human limb joint angles, torques and powers for typical walking patterns. In the design, the number of mechanical leg Degrees of Freedom (DoFs) is required to be close to the number of human lower limb DoFs. In general, those DoFs with the highest power consumption during gait cycles should be actuated while the remaining DoFs are passive with elastic elements. The proposed lower extremity has only one active DoF placed on the knee joint for each leg, as shown in Fig. 1. The prototype architecture of the exoskeleton robot, which has three main components, i.e., the leg segments with length adjustment mechanism, the trunk and the wearable shoes [28,29,30].

The leg segment is attached to the waist through a connection mechanism. All wires of control module are embedded into the mechanical structure through the wiring slot. The lower extremity exoskeleton is suitable for operators with the height in the range of 168 mm−188 mm, where length of thigh can be adjusted in the range of 430 mm−480 mm while the shank can be adjusted in the range of 470 mm−520 mm. The trunk of the exoskeleton includes the following parts, i.e., the connector to the leg, the adjustment mechanism for the waist width, the backpack and the elastic element. The elastic element with enough stiffness is utilized to support the weight of mechanism and transfer the weight to the ground. The length of waist can be adjusted in the range of 340 mm−400 mm. The backpack will be connected to an ergonomic mechanism which is tied with the human torso to carry the control enclosure, the power package and other equipment. The wearable shoe is made of rubber in order to guarantee the flexibility. The thin upper sole is fixed by bolts. Pressure sensors are placed into the lower sole and all wires are tired together through connectors and transferred to the control enclosure. The wearable shoe is connected with leg segment by the ankle joint.