SCIENCE CHINA
Information Sciences

• LETTER •

January 2023, Vol. 66 119205:1–119205:2
https://doi.org/10.1007/s11432-021-3389-7

Obstacle avoidance in human-robot cooperative transportation with force constraint

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Received 5 May 2021/Revised 6 August 2021/Accepted 24 November 2021/Published online 28 November 2022

Citation Zhang Y, Yang C G, Xu S, et al. Obstacle avoidance in human-robot cooperative transportation with force constraint. Sci China Inf Sci, 2023, 66(1): 119205, https://doi.org/10.1007/s11432-021-3389-7

Dear editor,

Robots are often conceived as human-like machines that can interact with humans naturally and safely. Human-robot interaction means that robots can communicate with people, understand their needs, and act accordingly [1]. This interaction is critical when two people are needed to finish a task cooperatively. For example, when two people must carry a large volume fragile object, the force exerted on the object needs to be constrained. Here, the robot can be regarded as a human that could cooperate with the other person to perform the task; hence, the robot must learn how to adjust its pose and force during the task execution [2]. When we place an object or install mechanical components accurately, the dimensional error of various objects may cause task failures. Besides, when the environment around the object changes, it is necessary to intervene manually to fine-tune the trajectory of the robotic arm; thus, the object can finally reach the ideal target point [3].

To solve the problems mentioned above, a complete human-machine co-working framework is proposed in this study. Figure 1 shows the overall diagram of the system proposed in this study. The system consists of the motion generation part, trajectory and force tracking part, and obstacle avoidance part. First, the Gaussian mixture model (GMM) and Gaussian mixture regression (GMR) are used to fit the multiple teaching trajectories to obtain an optimal trajectory having multiple trajectory characteristics, and then motion skills are learned based on the dynamic movement primitives (DMP) model. Next, a hybrid position/force controller is used to track the force and trajectory generated by the DMP models. Finally, when obstacles appear, the robot arm uses redundancy to avoid obstacles and completes the task smoothly.

The main contributions of this study are as follows:

(1) Force constraint is added based on the position constraint to guarantee performance with a contact force requirement.

(2) Obstacle avoidance function is added; thus, the robot can still complete a task smoothly when an obstacle appears.

(3) A framework of human-robot cooperative transportation is proposed. During the interaction, people can intervene online and adjust the motion trajectory in real time.

Motion generation. Recently, DMP models have been widely used in man-machine skill transfer tasks due to their remarkable generalization character. However, since the demonstrator is prone to shake in the teaching process, it is difficult to obtain a smooth trajectory through a single demonstration. To overcome this shortcoming of the classical DMP method, this study combines DMPs with GMR. The demonstrator can perform several demonstrations, and a new trajectory is generated by GMR [4]. Compared with the trajectory obtained by only one demonstration, the trajectory generated by the combination of GMM and GMR contains additional motion features.

Obstacle avoidance. Humans and robots may encounter unexpected obstacles in the process of jointly transporting objects. Therefore, obstacle avoidance should be considered so that the position and orientation of the end-effector of the robot arm can track the expected trajectory while avoiding obstacles.

In the obstacle avoidance process, the distance between the obstacle and the robotic arm needs to be calculated to determine whether obstacle avoidance is required. Here, we refer to the obstacle detection method in [5]. First, the K-means clustering method is used to segment the point cloud obtained by Kinect into hyperpixels. Next, the segmented point clouds are used to generate a simplified three-dimensional (3D) model of the robot. In the point cloud, points near the 3D model are recognized as obstacles. The distance between the obstacle and the robot arm can be obtained by calculating the minimum distance between the simplified 3D model and the object. Assuming that the coordinate of the obstacle is $\boldsymbol{p}_{\rm obj}$ and the coordinate of the closest point to the obstacle on the mechanical arm is $\boldsymbol{p}_r$, the distance between the obstacle and the robotic arm is defined as $L = \left\|\boldsymbol{p}_r - \boldsymbol{p}_{\rm obj}\right\|$. The end-effector moving speed of the robot arm is determined according to the distance between

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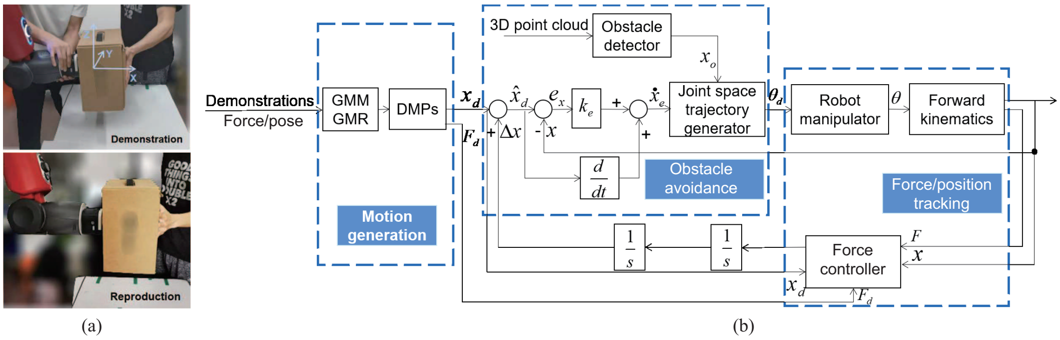

Figure 1 (Color online) (a) Demonstration and reproduction; (b) overview of the proposed approach.

the obstacle and the robot arm. Besides, the maximum and minimum thresholds of obstacle avoidance distance are set as $L_{\max}$ and $L_{\min}$. When $L > L_{\max}$, the obstacle is far away from the robot arm; thus, the obstacle avoidance is not needed, i.e., $\dot{\boldsymbol{x}}_o = \mathbf{0}$. When $L_{\min} < L < L_{\max}$, the obstacle avoidance speed increases gradually with the decrease in distance, and let $\dot{\boldsymbol{x}}_o = h(d)\boldsymbol{v}_{\max}$, where $h(d) = (L_{\max} - L)/(L_{\max} - L_{\min})$. To keep the arm moving away from obstacles, let $\boldsymbol{v}_{\max} = v_{\max}(\boldsymbol{p}_{\rm obj} - \boldsymbol{p}_r)/L$ denote the maximum speed of obstacle avoidance. When $L < L_{\min}$, the manipulator avoids the obstacle with the maximum speed $\boldsymbol{v}_{\max}$ [6]. When the obstacle is removed or avoided, the arm needs to return to the expected trajectory. Therefore, a parallel system is designed in the controller to restore the position of the manipulator when there is no obstacle.

Force/position tracking. In the experiment of human-machine joint transportation of objects, the force exerted on the object needs to be constrained. To avoid object falling due to small force or object distortion because of a large force, the force received by the object during the reproduction process should be maintained around the expected value. In this study, a force controller is added based on the position controller to constrain the manipulation force in the transportation process. The expected movement of the robot in the interaction process is as follows:

$$\Delta\ddot{\boldsymbol{X}} = \boldsymbol{K}_p\left(\boldsymbol{X}_d - \boldsymbol{X}\right) - \boldsymbol{K}_v\dot{\boldsymbol{X}} - \left(\boldsymbol{F}_d - \boldsymbol{F}_r\right), \quad (1)$$

where $\boldsymbol{K}_p$ and $\boldsymbol{K}_v$ represent damping and stiffness, respectively. The force tracking performance of the robot end-effector can be changed by adapting these two parameters. $\boldsymbol{X}_d$ and $\boldsymbol{X}$ are the expected trajectory and the actual trajectory, respectively. $\boldsymbol{F}_d$ and $\boldsymbol{F}_r$ are the expected force and the actual force, respectively. The output of the force controller is acceleration $\Delta\ddot{\boldsymbol{X}}$, and the force can be adjusted by integrating $\Delta\ddot{\boldsymbol{X}}$ twice and adding to the desired position, as shown in Figure 1(b).

Conclusion. This study proposes a framework for human-machine cooperation. Due to the simplicity of the DMP models and their powerful generalization ability, DMPs are used to learn and generalize the demonstration trajectories. In addition, extra motion information could be obtained from multiple demonstrations since GMM and GMR are integrated into the system. Based on learning the demonstration trajectories, the force trajectories in the demonstrations are also studied, and a force controller is applied to the proposed system to implement the force constraint on the object. Besides, in the force/position hybrid control mode, the human operator interacting with the robot can fine-tune the end-effector's motion trajectory online by changing the magnitude of the force. Finally, the obstacle avoidance function is also developed. We have designed some experiments for verification (see Appendixes B and C). Experimental results indicate that the proposed method can smoothly complete different object transportation tasks and avoid collisions with obstacles. Currently, the human-robot interaction only uses trajectory and force information. In future work, we will include additional modal information to enable robots to complete more complex tasks.

Acknowledgements This work was supported in part by National Nature Science Foundation of China (Grant Nos. 61861136009, U20A20200), Guangdong Basic and Applied Basic Research Foundation (Grant Nos. 2020B1515120054, 2019B1515120076), and Industrial Key Technologies R&D Program of Foshan (Grant Nos. 2020001006308, 2020001006496).

Supporting information Appendixes A–C. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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