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Assisting Humans in Human-Robot Co-Carry Tasks Using Robot-Trusting-Human Model

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Abstract

Robots are increasingly being employed for diverse applications where they must work and coexist with humans. The trust in human-robot collaboration (HRC) is a critical aspect of any shared task performance for both the human and the robot. The study of human-trusting-robot has been investigated by numerous researchers. However, robot-trusting-human, which is also a significant issue in HRC, is seldom explored in the field of robotics. In this paper we propose a novel trust-assist framework for human-robot co-carry tasks. This framework allows the robot to determine a trust level on the human co-carry partner. The calculations of this trust level are based on human motions, past interactions between the human-robot pair, and the human's current performance in the co-carry task. The trust level between the human and robot is evaluated dynamically throughout the collaborative task which allows the trust level to change if the human performs false positive motions. Additionally, the proposed framework can enable the robot to generate and perform assisting movements to follow human carrying motions and paces when the human is considered trustworthy in the co-carry task. The results of our experimentation with this framework show that the robot effectively assisted the human in real-world collaborative tasks through the proposed computational trust model.

Assisting Humans in Human-Robot Co-Carry Tasks using Robot-Trusting-Human Model

by

Corey Hannum

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CHAPTER I INTRODUCTION

1.1 Background and Motivation

In recent years, robots are more and more being introduced into environments where they must coexist with humans. As such, they will also be completing tasks alongside and in cooperation with people [1, 2]. This human-robot collaboration (HRC) will help to advance many technologies such as assembly line production. The goal is to remove as many of the barriers between robots and humans in these assembly facilities [3]. Removing these barriers will allow humans and robots to collaborate more effectively and regularly. Robot and human behavior must also be taken into account when designing HRC tasks. This was studied by Sauppe, where she explained her work of examining human behavior and then encoding those behaviors into a robot and testing which behaviors produced the best outcome [4]. This technique helps to allow better communication between human and robot which can also affect the trust that the human has in the robot. Another important goal of HRC is for the human collaborator to be able to easily predict what the robot is going to do next. One way to go about achieving this goal is to label the robots motion into the three categories: functional, predictable, and legible [5]. A functional movement by this definition would be any movement where the end effector reaches the goal without any collisions but is not necessarily easily predictable. On the other hand, a legible movement is a movement where the end effector reaches the goal without collision, but also moves in slightly exaggerated motion so that the human collaborator can more easily interpret the robot's goal. Robots must also to some extent be able to predict human intention when working collaboratively [6]. By anticipating human intention, the task will be able to be completed quicker than if the robot simply follows a strict set of steps. This can be done by tracking human limbs and using neural networks to attempt to predict the future motion of the limb [7]. There must also be a way in which tasks are split between the robot and the human. One challenge when determining this is human fatigue when performing tasks which may alter their performance. Although difficult, it has been shown that finding the tasks can be optimally split between the human and robot [8].

Human-robot co-carry or co-manipulation is the logical next step in the field of human-robot collaboration. The term human-robot co-carry is used to describe the manipulation of an individual object or item by both the human and the robot simultaneously. One of the reasons to pursue human-robot co-carry tasks is to reduce human fatigue [9]. Human fatigue in human-robot collaboration can lead to mistakes being made and possible injury. Allowing the robot to bear most of the force required to lift or move an object will provide the human with more ergonomic carrying methods [10]. Another reason for human-robot co-carry is that there are some tasks that the robot cannot complete on its own and requires some human interaction [11]. One other situation that this type of co-carry might be useful is when an object is of a size or shape that makes it difficult for a human to carry alone [12, 13]. This could mean anything that is very long, or that has a shape which does not provide any effective grip locations for the human. Human-robot surgical operations are another major area of study within human-robot co-manipulation. This is discussed in a paper where human-robot co-manipulation is used in an endoscopic endonasal surgery where the surgeon needs a high level of dexterity in a small workspace which can be improved with the use of robotic arms [14]. One other use of human-robot co-carry is through a swinging motion in order to move an object to a higher position than otherwise would be possible [15]. This is done by moving in a pendulum like motion to lift an object to a higher location.

The trust in human-robot collaboration is a critical aspect of any shared task performance for both the human and the robot. While limited research has gone into the concept of human-robot trust, there are several techniques that can be used to improve it. When a robot unavoidably encounters a failure of some kind, this will likely influence the level of trust that humans will have with the robot. The study of human-trusting-robot has been investigated by numerous researchers. However, robot-trusting-human, which is also a significant issue in HRC, is seldom explored. To this end, we propose a novel trust-assist framework for human-robot teams in collaborative tasks.

1.2 Contributions of This Work

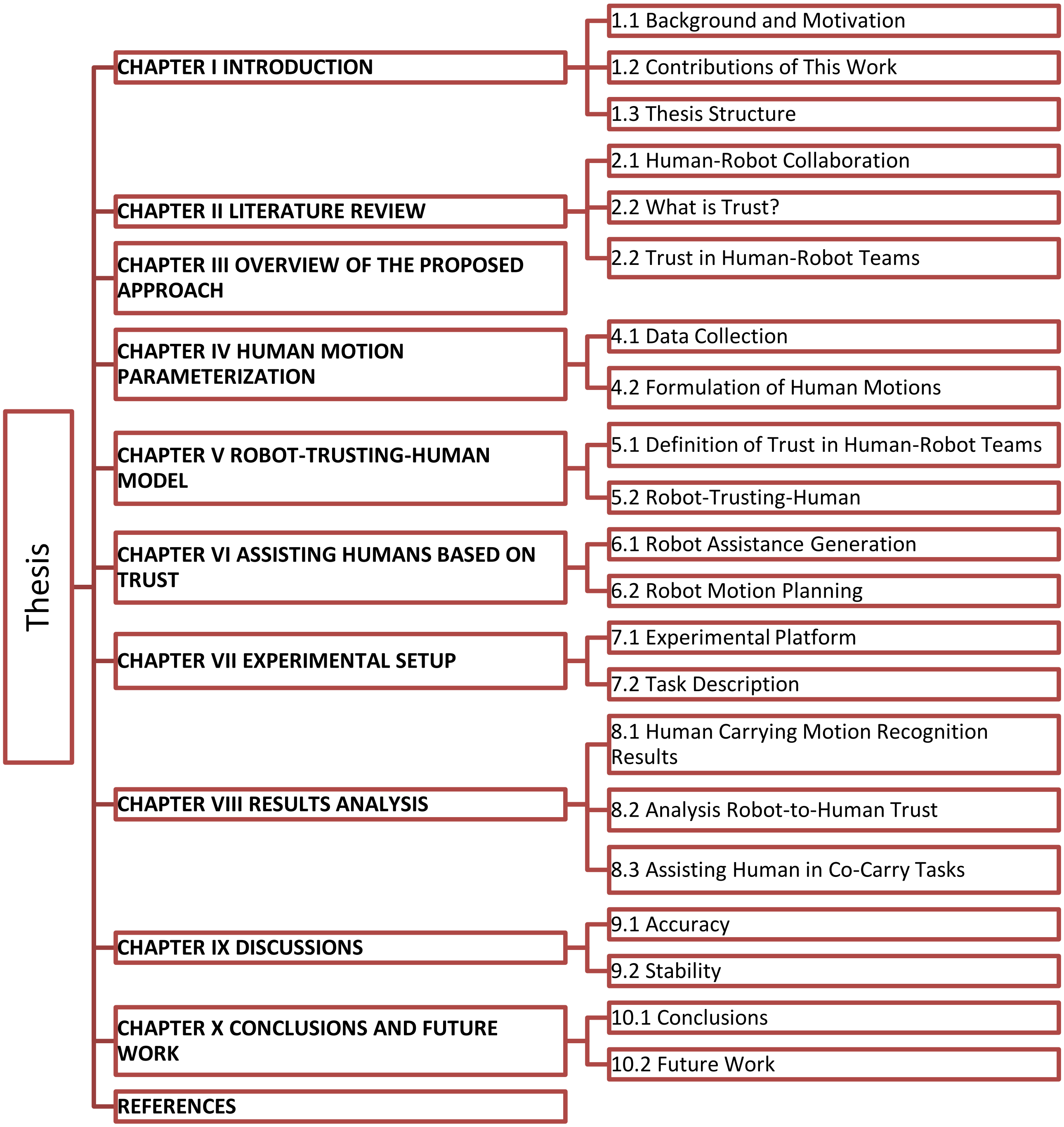
The contributions of this work can be summarized as follows.

(1) We propose an easy-to-implement computational trust-assist model for the robot to autonomously perceive its trust on human partners and accommodate assisting actions to improve task efficiency in human-robot collaborative contexts.

(2) The proposed trust-assist model is real-time sensitive to human false positive actions such as uneven or shaky motion during the human-robot co-carry process, which can enhance collaboration safety in human-robot teams.

(3) The proposed trust-assist model is experimentally implemented in real-world human-robot co-carry tasks. The results illustrate the advantages of the proposed approach in realizing the collaboration safety and efficiency.

1.3 Thesis Structure



CHAPTER II LITERATURE REVIEW

2.1 Human-Robot Collaboration

With more and more interaction between humans and robots happening in industrial and domestic environments, a lot of research has been done in order to make these interactions as efficient and as safe as possible. Many different techniques have been used to achieve this goal. One area of study in this topic is grasp planning in human-robot co-carry tasks. Tariq explored this topic and discussed a method that can be used so that the robot can grasp the co-carry object in such a way that it minimizes the force applied at that point [16]. Another research area has studied learning methods in order to teach the robot the different tasks that it may need to perform via human demonstrations [17, 18]. The robot was able to learn where to grip the object, then switched to a different mode to co-carry the object [19]. This could be very useful since the robot's motion would not need to be manually coded and instead demonstrated. There has also been research into using a nonholonomic constraint to simplify the movement of the object [20]. The researchers were able to verify that this kind of method was useful for human-robot co-carry of large objects in 3-D space. Neural networks have been used as well to predict future human movement. One paper outlined the use of motion and force with a neural network to anticipate the future motion of the human for the robot's motion planning [21]. Another paper discussed the use of both force feedback and computer vision to collaboratively manipulate deformable objects such as a piece of cloth [22]. The use of both force feedback and computer vision allowed this method to work well for non-rigid objects.

2.2 What is Trust?

There have been many researchers who have investigated the definition of trust since it is can be a very subjective term. One researcher first defined a set of epistemic properties such as sincerity, credibility, and validity then defined trust based on these properties. One such example is that agent A may trust agent B, if agent A believes that agent B is being sincere. In addition, the trust is also described as a strong belief by one agent that another agent is being truthful or correct [23].

2.3 Trust in Human-Robot Teams

The trust in human-robot collaboration is a critical aspect of any shared task performance for both the human and the robot according to Ososky's findings [24]. While limited research has gone into the concept of human-robot trust, there are several techniques that can be used to improve it. When a robot unavoidably encounters a failure of some kind, this will likely influence the level of trust that humans will have with the robot.

Several studies on human-trusting-robot in HRC have been conducted recently. Wang stated in his paper that for a robot to be able to perform optimally, the human operating that robot must be able to trust the robot's capability to perform the necessary task [25]. If a robot continuously failed to complete a specific task, the human counterpart will most likely begin to lose trust in the robot. Knowing this, any major robot failures should be corrected immediately to regain the trust of the human. Billings laid out three main questions that need to be investigated when researching human-robot trust. In this paper the three questions are explained as: What is being measured? How can it be measured? And finally, when should it be measured? These are the three main questions that need to be answered when developing a good model of trust [26]. Rossi explained that trust, once broken, can be a very difficult thing to fix [27]. This would be another factor that would need to be investigated when developing human trust in robots in HRC tasks. Stormont discussed some of the reasons that humans currently do not trust robots as much as they trust other humans when working collaboratively or performing a task for one another. The two factors that he mentioned were the robot's poor dependability when performing a task, meaning that the robot might fail more often than a human performing that same task would. The second issue impacting humans' trust in robots is the robots sometimes will act in unexpected ways [28]. Human trust in the robot's abilities will also affect how the robot is used. For example, if a robot is not fully trusted, it may not be used to the best of its ability or not be used appropriately [29]. Another researcher explained human trust in robots as a latent variable in the trust model [30]. This is a latent variable because it takes time for humans to gain trust in something like a robot. There will almost always be some uncertainty when interacting with a new robot. Another important concept in human trust in robots is over trusting [31]. If a human trusts the robot too much, it could lead to the robot being given tasks that it is unable to complete. This would then cause task failure and the human to lose trust in the robot.

Robot-trusting-human in HRC is seldom investigated in the field of robotics. This does not mean however that it is not an important topic that should be better studied. Robot trust in humans in HRC means that the robot performing a task should understand and believe that the task demonstrated by the human is correct and error free. As stated by the work [30] that human-robot trust is an “approximation of the interaction history”. It means that through several human-robot interactions, trust is built based on the success or failure of the tasks performed. One field of robotics that robot trust in humans is incredibly important for collaborative tasks. This trust should be measured in real time for the safety of both the human and the robot. In addition, trust-based robot motion planning is able to effectively improve the task quality and reduce uncertain failure in human-robot collaborative tasks. Therefore, developing a computational model of robot-trusting-human is necessarily to be solved in HRC.

Motivated by this problem, we propose a novel trust-assist (TA) framework for human-robot teams in collaborative tasks. By taking advantage of the developed computational robot-trusting-human (RTH) model, the robot can autonomously perceive its trust on the human in real time. The calculations of this trust level are based on human motions, past interactions between the human-robot pair, and the human's current performance in the collaborative task. Then a robot-assisting-human (RAH) model is established for the robot to actively accommodate and assist its human partner based on the trust in human-robot collaborative contexts. If the trust level is too low, the human motion will not be followed by the robot. By enabling the robot to only perform assisting movements when the human motion is considered trustworthy, we are able to achieve efficiency and safety in human-robot co-carry tasks.

CHAPTER III OVERVIEW OF THE PROPOSED APPROACH

The overview of TA framework for human-robot co-carry tasks is shown in Figure 1. This framework is composed of three parts including data acquisition and processing, trust-assist model, and human-robot co-carry. The overarching vision of the proposed framework is to enable robots to understand and assist humans based on the confidence coefficient derived from our developed trust-assist model in human-robot co-carry tasks.

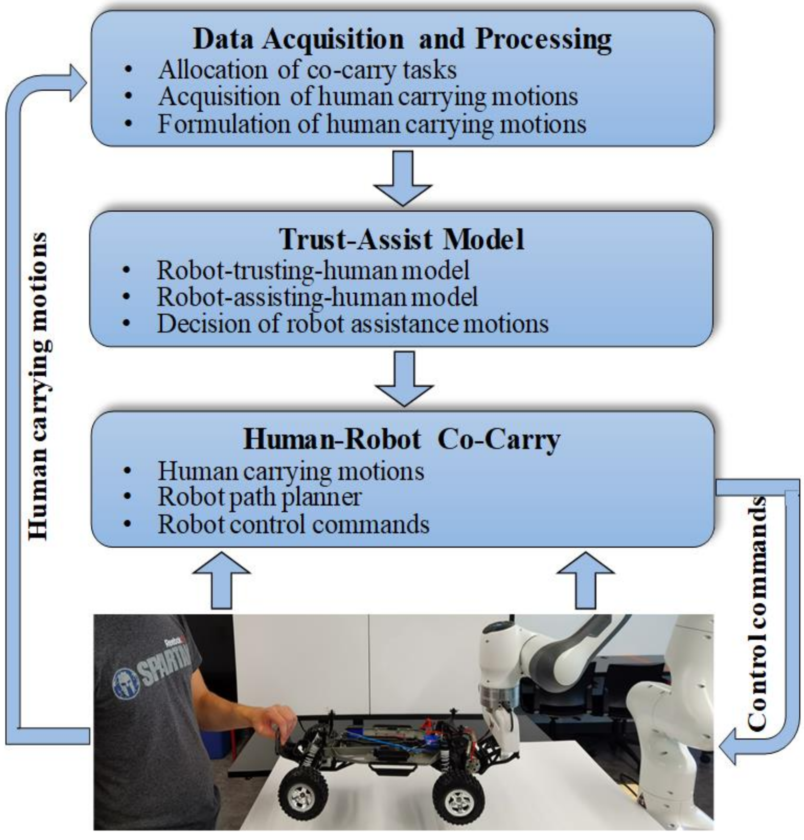


Figure 1 Overview of trust-assist framework for human-robot co-carry tasks.

The first step of this framework is to acquire and process the human carrying motion data. With the goal of human-robot collaboration, the robot must be able to detect the intention of the human. In order to do this, a camera is to be placed above the workspace to capture the entire collaborative workspace. This video feed is processed in real time to be effective for robot motion planning. As the raw video is being captured, it is processed using the Lucas-Kanade (L-K) optical flow algorithm for the robot to understand human carrying intentions. Both the direction and speed of the human motion can be calculated via this algorithm. Once this motion data is processed it is then passed to the TA model for further processing.

The TA model contains two sub-models: robot-trusting-human (RTH) model and robot-assisting-human (RAH) model. After receiving the parameterized human carrying motions from the L-K algorithm, an RTH model is developed to evaluate the trust level of these movements. This trust level works as the confidence coefficient for the robot on its human partner and must be in a certain trustworthy performance (see section III D and E for details). In this study, a trustworthy motion is characterized as smooth and continuous motion while untrustworthy movement is uneven or shaky motion. If the trust level keeps increasing in the human-robot co-carry process, the RAH model will be utilized for the robot to generate appropriate assisting actions to adapt human carrying motions.

In the human-robot co-carry stage, robot motion planning will take place based on the captured human motion data, evaluated trust level, and generated assisting actions in the TA model. The TA model is able to determine which precise movements by the human should be trusted and which should not be trusted. If the human carrying motion is determined to be trustworthy, the robot path planner will be invoked to schedule exact assisting carrying motions for the robot based on the generated assisting action information from RAH in the co-carry task. This planned path data is then used in the robot control commands to execute co-carrying movements.

CHAPTER IV HUMAN MOTION PARAMETERIZATION

4.1 Data Collection

To complete human-robot co-carry tasks, the human and robot must be able to communicate in some way. For this to be done, the robot must be able to interpret the human's motion and follow it so that the co-carry object is moved in the desired position. In this method the human motion is captured through a camera attached above the collaborative workspace. While the human and robot are both holding the co-carry object, the human can begin to move the object in the desired direction within the collaborative workspace.

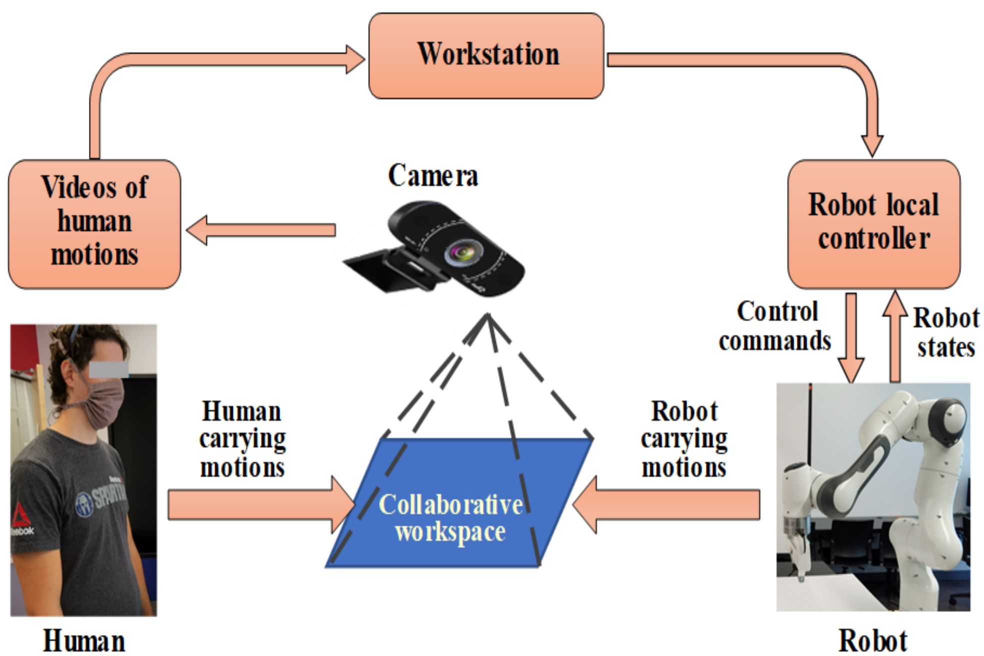


Figure 2 Human carrying motions acquisition and processing in human-robot co-carry tasks.

This video stream is then processed using the Lucas-Kanade optical flow algorithm. Using this algorithm, the previously selected points on the human hand are able to be tracked. By tracking these points, the human carrying motion is able to be interpreted and used for the robot motion planning. Before the data is sent to the robot local controller, it is first sent through the trust-assist model to determine the confidence coefficient of the motion. The human carrying motion is translated into numeric data which gives the direction and speed of the motion. This is important so that the robot is able to match not only the direction of movement but also the speed at which the human is moving. All of this data is then sent to the robot local controller to be further processed for robot motion planning.

4.2 Formulation of Human Motions

In order to assist its human companion in co-carry tasks, the robot should understand human carrying motions on the shared object. In this study, the Lucas-Kanade (L-K) optical flow algorithm [32] is used to parametrize human intentions in the human-robot co-carry process. The algorithm works under the following three assumptions: (a) brightness constancy during the human-robot co-carry process; (b) temporal persistence in the human-robot co-carry task; (c) spatial coherence in the human-robot co-carry task. Brightness constancy means that for a given pixel in a frame, the brightness intensity of that pixel will be the same in the next frame. The second assumption, temporal persistence, is used to mean that the movement from one frame to the next is slow and gradual. The third assumption is spatial coherence, which means that the pixels around a point have the same motion since they are considered to be on the same surface.

Suppose the human and the robot co-carry an object on the $x-y$ plane in a shared workspace. The goal of the L-K optical flow algorithm is to calculate the human carrying movement of points between two frames at time t and $t+\Delta t$. Let the brightness intensity at a point be $I(x,y,t)$ and the point moves by Δx,Δy over time Δt. Using the first assumption of brightness constancy, we get the following equation

$$I(x,y,t)=I(x+\Delta x,y+\Delta y,t+\Delta t). \tag{1}$$

By using Taylor series expansion and assuming movements are small, the following equation is derived from Eq. (1)

$$I(x,y,t)+\frac{\partial I}{\partial x}\Delta x+\frac{\partial I}{\partial y}\Delta y+\frac{\partial I}{\partial t}\Delta t=I(x+\Delta x,y+\Delta y,t+\Delta t) \quad , \tag{2}$$

which can be further reduced to

$$I_x V_x + I_y V_y + I_t = 0 \quad , \tag{3}$$

where x, y, and t represent the derivatives of the image at the point (x, y) at time t, and the V_x and V_y represent the x and y components of the velocity of $I(x, y, t)$.

Since this equation has two unknowns, it is unsolvable. However, by using the third assumption of temporal persistence, the local group of pixels have the same velocity, and the equation can be solved. By utilizing the temporal persistence constraint, a system of equations can be set up for the pixels in the surrounding $n\ x\ n$ region. Then using a weighted least squares approach, a good estimate of the optical flow is determined. The optical flow equations are created for all the pixels in the surrounding region. Then the velocity vector $V = (V_x, V_y)$ must satisfy the following system of equations:

$$\begin{cases} I_x(x_1,y_1)\cdot V_x + I_y(x_1,y_1)\cdot V_y = -I_t(x_1,y_1) \\ I_x(x_2,y_2)\cdot V_x + I_y(x_2,y_2)\cdot V_y = -I_t(x_2,y_2) \\ \cdots \\ I_x(x_n,y_n)\cdot V_x + I_y(x_n,y_n)\cdot V_y = -I_t(x_n,y_n) \end{cases} . \tag{4}$$

This system of equations can then be rewritten in matrix notation:

$$\begin{bmatrix} I_x(x_1,y_1) & I_x(x_1,y_1) \\ I_x(x_2,y_2) & I_y(x_2,y_2) \\ \vdots & \vdots \\ I_x(x_n,y_n) & I_y(x_n,y_n) \end{bmatrix} \cdot \begin{bmatrix} V_x \\ V_y \end{bmatrix} = - \begin{bmatrix} I_t(x_1,y_1) \\ I_t(x_2,y_2) \\ \vdots \\ I_t(x_n,y_n) \end{bmatrix} . \tag{5}$$

Since this system of equations has more equations than unknown, it is considered over determined and can be solved by the least squares method. Therefore, the velocity for each pixel can be calculated by the following equation:

$$V = (A^T A)^{-1} A^T b \quad , \tag{6}$$

where

$$V = \begin{bmatrix} V_x \\ V_y \end{bmatrix}, A = \begin{bmatrix} I_x(x_1, y_1) & I_x(x_1, y_1) \\ I_x(x_2, y_2) & I_y(x_2, y_2) \\ \vdots & \vdots \\ I_x(x_n, y_n) & I_y(x_n, y_n) \end{bmatrix}, \text{ and } b = \begin{bmatrix} -I_t(x_1, y_1) \\ -I_t(x_2, y_2) \\ \vdots \\ -I_t(x_n, y_n) \end{bmatrix}.$$

By taking advantage of Eq. (6), we can obtain the velocity data of human carrying motions, which includes magnitude and direction. The velocity magnitude at time t on the x axis and y axis can be calculated by $\|V_x\|$ and $\|V_y\|$ respectively. The direction of the human motion can be characterized as an orientation angle matrix $O(t)$ derived from

$$O(t) = \arctan \frac{V_y(t)}{V_x(t)} \quad , \tag{7}$$

where each element of $O(t) \in [-\pi, \pi]$. It can be seen that, based on the L-K algorithm, the human carrying motion information can be quantitatively evaluated in real time during the human-robot collaboration process.

CHAPTER V ROBOT-TRUSTING-HUMAN MODEL

5.1 Definition of Trust in Human-Robot Teams

Definition 1: In human-robot interaction, the trust of robot R on human H is denoted as $T_{R\rightarrow H}$, which is a real number and $T_{R\rightarrow H} \in [0,1]$.

$T_{R\rightarrow H} = 0$ means that the human and the robot have not interacted before or the robot distrusts the human fully in the human-robot interaction process. $T_{R\rightarrow H} = 1$ means that the robot definitely trusts the human in the interaction process.

Definition 2: In human-robot co-carry tasks, the human carrying intention C_H at time t is defined as

$$C_H(t) = \begin{cases} \dfrac{\overline{O}(t)}{\pi}, & \textit{human moves and human} - \textit{robot interaction} \neq \varnothing \\ \textit{null}, & \textit{human stops or human} - \textit{robot interaction} = \varnothing \end{cases}, \tag{8}$$

where $\bar{O}(t)$ is the arithmetic mean of $O(t)$, $\frac{\bar{O}(t)}{\pi} \in [-1,1]$.

If the human and the robot have not interacted before or the human stops during the human-robot co-carry process, the human carrying intention $C_H = null$.

5.2 Robot-Trusting-Human

In order to have a uniform interval with $T_{R\rightarrow H}$ for further mathematical combination in the computational trust model, the human carrying intention is transformed as

$$C_H(t) = \begin{cases} \dfrac{1}{2}\left(\dfrac{\overline{O}(t)}{\pi} + 1\right), & \textit{human moves and human} - \textit{robot interaction} \neq \varnothing \\ \textit{null}, & \textit{human stops or human} - \textit{robot interaction} = \varnothing \end{cases}, \tag{9}$$

where $\widetilde{C_H}(t) \in [0,1]$.

Further, the trust of robot on human $T_{R\to H}$ is defined as a weighted function that entails trust history and present human performance in the human-robot interaction process, which can be expressed as

$$T_{R\to H}(t) = 1 - \frac{1}{w_d[w_h T_{R\to H}(t-1) + w_p C_H(t)] + 1}, \tag{10}$$

where $w_h \in [0, 1]$ denotes the weight factor for trust history, $w_p \in [0, 1]$ denotes the weight factor for present human performance, $w_h + w_p = 1$, and w_d is the discriminant coefficient, which is defined as

$$w_d = \begin{cases} 1, & \left|\overline{O}(t) - \overline{O}(t-1)\right| \le \frac{\pi}{2} \\ 0, & \left|\overline{O}(t) - \overline{O}(t-1)\right| > \frac{\pi}{2} \ or\ C_H(t) = null \end{cases}. \tag{11}$$

In Eq. (10), w_h and w_p can be adjusted to appropriate values to give more weight for trust history or present human performance to evaluate online robot-to-human trust according to different tasking settings in human-robot collaboration. For example, if the human and robot have not worked collaboratively previously, the framework may give more weight to the present human performance. This is because the framework does not have any trust history between the human and robot pair and so it cannot make any assumptions about the human's trustworthiness. By doing this, the framework is able to learn information about the human movement which can be used in future collaborations. Conversely, if the human and robot have worked on many previous collaborative tasks, the framework may give more weight to the trust history value. If the human-robot pair have worked together previously, the framework is able to make determinations about the human trust based on the trust history. This allows the robot to trust or distrust the human regardless of the present human performance.

w_d is utilized to avoid unpredictable safety issues caused by human false positive actions in human-robot collaboration. False positives may occur when the human performs carrying motions. For example, if the human begins to move in nonuniform motions, this will cause the discriminant coefficient to be 0. This is done because nonuniform or shaky movement could cause the robot to move unpredictably and cause injury to the human or damage to the robot or co-carry object. Another way that this value could be set to 0 is if the human stops moving the co-carry object. The robot will not follow the human's movements during the specific motion that caused the discriminant coefficient to be set to 0. This is an important safety concern which can help the robot avoid making unpredictable movements during the co-carry task.

CHAPTER VI ASSISTING HUMANS BASED ON TRUST

6.1 Robot Assistance Generation

When the human performs carrying motions in the human-robot shared workspace, the displacement of human's hand from the start point to time t can be represented by a six-elements vector $(x_H(t), y_H(t), z_H(t), \phi_H(t), \theta_H(t), \psi_H(t))$, where x, y, and z describe the position of human's hand in the 3-D workspace, and ϕ, θ, and ψ present the rotation angles of human's hand. ϕ is the Roll rotation about the x-axis, θ is the Yaw rotation about the y-axis, and ψ is the Pitch rotation about the z-axis. Since the human and the robot co-carry an object on the $x-y$ plane, the Roll rotation is 0, the Yaw rotation is 0, the Pitch rotation can be evaluated by $\bar{O}(t)$, and z is a fixed value approximating to the vertical distance h between the workspace floor to human's hand. Therefore, the displacement of human's hand at time t can be evaluated by

$$\begin{cases} x_H(t) = \overline{V_x}(t) \cdot t \\ y_H(t) = \overline{V_y}(t) \cdot t \\ z_H = h \\ \phi_H(t) = 0 \\ \theta_H(t) = 0 \\ \psi_H(t) = \overline{O}(t) \end{cases} , \tag{12}$$

where $\overline{V_x}(t)$ and $\overline{V_y}(t)$ denote the arithmetic means of $V_x(t)$ and $V_y(t)$, respectively.

From Eq. (10), it can be observed that, if some false positive motions occur or the human stops moving, the trust of the robot on its human partner $T_{R\to H}$ will not be increased in the human-robot co-carry tasks. The robot does not need to execute may co-carry motions. If the human-robot team keeps a fluent collaboration, $T_{R\to H}$ will keep increasing. Therefore,

$$\frac{dT_{R\to H}(t)}{dt} > 0 . \tag{13}$$

The robot should perform the same pace to co-carry the object with its human partner if it trusts him/her. Suppose the displacement of human's hand between time $t + \Delta t$ and time t in the carrying motions is $\Delta\overrightarrow{S_H}(t)$, and the displacement of robot's end-effector in the assisting co-carrying motions is $\Delta\overrightarrow{S_R}(t)$, so the robot-assisting-human problem can be characterized as a constrained-optimization issue

$$\begin{aligned} & M_R^* = \arg\min_{M_R} \left\| \Delta\overrightarrow{S_R}(t) - \Delta\overrightarrow{S_H}(t) \right\| \\ & S.T.: \frac{dT_{R\to H}(t)}{dt} > 0 \end{aligned} , \tag{14}$$

where M_R^* represents the desired robot assisting co-carrying motion.

Further, suppose at time t the initial pose of human's hand is $\overrightarrow{P_{HI}}(t)$. After performing the carrying motion, the pose of human's hand at time $t + \Delta t$ is $\overrightarrow{P_{HP}}(t)$. Based on the L-K approach, the displacement of human's hand $\Delta\overrightarrow{S_H}(t)$ is able to be evaluated using a location vector $\overrightarrow{P_{HP}}(t) - \overrightarrow{P_{HI}}(t)$, which can be described by a linear combination of basic vectors as

$$\begin{aligned} \Delta\overrightarrow{S_H}(t) = \overrightarrow{P_{HP}}(t) - \overrightarrow{P_{HI}}(t) &= \Delta x_H(t)e_x + \Delta y_H(t)e_y + \Delta z_H(t)e_z \\ &+ \Delta\phi_H(t)e_\phi + \Delta\theta_H(t)e_\theta + \Delta\psi_H(t)e_\psi \end{aligned} . \tag{15}$$

Similarly, the displacement of robot's end-effector $\Delta\overrightarrow{S_R}(t)$ in the assisting co-carrying motion can be expressed by

$$\begin{aligned} \Delta\overrightarrow{S_R}(t) &= \Delta x_{M_R}(t)e_x + \Delta y_{M_R}(t)e_y + \Delta z_{M_R}(t)e_z \\ &+ \Delta\phi_{M_R}(t)e_\phi + \Delta\theta_{M_R}(t)e_\theta + \Delta\psi_{M_R}(t)e_\psi \end{aligned} . \tag{16}$$

In order to get the optimized result for Eq. (14), the robot assisting co-carrying motion M_R should minimize the approximation error between $\Delta\overrightarrow{S_R}(t)$ and $\Delta\overrightarrow{S_H}(t)$. Therefore, the waypoints on the desired robot assisting co-carrying motion can be derived by

$$
\begin{aligned}
&\left(\Delta x_{M_R^*}(t), \Delta y_{M_R^*}(t), \Delta z_{M_R^*}(t), \Delta \phi_{M_R^*}(t), \Delta \theta_{M_R^*}(t), \Delta \psi_{M_R^*}(t)\right) \\
&\quad = \left(\Delta x_H(t), \Delta y_H(t), \Delta z_H(t), \Delta \phi_H(t), \Delta \theta_H(t), \Delta \psi_H(t)\right) \\
&S.T.: \ \frac{dT_{R\to H}(t)}{dt} > 0
\end{aligned} \quad . \tag{17}
$$

6.2 Robot Motion Planning

In the human-robot co-carry process, after obtaining the executable waypoints based on the TA model, the RRT-Connect path planning algorithm is employed for the robot. As shown in Figure 3, the RRT-Connect path planner works by incrementally constructing two Rapidly-exploring Random Trees rooted at the two neighboring executable cleaning waypoints [33, 34]. The threes can explore space around to move towards each other by a greedy function and the path planning between the neighboring waypoints will be done once the two trees connect. The robot path planning algorithm for the co-carry task is illustrated in Algorithm 1, where the RRT_CONNECT_PLANNER denotes the RRT-Connect path planning function, of which details can be found in [33].

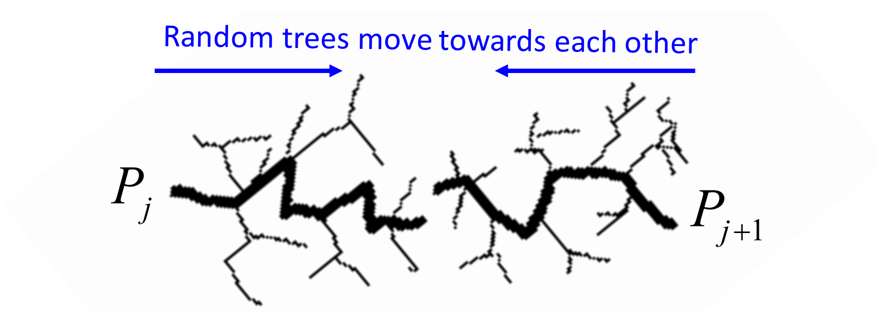


Figure 3 The RRT-Connect path planner utilized for the robot.

Algorithm 1: Robot path planning

Input: The executable waypoints generated via trust-assist model

Output: Planning paths

1 $n_i \leftarrow$ the number of executable waypoints;
2 *path_go* $\leftarrow$ 0
3 **for** *j* in n_i **do**
4   *RRT_CONNECT_PLANNER* (P_j , P_{j+1});
5   **if** *CONNET* (P_j , P_{j+1}) = true **then**
6   *path_go* $\leftarrow$ *PATH* (P_j , P_{j+1});
7   **else**
8   *path_go* $\leftarrow$ 0;
9   skip to 4;
10   **end if**
11   add *path_go* to the robot controller;
12 **end for**

CHAPTER VII EXPERIMENTAL SETUP

7.1 Experimental Platform

In this study, as shown in Figure 4, the experimental platform involves a collaborative robot, a web camera, a workstation, a target object, and a shared workspace. The robot used in this study is Franka Emika Panda, which is a 7-DoF collaborative robot with a robotic arm, a two-finger parallel gripper, a pilot user interface, and a Franka Control Interface (FCI) controller [35]. The robot can work with humans safely like human-to-human cooperation in collaborative tasks. Panda robot can be controlled in different modalities including torque-mode, position-mode, and velocity-mode. A dell desktop with Intel Core I7-9700 and 16 GB Memory serves as the workstation for human motion image processing, trust-assist model development, and robot path planning. A 1/10-scale vehicle is used as the target object in the human-robot co-carry task.

Robot Operating System (ROS) is utilized in the robot system control [36]. ROS is an open-source framework for large-scale cross-platform maneuvering and communication, which includes more than 2,000 packages and can provide specialized functionality in different application areas. In addition, the package MoveIt! running in the ROS framework is also employed. MoveIt! is a set of packages and tools to perform dynamic manipulation in ROS. It contains state-of-the-art software for the development of robot path planning algorithm [37]. To plan the robot in the human-robot co-carry task, the control commands are sent to the libfranka interface, which is a ROS package for Panda to communicate with the FCI controller. The FCI can provide the current robot states and enable the robot to be directly controlled by the commands derived from the trust-assist framework.

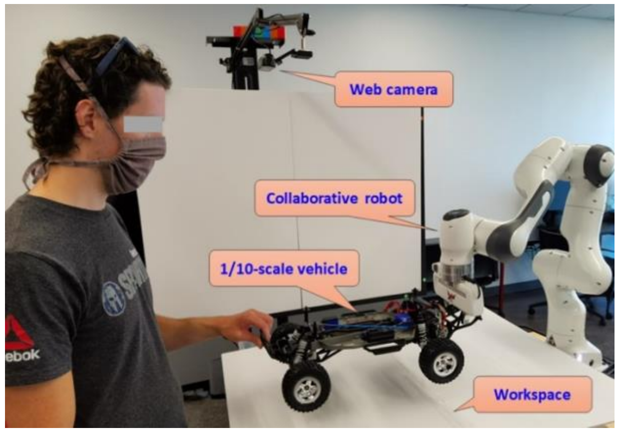


Figure 4 The experimental platform in this study.

7.2 Task Description

In this experiment, one type of human-robot co-carry task will be explored. As shown in Figure 5(a), this task is called lateral movement co-carry. The lateral movement is a motion in the left and right directions of the human in the co-carry task. In other words, this is a motion from side to side from the human's perspective. This type of movements allows us to primarily test the trust model since the direction of movement does not necessarily matter with regards to trust. This movement does also allow us to test the robot assistance as well because the motion planning still need to calculate the direction and velocity of the movement. In addition, our model can also be extended to the longitudinal movement co-carry and square movement co-carry, as shown in Figure 5(b) and Figure 5(c).

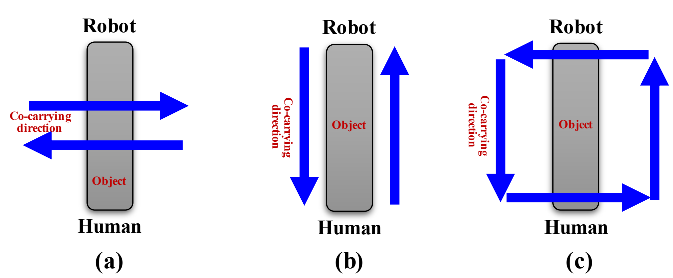


Figure 5 Three kinds of human-robot co-carry tasks in this study. a) Lateral movement co-carry. b) Longitudinal movement co-carry. c) Square movement co-carry.

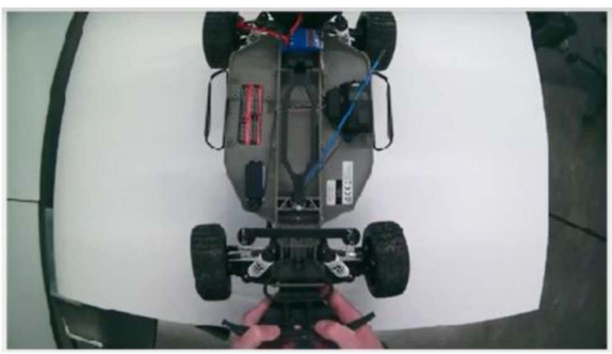
CHAPTER VIII RESULTS ANALYSIS

8.1 Human Carrying Motion Recognition Results

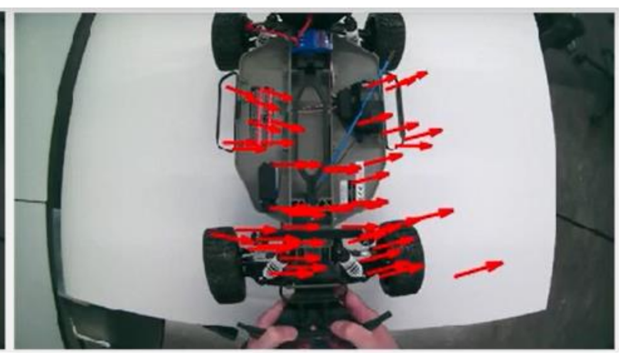
Figure 6 depicts the human carrying motion recognition process. Figure 6(a) shows the starting position of the co-carry task with no motion. In the starting position, the human holds one side of the co-carry object stationary, and the robot holds the other side. Since the human is not moving the object, the robot does not need to produce any assisting actions and the object remains stationary. In figure 6(b) and 6(c) the human is moving the object from left to right. This is the lateral direction of movement since it is side to side from the human's perspective. Figure 6(d) and 6(e) depict human motion in the right to left lateral motion. Although we only tested lateral human motion in this experiment, this model could easily be extended to detect both longitudinal (forward and back) motion as well as a combination of lateral and longitudinal motion. Once the human begins moving in the desired direction, they do not stop until reaching the desired position. This ensures that the motion continues in a single direction and does not drift backward in which case the robot may begin providing assisting motion opposite to the intended human motion. Although this is not detrimental to the model, it could cause the co-carry task to take longer than intended. Each of the arrows in the images represents the direction and rate of motion of a single point on the co-carry object. These points are chosen based on their perceived ease of tracking and are generally corners. Figure 6(f) shows the ending position of the co-carry task. The ending location does not necessarily need to be the same position as the starting location and in a real-world application, it most likely would not be the same as the starting location. Once the human reaches the desired ending location of a movement, they can either end the co-carry task, or reverse direction and continue the co-carry task. Since this could also be extended to longitudinal motion and a combination of motions, an end location could also represent a point at which the human will change from lateral to longitudinal motion or vice versa.

Through figure 6, it can be seen that the human carrying motion is recognized through the L-K optical flow algorithm. Each of the optical flow arrows represents a point on the object that is being tracked. If a point is moved out of view of the camera, the algorithm will attempt to find it again once back in view of the camera. However, this event is highly improbable in our experimental setup. By tracking several of these points, we are able to calculate an accurate representation of the human carrying motion. Through our implementation, we are also able to filter out some extreme outliers that may occur due to tracking errors. This also allows the model to still determine the direction of human motion even if one or two points are tracked incorrectly. This can be seen in figure 6(c) where the bottom left most arrow is pointing down instead of to the right like the rest of the points. Since there are many points being tracked, this does not significantly affect the overall motion recognition. These kinds of tracking errors are easily overcome by the model and does not affect the efficacy of the proposed model. Figure 6(a) and (f) also show that the model does not recognize the slight shakiness in a human hand while holding an object since no optical flow arrows are seen in these images. This means that any minor natural unsteadiness in a human hand while holding the co-carry object does not affect the overall performance of the model. Similarly, this also allows the model to disregard any human false positive movement that may occur while the human tries to hold the co-carry object stationary.

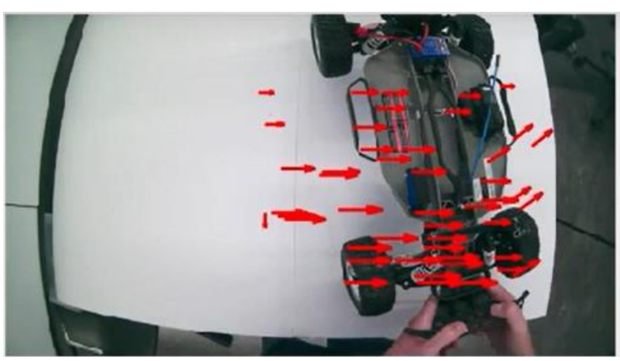
With this experiment we were able to verify the human motion recognition performance of this model. We showed that by using the algorithm and implementation that we selected, we were able to accurately and consistently model the human motion in a co-carry task. We also showed that the model is able to assist in filtering out small unintentional movement that would be considered human false positive motion. Any false positive motion that is too large to be filtered out at this point will be later removed by the trust model. This allows for some small unintentional human motion as well as some optical flow tracking errors to occur without significantly affecting the overall model of the human's motion. The tracking errors also happen infrequently enough that if they are not filtered out by the model, the vast majority of correctly tracked points are enough to correct for it. By overlaying the optical flow arrows on the video frames, it is also clear that the algorithm is accurately calculating the human path and motion which provides an excellent base for the trust-assist model to build off of.



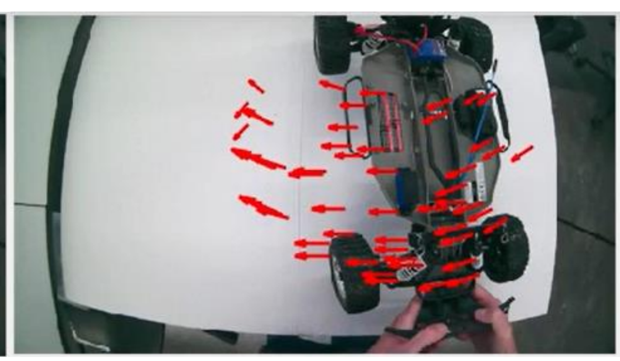
(a)



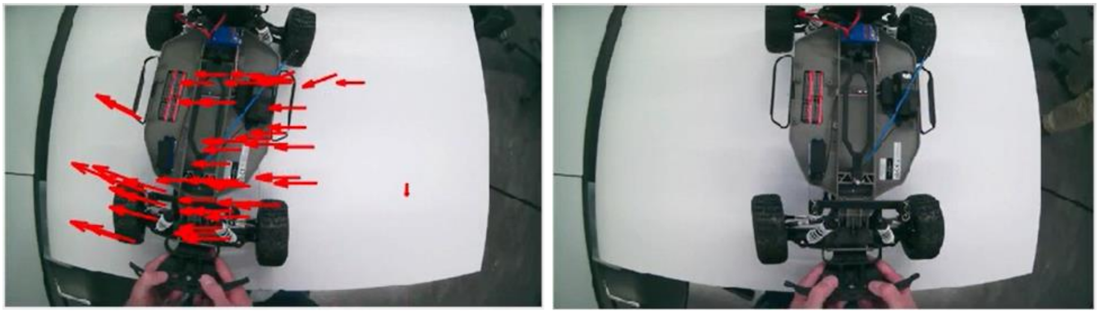
(b)



(c)



(d)



(e) (f)

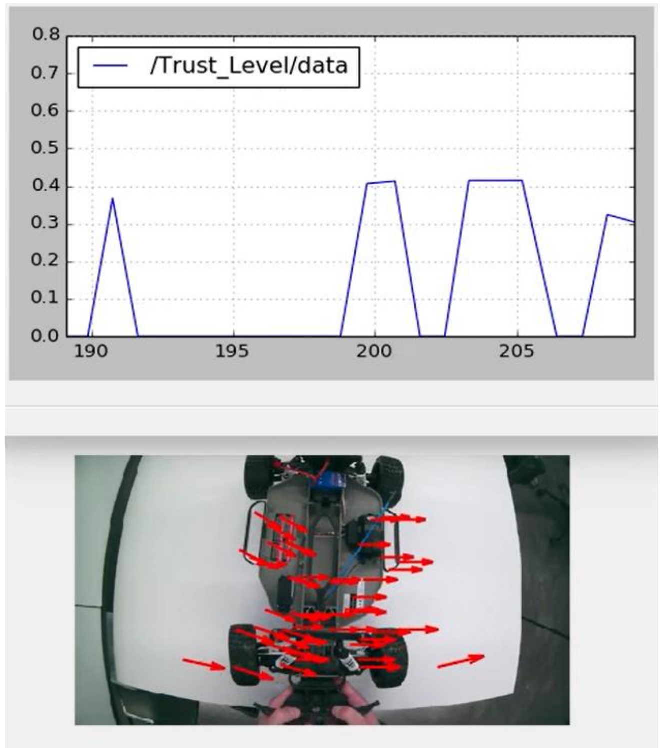
Figure 6 Human carrying motion recognition using L-K algorithms. a) Ready to move. b) Human carrying motion from left side to right side in the collaborative workspace. c) Approaching to the left end. d) Human carrying motion from left side to right side in the collaborative workspace. e) Approaching to the right end. f) Returning to the start station.

8.2 Analysis of Robot-to-Human Trust

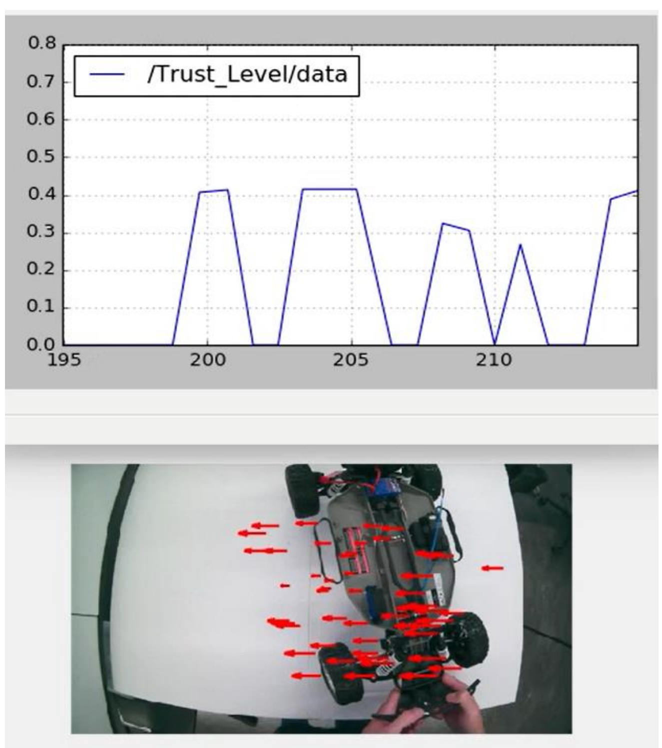
Figure 7 illustrates the trust level of the robot on the human throughout a co-carry task. Figure 7(a) shows the trust of the robot on the human when the human is moving the object from left to right in a lateral motion. In figure 7(b) the human is moving the object in a lateral right to left motion. In both scenarios, it is shown that the trust is dynamically evaluated throughout the motion. This allows the robot to determine whether or not to trust and assist the human motion at any given time. The values of the trust level graph depict times at which the human motion is at least somewhat trusted and the zero points on the graph represent times when the human motion is not trusted. This may occur if the trust model detects human false positive motion. Figure 7(c) shows the trust level of the robot on the human during a false positive motion. This false positive motion means that the human is shaking the object. Since this motion is recognized as a false positive motion, the trust level remains at 0. This is useful because the robot will not assist in human motion when the trust level is 0 and this provides a safer work environment. A major in the trust of the robot on the human during a false positive motion is the discriminant coefficient which is set to 0 when the object is in a shaky motion.

Figure 7(a) and (b) both show the trust level changing as the human moves the co-carry object in the desired direction. While the human moves the object, the trust level of the robot on the human is dynamically calculated based on the human's current performance and trust history. This can cause the trust level to fluctuate throughout the movement but while the trust level is above the trustworthy threshold, the robot will assist the human. Some small unintentional shakiness in the human movement may cause of trust level to drop. Since the model is able to dynamically determine a trust level, current human motion which could potentially lead to unpredictable robot motion can be determined to be untrustworthy. This provides more safety to both the human, and the robot as well as the co-carry object which could be damaged if the robot moves unpredictably. Figure 7(c) depicts the human performing a false positive motion. This kind of motion is movement that is shaky and could cause harm to the human or damage the robot if the robot attempted to provide assisting motion for the human movement. In the experimentation, the false positive movement was accurately detected, and the trust level remained at 0 throughout. This type of motion was tested several times, and the model consistently and correctly calculated the trust level to be 0. Since this motion is correctly determined to be untrustworthy, the robot does not attempt to perform assisting motion based on the false positive movement. This shows that the human false positive detection portion of this model has been successful.

We claim that our robot-trusting-human model is able to accurately and consistently calculate a trust level on the human based on the human movement and trust history. This model proved to be useful in co-carry tasks and could potentially be useful in co-assemble and many other human-robot collaborative tasks as well. Using the proposed framework, we were able to show that the trust level of the robot in the human is able to be dynamically calculated throughout the course of a task. Since the trust model dynamically evaluates the trust level, the trust of the robot in the human can change even through a single motion. By doing this, the robot is able to provide assisting motion in only trusted parts of the human motion and disregard any motions that are deemed untrustworthy. The trust model was consistently able to accurately calculate a trust level of the human motion. If the human moved the co-carry object in a smooth motion, then the robot would correctly trust the motion, but if the human moved the object in a shaky manner then the robot would not trust the movement. We were able to achieve high accuracy of human motion recognition through the use of the L-K optical flow algorithm which is a crucial aspect of the proposed trust model since the trust is in part based on current human performance. By using this algorithm, we tracked several points on the co-carry object, and human hand. Then, by taking the arithmetic mean of the velocity and direction of all of the points, we were able to calculate a very accurate model of the human motion. Using this data, the model was able to correctly calculate a trust level depending on if the movement was smooth or shaky. With the implementation of the discriminant coefficient, the model was also able to detect human false positive motion. When this motion was recognized, the discriminant coefficient was correctly set to 0 and so the trust was calculated to be 0 as well. The discriminant coefficient provided additional safety to both the human and robot throughout the co-carry task because it was able to consistently determine which human motion was correct, and which was false positive.


0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
/Trust_Level/data
190
195
200
205

(a)


0.8
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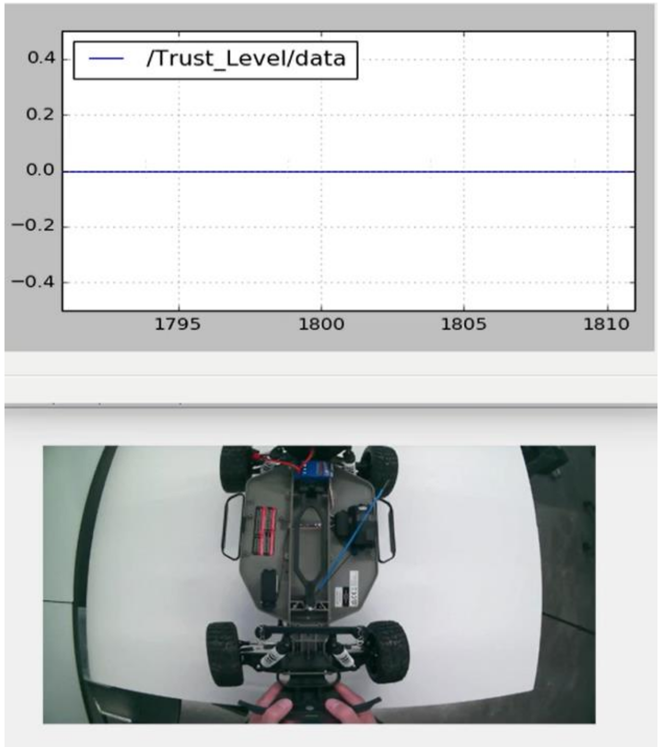
(b)



(c)

Figure 7 The robot's trust in human is dynamically evaluated in the human-robot co-carry process. a) Trust level evaluation when the human carries the object from left side to right side in the collaborative workspace. b) Trust level evaluation when the human carries the object from right side to left side in the collaborative workspace. c) Trust level evaluation when the human performs false positive actions.

8.3 Assisting Human in Co-Carry Tasks

The robot assisting the human in a co-carry task is show in figure 8. The top image shows the beginning of the co-carry task. The human and robot remain still at this stage while both hold the co-carry object, and the trust is 0 until the human begins to move. The trust is set to 0 at this point because the discriminant coefficient is always 0 if no motion is detected. At this stage, no robot assisting motion needs to be calculated because there is no motion to assist. In the middle image, the human begins to move the co-carry object in the right to left lateral direction. As this is done, the trust level can be seen to be changing dynamically. This could be caused by small unintentional variances in the human movement speed, or direction. In the bottom image, the robot begins its assisting movement to assist the human co-carry the object. This is done once the trust level reaches the threshold value and may be slightly delayed from the start of the trusted human motion. As can be seen again in figure 8, the trust level is constantly changing since it is dynamically evaluated during the co-carry task. This allows the robot to only assist in the precise movements by the human that have been deemed trustworthy.

In the top image of figure 8, since the human is not moving the object in any direction, the robot does not provide any assisting motion. Although some small shaky movements may occur here, they are small enough that they do not affect the model's ability to only assist with trusted movement. This shows that the model effectively filters out any human false positive movement. The robot correctly does not attempt to provide any assisting motion in this starting position. When the human begins moving the object in the middle image of figure 8, the trust level is immediately being calculated. As the human moves with some slight inconsistencies, the trust level fluctuates up and down. Although the movement may appear to be a smooth lateral motion to the human eye, the model is able to much more precisely spot any small changes in the human's movement that may affect the robots assisting capabilities. When these inconsistencies in the human motion are found by the model, the trust level will drop due to the unpredictability of the motion. Once the trust level meets the threshold again, the robot will begin with its assisting motion. This is why the dynamic capabilities of this model are of utmost importance to its performance. With this assisting motion, the robot matches both the direction and velocity of the human's movements. This allows the robot to move along with the human and not move too fast or slow. The direction and velocity of the human motions is accurately calculated by using the L-K optical flow algorithm data and so the robot's assisting movement is able to very closely match the humans. In this experiment, we found that the robot's assisting motion accurately mirrored that of the human's in both velocity and direction of movement.

Through this experiment, we proved that the model was able to correctly assist the human movement when trustworthy and reject the movement when untrustworthy. This means that any human false positive movement was correctly determined to be untrustworthy and therefore no assisting movements were performed by the robot. Once a movement was determined to be trustworthy, the robot began its assisting movement. The robot assisting motion can occur with a slight delay from the human movement as calculations are made based on the human's movement take a non-trivial amount of time to execute. Using the data collected from the L-K optical flow algorithm, the model was able to precisely assist trustworthy human movements. This was possible because both human velocity and direction of movement were calculated so that the robot is able to match both during its assisting motion. If during a human carrying motion, a movement is determined to be untrustworthy, then the robot will stop the assisting motion until the motion is verified to be trustworthy again. By doing this, the model is able to help to minimize the possibility of injury to the human or damage to the robot or anything within the workspace. Since the model calculated the trust level dynamically throughout the human-robot co-carry task, the trust level can change from being trustworthy to non-trustworthy at any moment. This means that a robot assisting movement does not necessarily encompass one entire human motion.

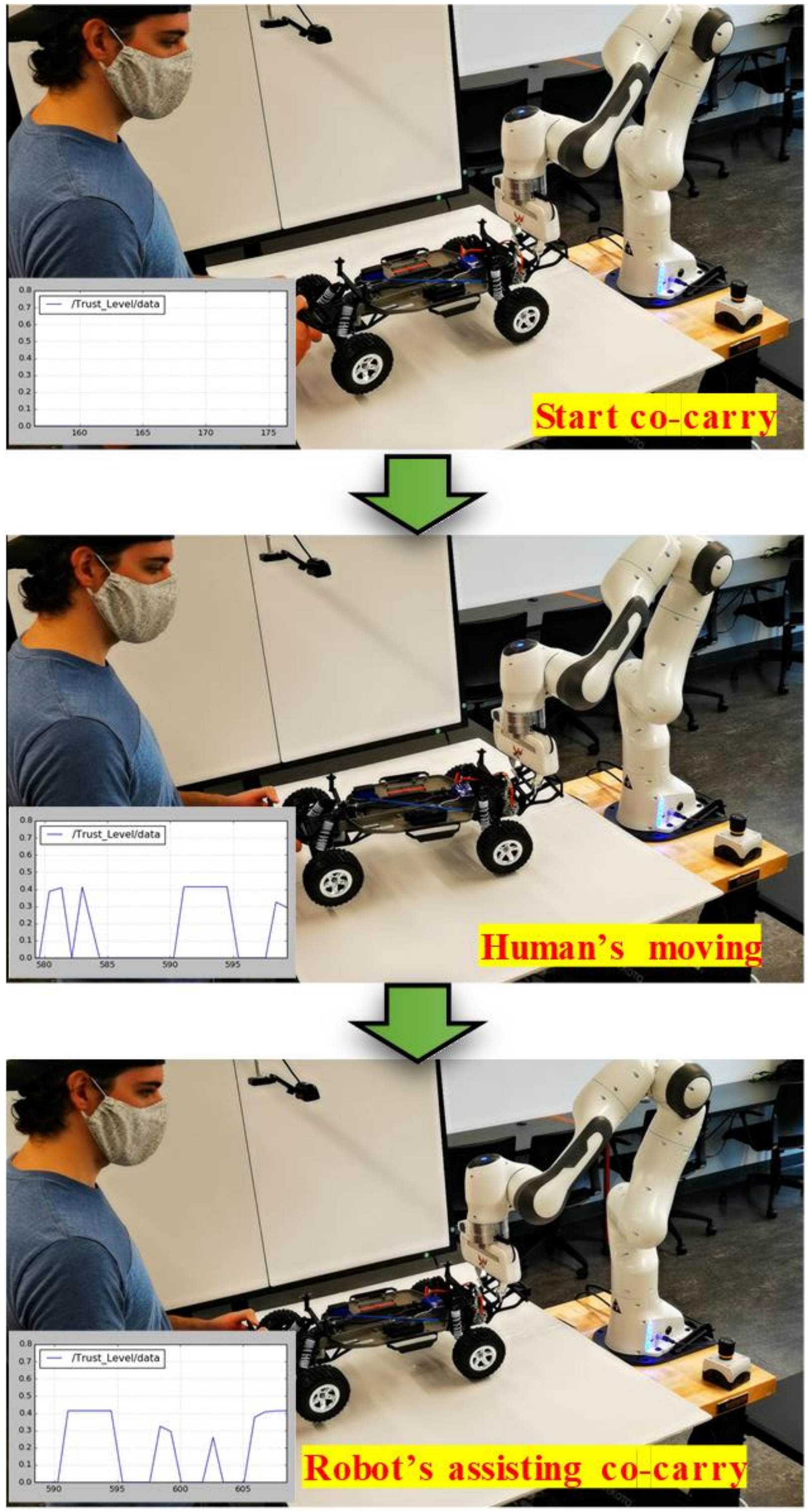


Figure 8 The robot assists its human partner based on trust levels in co-carry tasks.

CHAPTER IX DISCUSSIONS

9.1 Accuracy

Through the course of the experimentation, high accuracy was achieved in both trust level and assisting movement. The high accuracy in trust was determined by using smooth motions that have clear human intention, as well as mimicking false positive movement, such as a shaky hand. As presented in Figure 7, for the first scenario with smooth motion, the robot was able to correctly trust the motion, and provide assisting movement in the same direction as the human. This means that the robot was able to view the human movement as trustworthy, and also determine the intention of the human movement in order to provide the assistance. In the second scenario with shaky movement, the robot was able to accurately label that movement as untrustworthy and did not provide assisting movement to the human.

As shown in Figure 7, the assisting motion was also calculated accurately. When the human movements were determined to be trustworthy, the movements calculated by the robot motion planner accurately mimicked the human’s motion. By using the L-K optical flow algorithm on multiple points and taking the arithmetic mean of the direction and velocity data we were able to calculate an accurate representation of the human movements to be used by the motion planner.

9.2 Stability

Our experimentation showed that the model provides good stability for the robot. The continuous trust evaluation throughout the co-carry task provides the robot and human a stable collaborative work environment. The model also continued to work through longer co-carry tasks without running into errors or bugs. This grants the human and robot the ability to work collaboratively on a co-carry task for long periods of time without the concern that the model could fail at any point.

CHAPTER X CONCLUSIONS AND FUTURE WORK

10.1 Conclusions

In this paper we proposed a novel trust-assist framework for human-robot collaborative teams. The first part of our framework is the robot-trusting-human (RTH) model. This model has allowed the robot to determine a trust level in the human co-carry partner. The calculations of this trust level are based on human motion, past interactions between the human-robot pair, and the human's current performance in the co-carry task. This model calculates the trust level between the human and robot throughout the collaborative task which allows the trust level to change if the human begins moving in nonuniform ways. Then using the trust level calculated in the previous step, the robot-assisting-human model calculates the assisting motion based on Lucas-Kanade Optical Flow data. From this data, displacement vectors are determined for the human carrying motion. This displacement data is used to calculate the robot motion path to copy the human's motion and pace as closely as possible. If the trust level is too low, the human motion is not followed by the robot. By enabling the robot to only perform assisting movements when the human motion is considered trustworthy, we were able to achieve better efficiency and safety in human-robot co-carry tasks. The results of our experimentation with this framework show that the robot effectively assisted the human in co-carry tasks through the proposed computational trust model.

10.2 Future Work

The first area of future work is planning the robot assistance policy based on different trust levels. This means that for different values of trust that the robot has in the human, different motion planning will occur. One example of this could be if the human is moving the object in a slightly shaky motion but in a general direction, the robot could try to smooth out the motion instead of not following it at all. This could be useful for safety reasons so that the robot does not copy any shaky motion that the human may perform.

Another area of future study is evaluating robot trust in 3D human carrying motions. With the current model, human motion data is only collected though a camera mounted above the workspace. This limits the motion tracking with the optical flow algorithm to only horizontal motion. By adding a second camera mounted next to the workspace, data could be collected on the vertical motion of the human as well. This would allow for more freedom of movement by the human as well as to perform more complex carrying tasks. Such tasks could involve lifting the object and placing it on top of another platform within the workspace.

One final future area of study is to verify the performance of the trust model on more complex human-robot collaborative tasks. In our experimentation we primarily focused on moving the object in straight lines side to side. The more complex movements could be the human moving the co-carry object in a curved path around an obstacle or moving the object to a specific location in the workspace. This also relates to evaluating the trust model in 3D carrying motion since the 3D motion is much more complex than the 2D motion examined in this study.

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