A POMDP-based Robot-Human Trust Model for Human-Robot Collaboration

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***Abstract*—Trust is a cognitive ability that can be dependent on behavioral consistency. In this paper, a partially observable Markov Decision Process (POMDP)-based computational robot-human trust model is proposed for hand-over tasks in human-robot collaborative contexts. The robot's trust in its human partner is evaluated based on the human behavior estimates and object detection during the hand-over task. The human-robot hand-over process is parameterized as a partially observable Markov Decision Process. The proposed approach is verified in real-world human-robot collaborative tasks. Results show that our approach can be successfully applied to human-robot hand-over tasks to achieve high efficiency, reduce redundant robot movements, and realize predictability and mutual understanding of the task.**

Keywords—robotics, human-robot collaboration, trust, belief probability, POMDP

I. Introduction

Human-robot collaboration has been an active area of research for quite some time [1-5]. The basis of humans collaborating with robots, in most cases, is purely mechanical where the robot helps human partners with specific tasks to complete a process. Examples of tasks that have been exploited as parts of human-robot collaboration include but are not limited to manufacturing processes, guided navigation [6], games playing [7], and co-assembly tasks [8]. It is well recognized that the trust constitutes an important concern in human-robot collaboration. "Can humans trust in robots?" is a question that has been part of the human-robot collaboration research for a long time. Resulting in a lot of research work being dedicated to this area [9-11]. But "can robots trust in humans?" Or "how can we make robots trust humans?" present new research questions in human-robot collaboration, occurring with the increasing applications of robots in a wide range of areas.

Trust is a cognitive ability that is highly subjective due to its dependence on numerous factors such as knowledge base, observable and non-observable behavioral parameters, and cognitive biases. Trust is defined as a firm belief in the character, strength, or truth of someone or something [12, 13]. Belief can be seen as a measure of the probability of something being close to the expected truth. For a human being, a high level of trust in something means that they have a belief that the probability of it being close to their expectation is high. According to [14], the belief in humans comes from a combination of five factors – knowledge, environment, events, past results, and future vision. Behavioral consistency plays a major role in developing the trust. The importance of consistent behavior to build trust in employees and friends has been highlighted in [15] and [16]. We make use of this concept to determine the trustworthiness of human partners based on their intentions and faiths to carry out hand-over tasks with robots in human-robot collaboration.

The area of human-robot collaboration still lacks a certain understanding of trust, which is inherent in human-human partners. Human-robot collaborative tasks such as hand-over, which involves the work of humans and robots in close vicinity, needs trust between both parties. Humans are quite efficient in hand-over actions, as we can deduce the intention of our partners efficiently. With our approach, we take a step forward in the direction of 'humanizing' robots for collaborative tasks by enabling them to infer human intentions. Calculating trust levels of robots in humans could enable the robots to determine situations where hand-over actions of humans are expected versus in situations where hand-over actions are not intended due to some interferences or change of mind, etc.

Our proposed approach allows the robot to determine the trust levels in its human partner during the collaboration process. The approach consists of human hand-over pose determination, partially observable Markov Decision Process (POMDP) based planning component, and real-time trust determination. The trust is evaluated by judging the human intentions (to deliver or not deliver the object) during the hand-over task. A belief probability is used to calculate the probability of human intention to deliver objects. We take advantage of the object detection and human hand-over pose evaluation to estimate the human hand-over intentions. Based on the intentions, we calculate the robot's trust levels for its human partner in real-time. The major contributions of this work include: (1) We parameterize the human-robot hand-over process as a POMDP in human-robot collaborative contexts; (2) A computational robot-human trust model is built for the robot to evaluate its trust in its human partner in real-time; (3) The proposed approach is experimentally implemented in real-world human-robot collaborative tasks with success.

II. Related Work

For human-robot interactions, a lot of research has been conducted on whether humans can trust machines or robots. Most of the past work in this field has been focusing on determining the trust levels of humans in robots. The work in [17] investigated trust towards robots, while [18] delved into discussions on designing trustworthy AI and how trust is manifested and warranted. Little research has delved into exploring how robots can trust humans and if such trust models can be developed for robots to evaluate trust levels with humans. Azevedo-Sa et al. presented a trust model for human-robot interactions. They developed a trust model that could be used by human agents as well as robot agents. They named the trust as *human trust* and *artificial trust* based on who the trustor and the trustee were [19]. Another trust model was proposed by Dorbala et al., which used reinforcement learning for a robot to navigate in an office environment using vocal commands [20]. They proposed a robot trust metric derived from human trust metric. The researchers used '*affects*' (expressed emotions or feelings) to extract human behavior features. They determined human trustworthiness based on the human speech cues. The model proposed in [20] is based only on human verbal cues and language used. These cues, although, are extensive, but still demonstrate to be insufficient. Humans can make false statements fluently even when not confident or sometimes, even on purpose. Trust is a concept that cannot be determined solely based on language. Factors such as voice issues, stuttering, inefficient mechanisms to capture the voice, etc. could disrupt the captured data. Hence, using only language commands to determine trust could be ineffective and introduces error rates.

Amiri et al. presented the LCORPP algorithm for human intention prediction and sequential decision making [21]. The algorithm predicted human intentions based on the human motion trajectory and reasoning derived from contextual knowledge. The estimates were confirmed through interaction with the human. The algorithm made use of the Long short-term memory (LSTM) based supervised learning along with reasoning and POMDP based planning. Studies on human pose estimation for objects were also explored in order to detect and handle objects in 3D scenarios. In [22], Desingh et al. proposed a pull message passing belief propagation algorithm for the pose estimation of articulated objects. Their approach relied on scene grammar representation where the problem was formulated as a graph inference problem for a Markov Random Field (MRF).

In this study, our proposed trust model relies on intention estimates to determine the trust levels of robots in humans, rather than task capabilities as used in [19]. Task capabilities are highly conditional and could change due to unforeseen circumstances as opposed to human intention. The trust model proposed by [20] relies on verbal cues and is highly prone to noise. Our proposed model avoids noisy data by making use of only non-verbal cues to generate robot trust. The non-verbal cues are more reliable as voice data is more prone to noise as opposed to pictures. Furthermore, human verbal cues can vary along with many subjective factors such as work conditions, comfort levels, temperatures, physical conditions, stress levels, and health conditions. Our noise resistant approach makes use of vision-based object detection and wearable sensing-based hand pose evaluation to determine human intention. The approach in [21] suffers from limited scope due to the use of domain knowledge. To make the model extendable, we infer the input information directly without relying on preconceived notions that are subject to variation. As an advantage over [21], we are also able to provide a trust model built upon these estimates during calculations.

Our contributions lie in the scalability and transferability of the algorithm, containing differentiable components that can be used even individually for similar experiments, hence providing high usability and extensibility. Also, our work proposes a trust model for robots to determine the trust levels in human partners based on human intention estimates. The developed trust model can be extended for other human-robot interaction tasks.

III. Modeling Methodologies

A. Hand-Object Pose Estimation

We make use of the concept of hand-object pose, including human hand pose estimate and object detection, during the hand-over process. When handing over an object, the human is typically seen holding the object at one end, with their palms facing downward and their arm extended or, in some cases, not extended towards the receiver. As shown in Table I, we will determine these parameters for the human holding the object in human-robot hand-over tasks. The first parameter determines if the human is actually holding any object, the second parameter tells if the human arm is extended or not, the third parameter is if the human palm is facing downward, and the last one tells if the object is held at one end, aligning with the certainty that the human wants to deliver the object.

Table I. The proposed four parameters which will generate the initial observation for our POMDP-based hand-over problem.

Parameter	Description
$C_{is\_holding\_object}$	If the human is holding an object or not
$C_{arm\_extended}$	Is the human arm extended or not
$C_{palm\_downward}$	Is the human palm facing downward
$C_{held\_at\_end}$	Is the object held at one end

B. Object Hand-Over Planning as a Partially Observable Markov Decision Process

A partially observable Markov decision process (POMDP) is a combination of a Markov Decision Process (MDP) to model system dynamics with a hidden Markov model that connects unobservant system states to observations [23-25]. In the POMDP, the agent (e.g., the robot or the human) can perform actions which may cause the system (e.g., human-robot collaboration) state to change with the goal of maximizing a reward that relies on the agent's actions and the sequence of system state. The agent uses the observations, which are made depending on the state, to form a belief (described as a probability distribution) of the state the system is currently in [26]. The process of the human-robot object hand-over task can be defined as a POMDP, of which the parameters are defined as below:

STATES S = [s_0—No one is holding object, s_1—Human holding object with no intention to deliver, s_2—Human holding object with intention to deliver, s_3—Robot holding object, s_4—Robot not holding object, s_5—Terminal state].

ACTIONS A = [a_0—Grab, a_1—Recede].

OBSERVATION SET Z = [Force value on the object when it is held by the human].

TRANSITION FUNCTION $T(s, a, s') = P(s' \mid s, a)$ accounts for the action outcomes where $a \in A$ and $s \in S$.

OBSERVATION FUNCTION $O(s', a, z) = P(z \mid a, s')$, where $z \in Z$, $a \in A$ and $s \in S$, is used for modeling human hand's force feedback to the robot.

REWARD FUNCTION $R(s, a)$ corresponds to the reward received when action a is taken to transition to state s, where $a \in A$ and $s \in S$. A correct estimation yields a bonus, while a wrong estimation yields a penalty.

All the possible states can be enumerated into a state diagram that defines the POMDP states as shown in Fig. 1.

During the hand-over process, the human hand pose estimate and object detection are performed by a wearable sensory system and a vision system. The parameters as described in Table II are generated in real-time. These parameters are $C_{is\_holding\_object}$, $C_{arm\_extended}$, $C_{palm\_downward}$, and $C_{held\_at\_end}$. As shown in Table II, all these parameters can be characterized as either True or False. Let $s_0 \in S$ be the initial state of the system at this stage.

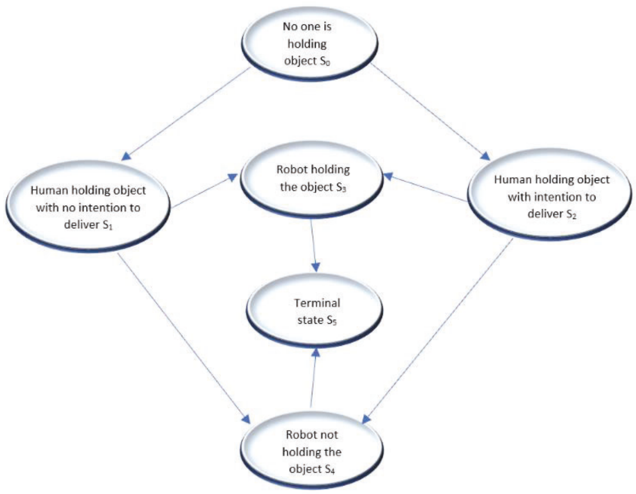

Fig. 1. The human-robot hand-over process is defined as a POMDP with states in the problem as described in the state diagram. The POMDP is defined by a number of possible states with each state S_i having a belief probability b_i.

Table II. Parameters and their possible values determined during hand-over tasks to generate initial intention estimates.

Parameter	Possible Values
$C_{is\_holding\_object}$	[True, False]
$C_{arm\_extended}$	[True, False]
$C_{palm\_downward}$	[True, False]
$C_{held\_at\_end}$	[True, False]

The next step is to determine the current state belief probability. Given k parameters of the system, the belief probability distribution $b(s)$ for the state s can be calculated as

$$b(s) = \frac{1}{k} * \sum_{i=1}^{k} C_i \tag{1}$$

The value of $b(s)$ is significant, as it shows the belief probability of being in state $s \epsilon S$ at this time step. From state $s \epsilon S$, the agent will take an action $a \epsilon A$ to go to the next state s'. Now, we need to determine the belief probability distribution $B(s')$ for the next state s'. We use the Bayes update rule for belief probability distribution

$$B(s') = \frac{O(s',a,z) \sum_{s \in S} T(s,a,s')\, b(s)}{pr(z|a,b)} \tag{2}$$

To calculate this value, we need to determine each of the terms individually. Here, $T(s, a, s') = P(s'|s, a)$, so

$$\sum_{s \in S} T(s,a,s')\ b(s) = b(s) * \sum_{s \in S} P(s'|s,a) \tag{3}$$

where $\sum_{s \in S} P(s'|s,a) = P(s_1|s,a) + P(s_2|s,a)$ which is equal to 1 as s' can only either be s_1 or s_2.

In addition, $O(s',a, z) = P(z|a, s')$, where $z \epsilon Z$ is observed by the force value on the object when it is held by the human. A sensory system worn on the human forearm will be used to evaluate the physical force that is being applied from the human hand on the object. $pr(z|a,b)$ is the normalizer, this value will be set as the maximum force value that can be read on the sensory system. It will normalize the force values observed in $z \epsilon Z$. Using these values, we can simplify the belief probability distribution for the state s' as

$$B(s') = \frac{O(s',a,z) \sum_{i=1}^{k} C_i}{k\, pr(z|a,b)} \tag{4}$$

where k is the number of parameters sensed, and C_i is the value for each hand-object pose estimation.

If the human is not holding the object, meaning that $C_{is\_holding\_object} = False$, we do not calculate the state belief $b(s)$, as this means that the observed human intention is "not to deliver". If the human is holding the object, we determine the hand pose values $C_{arm\_extended}$, $C_{palm\_downward}$, and $C_{held\_at\_end}$. The belief probability $b(s)$ and $b(s')$ are part of the POMDP planning component. The robot agent determines the human intention based on the state $b(s')$. The belief probability equations are also used to calculate trust levels for human partners based on their intention.

C. Robot-Human Trust Model

The trust of the robot in humans will be modeled as a function of probability of their intention to deliver the object. This will be calculated for every task execution in real-time by using the values for initial belief probability and observed value of intention. The initial belief probability is determined as part of the POMDP planning component. We calculate the belief probability for the next state s' only for cases when the human is holding the object. Otherwise, the trust levels are defined to be '*too low*' (since there is no object held, the intention is to not deliver). Also, the observed force measurements need to be in the optimum range for the robot to be able to carry out the hand-over. Hence, any negative force values and very high force values also generate trust levels of '*too low*'. The trust value is calculated as the product of the initial belief probability and the observed intent. Observed intent is the measure of the normalized force values. Hence, instead of relying solely on the force applied on the object to determine the trust level, our model introduces the probability factor to vary it according to the human intention. The trust τ of the robot in its human partner is defined as

$$Trust_{R \to H}, \tau = z * B(s') \tag{5}$$

Applying Eq. (4) to Eq. (5), the trust can be evaluated as

$$Trust_{R \to H}, \tau = z * \frac{O(s',a,z)}{pr(z|a,b)} * \frac{1}{k}\left(\sum_{i=1}^{k} C_i\right) \tag{6}$$

This model is used to determine the trust values in real-time during the object hand-over. The calculations effectively provide the level of trust of the robot in its human partner.

Table III shows some sample values for $b(s')$, z observation, and the corresponding trust level for a particular state. The trust levels are generated in real-time based on the next state probability and observation. The probability of the system being in a state $B(s')$ calculated using Bayes update rule forms the first parameter. The observation z is a factor of the parameters that are used to observe hand-object pose estimation. The observed force measurements and the estimated intention (belief probability) form the basis of our trust calculation.

To explain the significance of the values and trust level determination, let us take for instance, the first row in Table III. The probability of the system being in the state s_2 $(B(s'))$ is 1.0. This means that (as defined earlier s_2—Human holding object with intention to deliver) the system estimates the probability that the human wants to deliver is 1.0. This forms our initial intention estimates and we can say that the human wants to deliver the object and our estimated probability for this estimation is 1.0.

Table III. Sample values for belief probability, observation z and trust values.

STATE	*B(s')*	*z*	*z*B(s')*	Trust Level
s_2	1.0	0.8	0.8	Very high
s_2	0.67	0.8	0.536	High
s_2	0.67	0.25	0.168	Very low
s_1	0	1.0	0	Very low
s_1	0.67	0.5	0.335	Very low
s_2	0.67	0.95	0.637	High

Now for the final intention estimate, we look into the observed parameter derived from the force sensors. For the same row, the observation parameter z is 0.8. This is a normalized value of the force as measured by the sensory system. The belief probability multiplied with the value in observation z, gives us the trust level for the hand-over task. In this case, it comes to 0.8 indicating a 'very high' trust level. The estimation here makes use of the concept where, we calculate the probability of whether the human partner can be trusted for the hand-over task based on the human's actions along with the non-verbal cues (hand pose) demonstrated unintentionally by humans.

Taking another example, where $B(s')$ is 0 as shown in the fifth row. This is for state s_1, when the human does not want to deliver. As per observation, $z = 1.0$ (high force applied on an object which is otherwise not intended to be delivered), which means that the observed intention shows that the human intends to deliver. Calculating trust considering only the measured force would have resulted in a high trust level, but the initial belief probability $B(s')$ gives a trust level as 'very low'. Hence, our calculated trust levels in robots for human partners is dependent on the human intention to deliver along with the action taken to deliver the object. As seen in row 4, even a high probability of intention to deliver the object, if not supplied with enough force, will lead to a 'very low' trust level.

IV. Experimental Results and Analysis

A. Experimental Setup

As shown in Fig. 2, the experimental platform consists of a collaborative robot, a web camera, a wearable sensory system, a workstation, and a shared workspace. In our experiments, the human (wearing a white glove) delivers a blue car model to the robot. The robot employed 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 [27]. This robot can work with humans safely like human-to-human cooperation in collaborative tasks. A wearable sensory system Myo, which can be worn on the human forearm, is utilized to estimate human hand poses during the object delivery process based on our previous work [28]. The scene is captured through the web camera, and Python-OpenCV is used for the robot to detect the human hand (white) and the car (blue) delivered by the human via color identification approaches [29, 30]. The Robot Operating System (ROS) is adopted in the robot system control [31, 32]. ROS is an open-source framework for cross-platform maneuvering and communication. In addition, the MoveIt! running in the ROS framework is also utilized [33]. To plan the robot movement in human-robot hand-over tasks, the control commands are sent to the libfranka interface, which is a ROS package for Panda to communicate with the FCI controller. The FCI will provide the current robot states and enable the robot to be directly controlled by the commands derived based on the real-time trust levels of the robot in its human partner.

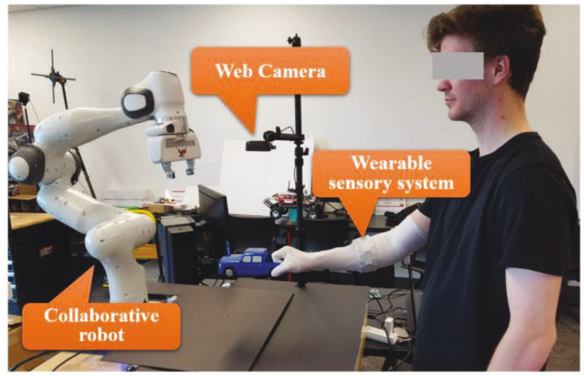

Fig. 2. Experimental setup for real-world human-robot hand-over tasks.

B. Human-Robot Collaboration Results and Analysis

1. Trust level comparison of human holding object and not holding object

As shown in Fig. 3(a), the human is holding an object in front of the robot. The robot detects the object and human hand using visual information from its camera and EMG signals acquired by the wearable sensory system. Based on our proposed trust model, the robot predicts the intention of the human to deliver the object and plans its action accordingly by calculating the next state belief probabilities. Fig. 3(b)-(c) shows the scenario where the robot predicts a high level of trust for the human and hence moves its arm towards the object for the hand-over task. The camera and the sensor data form the basis for the trust calculations. Since the human is seen holding the object, the robot then checks the human hand pose while holding the object. In this case, the human hand pose satisfies the conditions of high trust levels for the robot to participate in the hand-over process.

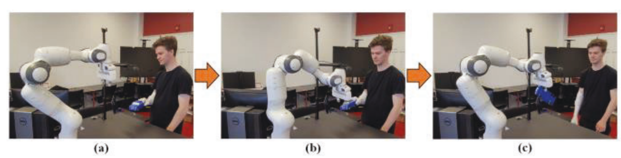

Fig. 3. Object hand-over from the human to the robot when the human is holding the object and the robot trusts in the human.

Fig. 4. When the human is not holding any object and the robot does not trust the human. The robot moves away from the human showing a low trust level.

Fig. 4 shows the scenario where the human is not holding an object. In this case, the object is placed on the workspace table, but the human hand is not seen holding the object. The trust framework generates a very low trust level in this case, due to which, the robot does not participate in the hand-over process. For the human not holding an object, the robot does not show any movement towards the human. The human hand pose, though, is similar to when the human is holding the object. Since there is no object in the human's hand, the trust level does not satisfy the condition for the robot to participate in the hand-over. When the human is not holding any object, rather the object is only kept in front of the human, the robot predicts a very low trust level estimate and does not move towards the human. On the contrary, it moves away from the human showing a low trust level.

2. Trust level comparison of human arm extending and not extending while holding an object

Our second set of experiments consist of scenarios where the human has extended his arm towards the robot. As seen in Fig. 5, the human is holding an object and has extended his arm towards the robot. Based on the information about the human holding the object and human hand pose while holding the object, the robot generates a very high level of trust that the human intends to deliver the object. With the very high level of trust, the robot participates in the hand-over process and extends its own end effector towards the object to carry out the hand-over task. This results in a successful hand-over of the object from the human to the robot.

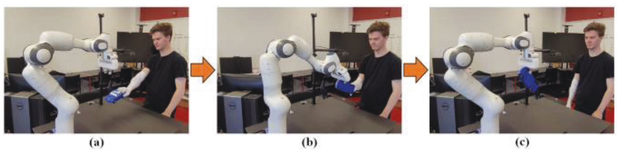

Fig. 5. Object hand-over when the human extends his arm towards the robot. The robot shows high trust in the human and participates in the hand-over task.

The human holding an object with his or her arm extended towards the robot generates a very high level of trust for the robot in the collaborative task. This aligns with the idea that a successful hand-over should ensure that both parties have an understanding and judgment of scenarios where a hand-over is expected versus when it is not. Another scenario is where the human is holding an object, but his arm is not extended as shown in Fig. 6. Based on the information captured from its camera and sensors, the hand pose of the human conveys a high level of trust to the robot. This generates a high trust level for the robot in its human partner and consequently, the robot again participates in the hand-over process. This scenario shows the case where the human hand pose is taken into consideration to determine trust levels for the robot in its human partner during hand-over task. In this case, the human is holding the object, but the arm is not extended towards the robot. This conveys a scenario when the human might just be holding an object in front of the robot and his hand pose (palm down) indicates an intention to deliver the object. The robot perceives this and moves towards the human to complete the object hand-over.

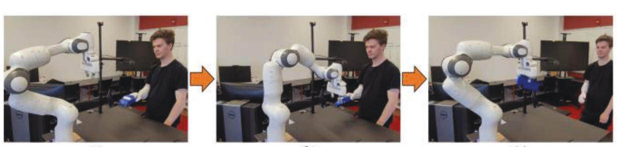

Fig. 6. The human is holding the object with his arm not extended towards the robot, but his hand pose indicates an intention to deliver. The robot generates a high level of trust in this case and participates in the hand-over.

3. Trust level comparison of human hand blocking the object and not blocking the object

As presented in Fig. 7, the human is holding the object. Also, his hand pose shows intention to deliver the object, possibly generating high values of trust. But the object being held is not completely visible to the robot. The human hand is holding the object in a way that blocks the object's visibility to the robot. This generates a very low trust level for the robot in the human. The object's visibility information is obtained by the camera and the robot differentiates the object from the human hand to figure out the object boundaries and overall surface. This is useful to include cases even when the human intention is high but the hand-over might not be successful due to bad hand poses. Hence, the robot shows a low level of trust by moving away from the human and does not participate in the hand-over in this case. The object, when held by the human and is clearly visible to the robot, results in a successful hand-over as shown in Fig. 8.

In Fig. 8, the human is holding the object, with his arm towards the robot and the object is clearly visible to the robot. In this case, the robot shows a high level of trust in the human. Based on these parameters, the robot participates in the hand-over by moving towards the object and successfully grasping it. Fig. 7 and Fig. 8 show the experiments where the robot generates trust levels based on its ability to view the object completely and clearly. This is helpful in collaborative processes where the human might be holding an object but due to low clarity, the robot is unable to judge its arm movement and object grasping. Such a scenario could prove harmful to the human as well as the robot arm, and hence, a high level of trust ensures that the task is only carried out when the robot highly trusts its partner.

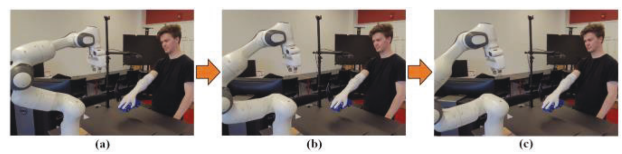

Fig. 7. The human is holding the object, but his hand blocks the object and hinders its visible surface to the robot. The robot predicts a very low trust level and moves away from the human, resulting in no hand-over.

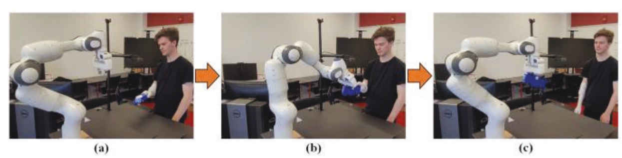

Fig. 8. The human is holding the object with the object clearly visible to the robot. The robot predicts a high level of trust for the human and participates in the hand-over.

V. Conclusions

Trust is a cognitive ability that is based on factors such as historical data, task performance, and intent recognition. In this study, we have made use of the human hand pose estimate and object detection for robots to define if and how much the robot trusts in the human for collaborative tasks. A POMDP-based computational robot-human trust model is proposed. All factors considered for trust generation are based on real-world scenarios that may occur in manufacturing industries and other fields. With our experiments, we are able to successfully conclude that the proposed approach can be applied to real-world human-robot collaborative tasks to achieve high efficiency, reduce redundant robot movements, and realize predictability and mutual understanding between robots and humans. The proposed trust model yields high trust levels when the human holds the object in a way that is suitable for the robot to grasp. Very low trust levels are seen in cases when the human is either not holding the object at all or is holding the object in a way that blocks the object's visibility and clarity and is not suitable for the robot to grasp. Estimating the trust of robots in humans is an emerging area of research and this work proposes a new approach towards conceptualizing the robot-human trust and enabling efficient human-robot collaboration.

ACKNOWLEDGMENT

This work was supported in part by the National Science Foundation under Grant CNS-2104742 and in part by the National Science Foundation under Grant CNS-2117308.

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