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A novel human–manipulators interface using hybrid sensors with Kalman filter and particle filter

Guanglong Du, Ping Zhang*

Department of Computer Science, South China University of Technology, PR China

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ABSTRACT

This paper presents a novel method for a human–manipulator interface, which estimates the position and orientation of the human hand using a 3D camera and an inertial measurement unit (IMU). In the proposed method, a 3D camera is used to locate the human hand with the help of Camshift algorithm and an IMU is employed to measure the orientation of the human hand. Although the position and the orientation of the human hand can be obtained from the two sensors, the measured error increases over time due to the noise of the devices and the tracking error. Particle filter (PF) and Kalman filter (KF) are used to estimate the orientation and the position of the human hand. Finally, a finite impulse response (FIR) filter is used to detect the PF failures. The human hand is mapped to the robot EE so that human could control the robot just like controlling his/her own hands. The greatest advantage of this method is that the human can complete the high precision task without much training beforehand. The human–robot interface system was experimentally tested in a lab environment and the results indicate that such a system can successfully control robot manipulator.

1. Introduction

Human intelligence is required to make a decision and control the robot especially when it is in unstructured dynamic environments. So robot teleoperation is necessary especially when the robot is in highly unstructured environments, where objects are unfamiliar and of changing shapes. There are some human–robot interfaces [1] like joysticks [2,3], dials and robot replicas which have been commonly used. However, for completing a teleoperation task, these contacting mechanical devices always require the unnatural hand and arm motion.

There is another way to communicate complex motions to a remote robot and it is more natural compared with contacting mechanical devices. This method tracks the operator hand-arm motion which is used to complete the required task using inertial sensors, like contacting electromagnetic tracking sensors, gloves instrumented with angle sensors, and exoskeleton systems [4]. However, these contacting devices may hinder natural human-limb motion.

Compared with the above methods, vision-based techniques are non-contacting and they are less hindering the hand-arm motions. Vision-based methods always use physical markers which are placed on the anatomical body part [5,6]. There are a lot of applications based on marker-based tracking of human motion [5,7]. However, because body markers may hinder the motion and operators may get occluded in some highly dexterous tasks, the marker-based tracking is not always practical. Thus, a markerless approach seems better for many applications.

Compared with image-based tracking method which uses markers, markerless approach is not only less invasive, but also eliminates problems of marker occlusion and identification [8]. Thus, for robot teleoperation, markerless tracking may be a better approach. However, existing markerless human-limb tracking techniques have a lot of limitations so that they may be difficult to be applied in robot teleoperation. Many existing markerless-tracking techniques capture images and then compute the motions later [9,10]. However, the robot manipulator should be controlled with the continuous robot motion by the markerless tracking. To allow the human operator to perform hand-arm motions for a task in a natural way without any interruption, the position and orientation of the hand and arm should be provided immediately. Many techniques can provide only 2D image information of the human motion [11], thus the tracking methods cannot be extended for accurate 3D joint-position data. An end-effector of a remote robot would require the 3D position and orientation information of the operator's limb-joint centers with respect to a fixed reference system. The problem how to identify human body parts in different orientations has always been a main challenge [9,12].

* Corresponding author.
E-mail addresses: medgl@scut.edu.cn (G. Du), pzhang@scut.edu.cn (P. Zhang).

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For robot teleoperation, some limited researches towards markerless human-tracking have been done. Many techniques have used a human–robot interface based on hand-gesture recognition to control a robot motion [13–15]. Method [16] developed markerless hand-gesture recognition methods which can be used for mobile robot control where only a few different commands are sufficient, such as “go” , “stop” , “left” , “right” and so on. However, for object manipulation in 3D space, it is impossible to achieve natural control and flexible robot motion by using gestures only. If a human operator wants to use gestures, he/she needs to think of those limited separate commands that the human–robot interface can understand like move up, down, forward, and so on. A better human–robot interaction method should permit the operator focus on the complex global task as a human naturally does when grasping and manipulating objects in 3D space instead of thinking about what type of hand motions are required [17]. To achieve this goal, a method [18] that allows the operator to complete the task using natural hand-arm motions provides the robot with the position and orientation data of hand and arm in real time. However, method [18] is not stable because it uses the API of Kinect to capture the motion of the human hand. The API is designed for games so that it is not ensure the accuracy and stability of capturing motions. Moreover, although over damping method can eliminate the effect of capturing failure, it is inefficient. Finally, method [18] does not integrate the position with the orientation of the human hand. In order to obtain more accurate state estimation, a position sensor can be integrated with an IMU since the drawbacks of them can be compensated. In order to decrease the computational complexity, the linear Gaussian part can be solved by using a KF while the remaining part is solved by using a PF [19].

The proposed system uses a 3D camera to locate the human hand and an IMU to measure the orientation of the hand (Fig. 1). This paper proposed Camshift method to track the human hand. To integrate the position with the orientation, KF and PF are used to estimate the position and the orientation of the hand. Besides, in order to overcome the sample impoverish problems in PF, FIR filter is applied to detect the PF failures and recovers the failed PF by resetting the PF using the output of the FIR filter [20–22]. Experimental results to validate the proposed methods are also presented.

The remainder of the paper is organized as follows. In Section II, an overview of this paper is described. The human hand tracking system and posture estimation are detailed in Section III and IV. Experiments and results are presented in Section V. Discussions are detailed in Section VI, followed by concluding remarks in Section VII.

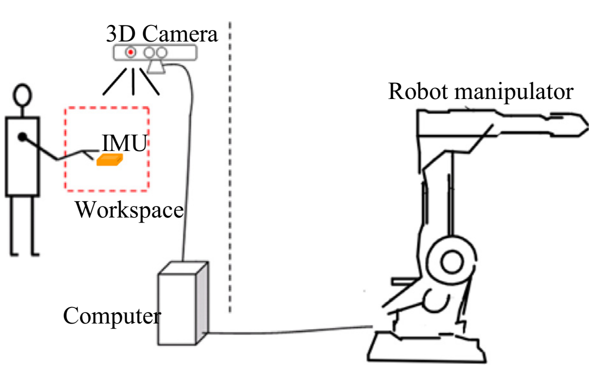

Fig. 1. Proposed robot teleoperation system.

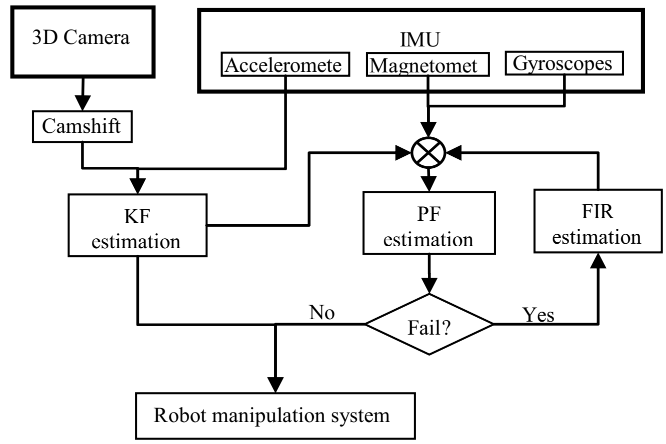

Fig. 2. Outline of the proposed algorithm.

2. Overview

Fig. 1 shows the structure of the proposed system. A 3D camera provides the location of the human hand and an IMU provides the orientation of the human hand (Fig. 2). We use Camshift to track the human hand. A KF estimation algorithm is used to estimate the position and the acceleration of the hand. An IMU consisting of gyroscopes and magnetometer measures the orientation of the hand. A PF and FIR filter is applied to estimate the orientation and the angular velocities of the hand.

3. Hand tracking

Since the human operator holds the IMU to measure the orientation of his hand, the position of the IMU is equal to the position of the human hand. Moreover, the color of the IMU is special. Thus the IMU is easier identified than the human hand. In the IMU position tracking system, IMU position is tracked through Camshift algorithm, which is more and more noticed by means of its favorable performance in reality and robustness [23].

Camshift algorithm adopts a non-parameter method and searches target by a clustering method. Camshift algorithm makes use of color information in region and finds the target through the color matching. Since the object has a very big similarity in the image sequences, the Camshift algorithm has good robustness. Camshift tracking system consists of two parts: color probability distribution and Camshift flow. The process of Camshift flow is as follows:

1) Select search window with the size of s in I and determine the original center position of the search window.

2) Calculate the 0th and 1st order moment:

$$M_{00} = \sum_x \sum_y I(x, y),\ M_{10} = \sum_x \sum_y xI(x, y),$$
$$M_{01} = \sum_x \sum_y yI(x, y) \tag{1}$$

3) Calculate the mass center of the search window

$$x_c = \frac{M_{10}}{M_{00}},\ y_c = \frac{M_{01}}{M_{00}} \tag{2}$$

4) Set the center of the window as the mass center and follow steps 2, 3 repeatedly until the mass center position converges to a point.