Research on Cobot Action Decision-Making Method Based on Intuitionistic Fuzzy Set and Game Theory

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This work was supported in part by the Natural Science Foundation of Shaanxi under Grant 2022JQ-402, in part by the Natural Science Foundation of Shaanxi under Grant 2022JQ-546, and in part by the Key Laboratory Scientific Research Program under Project 13JS070.

ABSTRACT The bounded rational properties of humans in human-robot collaboration (HRC) is a fundamental reason for collisions in proximity HRC. As HRC scenarios in manufacturing become increasingly popular, robot action decision-making needs to consider such properties of humans. In previous studies, humans are usually regarded as rational agents whose behaviors are predictable and planned. Still, humans are susceptible to distractions caused by external disturbances, and different cognitive processes of the task can produce unpredictable behaviors. To better simulate human bounded rational behavior, based on an intuitionistic fuzzy (IF) multi-attribute decision algorithm, we propose a cobot action decision-making method that integrates human intention, safety, and efficiency, to produce a human-like decision. We use the IF set to calculate the score and accuracy values of two Nash equilibria of a static chicken game, which can predict human action intentions with collision risk and provide optimal action decisions for the robot simultaneously. We generated 10,000 sets of data using the Monte Carlo method and validated the effectiveness of our proposed method by comparing it with MDP and POMDP methods. The results showed that the decision-making method could effectively perform the task of making action decisions for the robot. Simulation experiments and Turing test results show that our proposed method can predict a human’s subjective action decision intention in a situation with potential collision risk with 85.62% accuracy. At the same time, the experimental participants believe that the robot can get 4.83 out of 5 satisfaction points for an action decision.

INDEX TERMS Bounded rationality, cumulative prospect theory, decision-making, game theory, human action intention, human-robot collaboration, intuitionistic fuzzy set.

I. INTRODUCTION

The decision-making capability of cobots is an effective means to reduce the collision risk with workers and improve the efficiency of collaboration, which is essential to achieving safe, intelligent, and flexible cobots. However, the current decision-making capability of cobots does not satisfy the complex industrial manufacturing field [1], [2]. Many studies [3], [4] have developed safety systems for human-cobot proximity collaboration that can accurately sense and quickly calculate the separation distance between the human and cobot to reduce the human-cobot collision risk. Some international standards [5], [6] limit robot speed, mass, and kinetic energy to ensure worker safety. However, most cobots cannot adjust their motion trajectories according to real-time working conditions, sense workers’ intentions, or make decisions about their behavior based on the potential collision risk and work efficiency. They just can only mechanically take passive collision avoidance than human-like behavioral actions. Such an approach changes the cobot’s original better path, wastes
time to complete the task, and reduces human trust and comfort with the cobot. In a complex dynamic system with human presence, relevant research does not consider efficiency, collision risk, workers’ bounded rationality, and other factors related to the cobot’s collision avoidance decision behavior.

The scenario in Fig. 1 presents the challenges of human-robot interoperability in a shared space. In this figure, the human and the cobot pick up parts in the same target area to complete the assembly. If the human occupies the target area, the cobot cannot avoid collision by changing its trajectory but can only temporarily choose to stop or accelerate to reach the target area. The limited space leaves the cobot with the choice of temporarily stopping its actions to ensure safety or accelerating through to improve efficiency and ensure safety. More interestingly, we found through experiments that people rarely let their hands pass under the end-effector to grasp the part. This phenomenon is because the action of the hand passing under the end-effector to get the part is likely to lead to a collision, and this action can create much psychological stress. People primarily do not choose to perform tasks this way and avoid collisions. Such will also change three-dimensional spatial collision avoidance to two-dimensional spatial collision avoidance. In a narrow space, the human and cobot can only temporarily choose one side through the scene also belongs to such situations.

However, in this case, the combined judgment of human factors such as safety, efficiency, and desire to get the job done is often very subjective. At this moment, the human often shows irrationality and decides whether to pass the potential collision area in a short time. Human irrational factors pose a significant challenge for cobot decision-making, and as the distance between the human and cobot decreases, the challenge of optimal behavioral decision-making becomes greater.

The main reason for this challenge is that to make an optimal decision, the cobot needs to consider three factors simultaneously and combine them to make a comprehensive judgment and make a safe and reasonable decision quickly. The three factors are how willing a person is to pass through the potential collision area, the equipment and algorithm to accurately detect the collision distance between human and cobot in real-time, and its efficiency. The judgment of the three factors is inaccurate and fuzzy, especially since the human intention of the assessment is often vague and probabilistic, which is because human is not fully rational intelligence. The judgment and decisions made by the human are often subjective and bounded rational, and when the human and machine work in proximity in scenarios with potential collision risk. The frequent judgment of collision risk will significantly increase the cognitive load of the human work, resulting in errors in judgment leading to increased collision risk. Therefore, only the human-like decision-making action of cobots can reduce the cognitive load of human judgment on cobot behavior, reduce human psychological pressure, and improve the efficiency of both the human and cobot while ensuring safety.

For a proximity HRC scenario such as Figure 1, a rapid decision must be made for the cobot’s action. Most importantly, the decision at this point needs to be based on an accurate judgment of the human’s action intention. Previous studies on similar scenarios [7], [8], [9] proposed using methods such as game theory to make decisions about the cobot’s actions. However, they were based on the other party being a fully rational agent, which is against the bounded rationality characteristic of humans in reality. Although some studies have investigated the bounded rationality problem [10], [11], they have not studied the scenarios with potential collision risk in extremely proximity HRC scenarios. In the scenario of proximity HRC, human thinking time is concise. Most decisions are made through experience and intuition, with a vital characteristic of limited rationality. Moreover, if accurate judgments of human intentions cannot be made, safer action decisions cannot be made for the robot, and trust in the robot cannot be improved.

There is a great need for a method to measure human fuzzy decision intentions and formulate decisions to solve the cobot decision problem to improve cobot efficiency and safety, reduce human cognitive load and enhance comfort and trust.

Statistical methods have analyzed most studies on the problem of prediction of human intentions and then expressed them in the form of probabilities. However, in real scenarios, human perceptions of such issues are vague and can only give vague ranges, which cannot be expressed in a definite given IV number. In contrast, in the scenario presented in this paper, human intentions expressed in probability can only reflect whether two intentions are passed or not. In reality, humans will have a large proportion of hesitation states, which cannot be expressed in probabilistic form, which results in misjudgment of human intentions and low satisfaction with robot action decisions. On the other hand, the IF set uses the subordination and non-subordination functions to express the intention of passing well, not passing and hesitating that appears in the human at this time, which provides more reference for the development of the robot’s action decision. The decision is made according to the size of the hesitation state of the person at this time. For example, the cobot decides to pass when the hesitation intention is significant to improve efficiency, and vice versa, not to pass to ensure the
person’s safety and ultimately enhance the satisfaction of the person.

In addition, in the scenario studied in this paper, improving efficiency and ensuring human safety are a pair of contradictions, and how to balance the needs of both to achieve both efficiency and safety is the ultimate goal of decision-making. At the same time, game theory is a mathematical theory that studies phenomena with struggle and can consider the predicted and actual behaviors of individuals in the game and study their optimization strategies, which is very suitable for dealing with the scenario mentioned in this paper.

This paper proposes a cobot action decision-making method based on the IF set and game theory to allowcobots to select an appropriate action based on human collaborators’ actions in real-time when collaborating in proximity. The proposed method takes a narrow scene in which the cobot cannot achieve collision avoidance by changing its trajectory and can only achieve collision avoidance by stopping or accelerating as the object of study. The method makes decisions for cobot action selection by comparing the score and accuracy values of two Nash equilibria in a static chicken game.

The main contributions of this paper are as follows:

1. Focused on the action decision-making method to ensure the cobot work efficiency and human safety in the narrow working space, where the human and the machine converge to the common goal simultaneously, and it is impossible to avoid obstacles by changing the trajectory. There is a significant risk of collision. Our proposed approach establishes human cognitive and decision-making mechanisms for proximity human-computer collaboration scenarios.

2. Integrating the cumulative prospect theory and comfort model to establish a collaborative object action intention model with bounded rationality, i.e., the IF set of human action intention. Our method uses the IF set of human action intentions to predict human action intentions in potential collision risk scenarios.

3. A robot action decision method is established based on an IF multi-attribute decision algorithm by fusing the IF set of human action intention, the IF set of cobot for safety, and the IF set of cobot for safety efficiency. The method decides whether the cobot passes or not the action in a scenario with potential collision risk.

The rest of the paper is organized as follows. The second part summarizes some related work. The third part proposes a model for subjective human evaluation of work efficiency based on CPT, a model for determining collision risk, and a cobot action decision-making method based on an IF multi-attribute decision algorithm. The fourth section outlines the application of the method in HRC scenarios with potential collision risk. The fifth section verifies the effectiveness of the method through experiments. The sixth section discusses the obtained results and points out future research directions to overcome current limitations. The last section concludes with a summary of this work.

II. RELATED WORK

This section presents the application of game theory to robot motion planning and collision avoidance decision-making problems. Different solutions to the issues of collision avoidance and interaction-aware modeling in HRC have been given in autonomous driving and robot motion planning. In particular, the interaction-aware modeling problem is increasingly attracting the attention of researchers in socially aware robot navigation [7], [12]. Interaction-aware modeling is the basis for solving HRC decision-making problems, and decision-making methods model the relationships between agents, actions, environments, and tasks [13]. Decision-making selects the best move for the robot based on the payoff calculated from the utility function of each job.

Probabilistic methods, deep learning, and game theory are among the most widespread decision-making methods. For probabilistic methods, Markov decision processes (MDP), Bayesian processes, and graph theory are some of the most widely used methods. For instance, Roveda [10] et al. use Hidden Markov Models (HMM) to teach the robot how to achieve the task based on human demonstrations and use Bayesian optimization-based algorithms to maximize task performance.

However, probabilistic models do not satisfactorily deal with bounded rational behavior and uncertainty problems. Many studies have addressed similar issues using deep learning or reinforcement learning approaches to enable the correct processing of boundedly rational behavior. For example, Roveda [10] et al. used partially observable Markov decision processes (POMDP) to develop a framework for planning collaborative robot tasks in assembly, considering both the designer and operator’s intents. The designer’s CAD data automatically derives a set of potential assembly plans and translates it into a state graph from which the operator’s intentions follow. However, the drawbacks of deep learning and reinforcement methods are the computation cost and slow learning speed. Game theory methods in decision-making processes have only recently been exploited. They can model most of the tasks of a group of agents (players) in collaboration or competition. Game-theoretic methods have been used in different HRC applications. For example, Gabler [8] et al. proposed a game-theoretic-based action selection framework for HRC that allows robots to select appropriate actions based on the behavior of their human colleagues during proximity collaboration. The proposed framework models the HRC scenario as a non-cooperative game model and selects action strategies for the robot by the Nash equilibrium results. The framework selects the optimal trajectory from the action set to assign to the robot, completes the work, and avoids collisions.

However, the research considers people to be fully rational when building game models, which has a large gap from the actual situation. People often make decisions with bounded rationality in real work scenarios due to their personality, work environment, and fatigue. Similar studies [7], [9] proposed a multi-intelligent body motion planning
algorithm for dynamic environments to generate human-like motion trajectories. The proposed motion planning algorithm searches for Nash equilibrium solutions based on repeatedly performed static non-cooperative games, approximating the human decision-making process for navigation in a densely populated environment. The Turing test found that the experimenters can not distinguish the human motion behavior or the behavior generated based on game theory.

Camara [14] et al. proposed a theoretical model based on the chicken game for providing the best strategy for automated vehicles when encountering pedestrians crossing the road at intersections with no obvious traffic signals. The experimental results show that the pedestrian crossing intention on the standard Daimler dataset can be accurately estimated with 96% accuracy. This result is essential in restricting scenarios with a clear winner. It can be easily predicted with the simple heuristic, which may require more complex game-theoretic models to predict and control. Park [15] et al. used non-cooperative game theory to analyze the decision-making of navigators and discussed the causes of frequent collisions in the context of increasing technological and automated navigation systems. They proposed a collision avoidance method for ships using game theory in which both parties to a collision change their course to avoid collision in the case of a head-on collision.

Similar decision methods give a good or optimal trajectory for both sides of the game under the condition of potential collision risk. But they ignore that both sides of the game are bounded rational intelligence, which is affected by complex factors such as psychological factors, personality, working environment, etc. These studies treat both sides of the game as fully rational when building the game model. The intention of bounded rational intelligence to make irrational decisions cannot be estimated. El-Nasr and Skubic [16] proposed a fuzzy logic model that applies emotional factors to the decision-making process of a mobile robot that can capture the internal uncertainty of emotions. The model generates decisions based on internal and external states combined with sensory information to extract environmental conditions. In this way, the intelligence will respond to the changing environment and can act on a mixture of emotions generated by multiple states. Bahram [17] et al. proposed a game theory-based prediction and planning framework for cooperative driving in dynamic environments. The proposed algorithm can predict the interaction perception of all vehicles in the scenario. It can be used for automated driving on highways or as a complex prediction module for advanced driver assistance systems that do not require inter-vehicle communication. The paper mainly focuses on action decisions with sequential order in the open road scenario as the research object. However, due to the close distance between humans and autonomous vehicles (AVs), the action decisions of humans and AVs are not sequential, and human choice is not considered an irrational factor in the paper.

In our paper, we focus on the following three aspects: 1. In the process of proximity HRC, there is no optimal path for avoidance or inconvenient avoidance for human-cobot simultaneous convergence to the same target. 2. Human action intention under the combined effect of efficiency requirements, subjective risk perception, and irrational factors. 3. Robot integrated efficiency, safety, and human action intention to make the optimal action strategy.

III. METHOD

This section outlines our proposed cobot action decision-making method based on the IF set and game theory. First, we outline the scenario and object to be studied, simplifying the scenario to a static chicken game and treating the human and cobot as agents. Second, the action decisions of the human and cobot are modeled. We established four IF sets, the IF set of human for efficiency, the IF set of human for comfort, the IF set of cobot for efficiency and the IF set of cobot for safety. Thirdly, the IF set of human action intention is established by integrating the IF set of human for efficiency and comfort. The IF set of collision avoidance is found by integrating the IF set of human action intention and the IF set of cobot for efficiency and safety. Finally, the cobot collision avoidance decision-making method is established by calculating the exact value of the IF set of the Nash equilibrium solution. The cobot action decision method framework based on the IF set and game theory is shown in Fig. 2.

A. INTERACTIVE SCENE

Our focus is similar to the scenario shown in Fig. 1, where a person and a cobot tend to grasp parts towards the same target in a tight space simultaneously. Due to the extreme reaction time, it is impossible to communicate between the human and cobot through language to plan the sequence of actions between the human and cobot in actual HRC scenarios. Such scenes also cause a potential collision risk between the human and the cobot. Moreover, it is impossible to avoid collision by optimizing the cobot’s trajectories due to space constraints, and one of two agents must adopt a temporary yielding strategy to avoid a collision.

Previous experiments found that people prefer to accelerate through potential collision areas to improve efficiency when working in a seated position or in a state where they cannot move their current position at will. And it is interesting to note that in actual experiments and HRC scenes, humans also
TABLE 1. Chicken game and Nash equilibrium.

| Own  | Strategy | Opponent  | Through | Yield |
|------|----------|-----------|---------|-------|
|      | Through  | (-10, -10) | (10, 0) |
|      | Yield    | (0, 10)   | (0, 0)  |

expect cobots to adopt similar action strategies to improve collaboration, which can increase trust in the robot, similar to the idea proposed in the literature [7]. This phenomenon is because such an action strategy is more in line with the human-robot collaborative behavior pattern rather than allowing the cobot to pass over the human hand, which is uncomfortable or unsafe. However, it does avoid collision and reduces time wastage.

This scenario is similar to the “chicken game” proposed in game theory [14] when both agents wish to cross the one-way bridge. If both agents choose to pass, there will be a lose-lose result, and if both agents choose to yield, neither agent can pass; only one agent can pass, and the other agent can yield temporarily to let both agents cross the bridge safely. However, the time passing the bridge is prolonged for the agent that chooses to yield. Game theory assumes that the two agents of a chicken game are non-cooperative, finite-strategy, non-zero-sum games. The static chicken game has two Nash equilibrium solutions, as shown in Table 1. There are only two ways to reach strategic equilibrium when both agents of the game are fully aware of the other agent’s strategies and choose them simultaneously. If mixed strategies are allowed to exist, both agents will select their respective strategies to reach equilibrium in the form of probabilities so that both agents’ gains will be balanced. Both agents cannot lower the other agent’s gain by changing their respective strategies. For example, in [15], it is proposed that two ships that meet face-to-face hope that the other agent can decide to change the course with a probability of 0.5. The Nash equilibrium cannot predict which ship will choose to maintain or change the course. The result explains the occurrence of collision accidents. Therefore, to solve this scenario, it is also necessary to compare the payoff of different strategies and find the one with the lowest payoff as the solution of Nash equilibrium as their respective strategies.

In this scenario, according to game theory, we describe the HRC scenario at this time as a human-cobot game scenario: $a^1$ and $a^2$ represent the human and the cobot, respectively. The strategies adopted by both game agents $A^1$, $A^2$ represent pass-through and yield, respectively. $J^1_i$, $J^2_i$ define the payoff functions for both agents to choose pass-through and yield. $i$ always represent the agent $a^i$. Each agent can choose a different strategy.

B. PRELIMINARY KNOWLEDGE OF IF SET

IF set were proposed by Atanassov [18] in 1986, which was built on the basis that fuzzy sets use a single scale (i.e., membership) to represent both support and opposition states and use two scales (i.e., membership and non-membership) to portray fuzziness [19]. It can simultaneously represent three states of support, opposition, and neutrality, which can describe the natural properties of objective phenomena more delicately and comprehensively, so IF set are widely used in economic management decision problems. We introduce the basic concepts of IF set in the following.

**Definition 1:** Let $X$ be a universe if there are two functions on $X$, i.e., $\mu_A : X \rightarrow [0, 1]$ and $v_A : X \rightarrow [0, 1]$, such that

$$x \in X \mapsto \mu_A (x) \in [0, 1]$$

and

$$x \in X \mapsto v_A (x) \in [0, 1]$$

define the degree of membership and the degree of non-membership of an element $x \in X$, such that they satisfy the following conditions:

$$0 \leq \mu_A (x) + v_A (x) \leq 1$$

Then $\mu_A$ and $v_A$ determine an intuitionistic fuzzy set on universe $X$, which can be abbreviated as:

$$\tilde{A} = \{ (x, \mu_A (x), v_A (x)) | x \in X \}$$

**Definition 2:** (Trapezoidal Intuitionistic Fuzzy Number): A trapezoidal intuitionistic fuzzy number (TIFN) denoted by $\tilde{a} = (a, a_1, a_2, \tilde{a})$; $w_{\tilde{a}}, u_{\tilde{a}}$ is a special IF set on a real number set $\mathbb{R}$, whose membership function and non-membership functions are defined as follows:

$$\mu_{\tilde{a}} (x) = \begin{cases} (x - a) w_{\tilde{a}} / (a_1 - a) & (a \leq x < a_1) \\ w_{\tilde{a}} & (a_1 \leq x \leq a_2) \\ (\tilde{a} - x) w_{\tilde{a}} / (\tilde{a} - a_2) & (a_2 < x \leq \tilde{a}) \\ 0 & (x < a, x > \tilde{a}) \end{cases}$$

and

$$v_{\tilde{a}} (x) = \begin{cases} [a_1 - x + u_{\tilde{a}} (x - a)] / (a_1 - a) & (a \leq x < a_1) \\ u_{\tilde{a}} & (a_1 \leq x \leq a_2) \\ [x - a_2 + u_{\tilde{a}} (\tilde{a} - x)] / (\tilde{a} - a_2) & (a_2 < x \leq \tilde{a}) \\ 1 & (x < a, x > \tilde{a}) \end{cases}$$

where $w_{\tilde{a}}, u_{\tilde{a}}$ denote the maximum and minimum membership degree of $\tilde{a}$ respect, such that they satisfy the conditions $0 \leq w_{\tilde{a}} \leq 10 \leq w_{\tilde{a}} + u_{\tilde{a}} \leq 1$. The quantity

$$\pi_{\tilde{a}} (x) = 1 - \mu_{\tilde{a}} (x) - v_{\tilde{a}} (x)$$

is called the measure of uncertainty.

**Definition 3:**

The sum of IF sets:

$$\tilde{A} + \tilde{B} = \{ (x, \mu_{\tilde{A}} (x) + \mu_{\tilde{B}} (x) - \mu_{\tilde{A}} (x) \mu_{\tilde{B}} (x), v_{\tilde{A}} (x) v_{\tilde{B}} (x)) | x \in X \}$$

The product of IF sets:

$$\tilde{A} \tilde{B} = \{ (x, \mu_{\tilde{A}} (x) \mu_{\tilde{B}} (x), v_{\tilde{A}} (x) + v_{\tilde{B}} (x) - v_{\tilde{A}} (x) v_{\tilde{B}} (x)) | x \in X \}$$
Definition 4: The score value \( M(\tilde{A}) \) and exact value \( \Delta(\tilde{A}) \) of \( A \) are:

\[
\begin{align*}
M(\tilde{A}) &= \mu - \nu \\
\Delta(\tilde{A}) &= \mu + \nu
\end{align*}
\]

1. If \( M(\tilde{A}_j) > M(\tilde{A}_k) \), then \( \tilde{A}_j \) is greater than \( \tilde{A}_k \), which is denoted as \( \tilde{A}_j > \tilde{A}_k \).

2. If \( M(\tilde{A}_j) = M(\tilde{A}_k) \), then
   - If \( \Delta(\tilde{A}_j) = \Delta(\tilde{A}_k) \), then \( \tilde{A}_j \) is equal to \( \tilde{A}_k \), which is denoted as \( \tilde{A}_j = \tilde{A}_k \).
   - If \( \Delta(\tilde{A}_j) < \Delta(\tilde{A}_k) \), then \( \tilde{A}_j \) is smaller than \( \tilde{A}_k \), which is denoted as \( \tilde{A}_j < \tilde{A}_k \).
   - If \( \Delta(\tilde{A}_j) > \Delta(\tilde{A}_k) \), then \( \tilde{A}_j \) is greater than \( \tilde{A}_k \), which is denoted as \( \tilde{A}_j > \tilde{A}_k \).

C. THE IF SET OF HUMAN AND ROBOT FOR EFFICIENCY

For HRC scenarios like Fig. 1, human judgments of work efficiency are subjective and vague. The decisions are based mainly on the type of cobot, the speed and distance between the human and cobot, experience working with the cobot, and instinctive intuition. Some studies express this in the form of probabilities. Still, probabilities cannot describe the degree of hesitation of individuals in judging things, which results in inaccurate models of human cognition.

Human subjective judgment is made based on intuition. Intuition is a cognitive activity in which the human brain makes judgments about the original appearance, nature, and laws of change of things based only on the revelation of senses or a small amount of perceptual information and its own experience and knowledge. Accurately describing this model of the human being’s degree of hesitancy about things, i.e., membership and non-membership, is the key to simulating the human judgment intention.

Since human judgments of efficiency are bounded rational, subjective emotional influences exist, and humans have a different understanding of the loss of efficiency caused by whether the cobot hinders them. Those who dislike being blocked think that the efficiency loss is greater than the actual loss, which is in line with the cumulative prospect theory (CPT). The CPT [20], [21] argues that uncertainty-based decision-making choices depend on the difference between the outcome and the expectation rather than the outcome itself. People make decisions with a reference standard in mind and then measure how much the outcome of each decision differs from this reference standard. They tend to prefer risk when faced with losses, which is more in line with psychological observations. Due to the existence of such psychological expectations of people, it is likely to accelerate the completion of work to reduce the loss of efficiency. But this also dramatically increases the collision risk, so the robot must pay attention to the such psychological perception of people when making decisions.

Therefore, we establish a model of human cognition of efficiency based on the CPT and establish the IF set of human for efficiency. Assume that the process of the human alone to complete the assembly task, the time \( t_s \) required for the maximum speed of 1.8m/s is recorded as the maximum efficiency, at which time the efficiency is 100%. The time \( t_0 \) needed to reach the target from the current position at the current speed is the reference point when the efficiency is \( t_s / t_0 \). Suppose one’s perception of efficiency is entirely rational, and the result of decreasing efficiency with increasing arrival time is well understood. In that case, i.e., one maintains a neutral attitude toward the relationship between efficiency and speed, we construct the expected utility function of the neutral attitude with these two efficiencies.

\[
f_E(t) = -\frac{(t - t_s)}{t_0} + 1
\]

Based on the expression for the value function in the CPT, we determine the value function of efficiency as perceived by the person.

\[
f(t) = \begin{cases} 
\frac{(t_0 - t)^\alpha}{(t_0 - t)^\alpha + \lambda(t_0 - t_0)^\beta}, & (t_s \leq t \leq t_0) \\
-\frac{\lambda(t_0 - t)^\beta}{(t_0 - t)^\alpha + \lambda(t_0 - t_0)^\beta}, & (t_0 < t \leq t_1)
\end{cases}
\]

The decision weight function as perceived by the person:

\[
w^+(p) = \frac{p^\gamma}{[p^\gamma + (1-p)^\gamma]^{1/\gamma}}
\]

\[
w^-(p) = \frac{p^\delta}{[p^\delta + (1-p)^\delta]^{1/\delta}}
\]

In Eqs. (2) to (4), \( \alpha \) and \( \beta \) reflect the level of risk preference of the decision-maker. In the value function \( f(t) \), the smaller the value indicates, the higher the decision-maker’s sensitivity to risk and \( p \) denotes the probability of reaching the target at time \( t \). \( \lambda \) is the loss aversion coefficient, and when \( \lambda > 1 \), one values losses more than gains. \( t_1 \) is the maximum time corresponding to the time when \( f_E(t) = 0 \). The \( w^+(\cdot) \) and \( w^-(\cdot) \) represent the values of the decision weight function in the gain and loss regions, respectively. The decision weight function is inverted “S” shaped, as shown in Fig. 3.

The smaller the parameters \( \gamma, \delta \) (0 < \( \gamma \), \( \delta < 1 \)), the more curved the function shape is, and the more decision-makers tend to overestimate small probability events and underestimate significant probability events.

According to the CPT, the prospect of a person approaching the target area at the current speed, i.e., the model of human perception of efficiency, can be expressed as:

\[
V = w^+(p)f(t)(t_s \leq t \leq t_0) + w^-(p)f(t)(t_0 < t \leq t_1)
\]

\[
= \left(1 - \frac{t_s}{t_0}\right) \cdot w^+(p) \frac{(t_0 - t)^\alpha}{(t_0 - t)^\alpha + \lambda(t_0 - t_0)^\beta} \cdot \ldots + \left(1 - \frac{t_s}{t_0}\right) \cdot w^-(p) \frac{-\lambda(t_0 - t)^\beta}{(t_0 - t)^\alpha + \lambda(t_0 - t_0)^\beta}
\]
The relationship between the expected utility function and the cumulative prospect function can be seen in Fig. 4. We use the cumulative prospect function as the membership function, and the membership and non-membership functions of the IF set of human for efficiency $\hat{E}_H = \langle \mu_H (t), \upsilon_H (t) \rangle$ are as follows:

$$\mu_H (t) = \begin{cases} 1 & (t < t_s) \\ w^+ (p) f (t) & (t_s \leq t \leq t_0) \\ \ldots + w^- (p) f (t) & (t_0 < t \leq t_l) \\ 0 & (t_l < t) \end{cases}$$ (6)

$$\upsilon_H (t) = \begin{cases} 0 & (t < t_s) \\ 1 - w^+ (p) f (t) & (t_s \leq t \leq t_0) \\ \ldots + 1 - w^- (p) f (t) & (t_0 < t \leq t_l) \\ 1 & (t_l < t) \end{cases}$$ (7)

The cobot is a fully rational intelligent unit, so the IF set of cobot for efficiency $\hat{E}_R = \langle \mu_R (t), \upsilon_R (t) \rangle$ membership and non-membership functions of the cobot are as follow:

$$\mu_R (t) = \begin{cases} 1 & (t < t_{sr}) \\ t_{sr} \cdot (t - t_{sr}) & (t_{sr} \leq t \leq t_{lr}) \\ t_r \cdot (t_r - t_{sr}) & (t_{lr} < t) \end{cases}$$ (8)

$$\upsilon_R (t) = \begin{cases} 0 & (t < t_{sr}) \\ t_{sr} \cdot (t - t_{sr}) & (t_{sr} \leq t \leq t_{lr}) \\ 1 & (t_{lr} < t) \end{cases}$$ (9)

The IF set of human and cobot for efficiency are shown in Fig. 5 and 6, respectively.

**D. THE IF SET OF HUMAN FOR COMFORT**

The human perception of collision risk is different from the cobot. The human perception of collision risk depends not only on the relative distance and speed of the human and the cobot but also on a variety of subjective factors such as the human’s perception of the cobot’s appearance, experience, and trust. The direct use of relative distance and speed cannot accurately measure the human perception of collision risk. Our previous study established a psychological safety field ($SE_{Ph}$) model to calculate the psychological impact of a cobot approaching different human body parts with a certain speed, minimum separation distance, and direction. When the psychological safety field strength is large enough, a person perceives that they will choose to avoid the cobot.

The literature [22] and our previous research [23] found that the acceptable cobot motion speed range is between 0.3m/s and 1m/s, and the range of speed considered comfortable is between 0.5m/s and 0.8m/s. At this time, the psychological safety field strength $SE_{Ph}$ can be calculated...
in real-time by the psychological safety field strength formula, with the speed of 0.3, 0.5, 0.8, and 1m/s ($v_i = 0.3, 0.5, 0.8, 1.0$m/s). The trapezoidal IF set of human for comfort is obtained by comparing $SE_{P_h}$ and $SE_{P_f}$.

The membership and non-membership functions of TIFN of humans for comfort are obtained using definition 2, as shown in Fig. 7. (10) and (11), as shown at the bottom of the next page, where $w_S = 0.7$, $w_R = 0.2$ we set the maximum membership degree to 0.7 and the non-membership degree to 0.2, the hesitation degree is 0.1, indicating that people have a hesitation degree of 0.1 in judging the comfort degree. The membership and non-membership degrees are calculated by comparing the values of $SE_{P_h}$ and $SE_{P_f}$.

Unlike humans, cobots can measure the distance between the human and cobot more accurately in real-time by external devices, which can be used to achieve collision risk assessment [24]. The cobot can accurately calculate the human-cobot separation distance and control the speed of the cobot [4]. So we calculate the IF set of cobot for safety using the method of collision risk assessment in the literature [8]. Calculate the time $TTR_h$ and $TTR_r$ for the human and cobot to move to the potential collision area at the current speed. Because the distance between human-cobot is often between 0m and 1.5m, the collision caused by untimely cobot deceleration is likely to occur due to the sudden movement of the human. Therefore, once the robot decelerates, the maximum cobot acceleration to stop is $TTS_r$.

$$TTR_h = \frac{p_h - p_c}{v_h}$$

$$TTR_r = \frac{p_r - p_c}{v_r}$$

$$TTS_r = \frac{v_r}{a_c}$$

$$\nabla t_e = [TTR_h - TTR_r] - TTS_r$$

where $p_h$ is the current position of the human, $p_c$ is the position of the potential collision region, $p_r$ is the current position of the cobot, $v_h$ is the velocity of the human, $v_r$ is the velocity of the cobot, and $a_c$ is the acceleration of the cobot. Therefore, the IF set of cobot for safety $\tilde{S} = (\mu_S(x), \nu_S(x))$ non-membership and membership functions are as follows:

$$\nu_S(x) = \begin{cases} 1 & (\nabla t_e \leq 0) \\ 1 - \exp \left(-\nabla t_e^2 / 2 \cdot \left(\frac{v_r - v_h}{2}\right)\right) & (0 < \nabla t_e) \end{cases}$$

$$\mu_S(x) = 1 - \nu_S(x)$$

**E. THE IF SET OF HUMAN ACTION INTENTION AND THE IF SET OF COLLISION AVOIDANCE**

People synthesize their judgments about efficiency and comfort to get their action intentions. However, people have different judgments on the importance of efficiency and comfort, and they usually can only give fuzzy conclusions intuitively. Therefore, the IF set of various factors is given different weights, and then the IF set of various factors are weighted and aggregated by the weighted aggregation method.

Since the human perception of the ranking of efficiency and safety is vague, it is impossible to accurately determine the importance ratio of efficiency and safety. Therefore, to be closer to the real situation, we randomly interviewed five team members and collected their perceived importance weights for efficiency and comfort. The IF set of human for efficiency and comfort are weighted together to obtain the IF set $\tilde{K} = (\mu_K(x), \nu_K(x))$ of human action intention on whether to continue moving towards the target through the potential collision area for the current situation.

$$\tilde{K} = (\mu_K(x), \nu_K(x)) = w_E \tilde{E}_H + w_SE \tilde{E}_P$$

From the above analysis, it is concluded that the cobot needs to consider three factors: safety, human action intention, and work efficiency to consider whether to use the original action of continuing to move towards the target or choosing the strategy of temporarily yielding. For this reason, to ensure safety, we first set the weights of the three factors as $w_S = (0.95, 0.05)$, $w_K = (0.8, 0.2)$ and $w_E = (0.6, 0.2)$ respectively. The IF weights $w_E w_SE w_S w_K w_ER$ in the paper can be obtained by sensitivity analysis to get the range of attribute weights changes when the ranking of decision options’ advantages and disadvantages is kept constant. Using the sum and product of the IF set, the action decisions made by the cobot considering the three factors together are weighted and assembled to obtain the IF set of collision avoidance $\tilde{C} = (\mu_C(x), \nu_C(x))$.

$$\tilde{C} = (\mu_C(x), \nu_C(x)) = w_S \tilde{S} + w_K \tilde{K} + w_E \tilde{E}_R$$

When a person passes through the potential collision area and the cobot temporarily yields, we record the IF set of collision avoidance as $\tilde{C}_C = (\mu_{C_C}(x), \nu_{C_C}(x))$; The opposite strategy is recorded as $\tilde{C}_K = (\mu_{C_K}(x), \nu_{C_K}(x))$. It is necessary to give the ranking method of intuitionistic fuzzy sets to judge the size.
By comparing the scored values with the corresponding accuracy values, the active decision of whether the cobot takes avoidance or not can be obtained.

IV. VALIDATION

To verify the effectiveness of the method proposed in this paper. We choose two classical decision-making methods, MDP and POMDP, to compare and validate the method proposed in this paper. By making decisions on the same scenarios, we generated 10,000 sets of data using the Monte Carlo method to simulate scenarios where a man and a cobot tend to grasp parts in the same target area simultaneously. We used the three methods to make decisions on the cobot’s actions in the conflict scenarios to verify whether the method proposed in this paper can improve human satisfaction, cobot efficiency, and safety.

Assuming that the initial position of the hand is in the negative half-axis of the x-axis, we generate the data with $-0.85m$ as the mean and $0.2125$ as the variance. The speed of the hand is $0.75m/s$ as the mean and $0.1875$ as the variance to generate the data. The end-effector’s position is in the negative half-axis of the y-axis, with $-0.45m$ as the mean and $0.1125$ as the variance-generated data. The speed of the end-effector is also $0.75m/s$ as the mean value and $0.1875$ as the variance generation data. The potential collision area is set in a square area with the center point $(0,0)$ and the side length of $0.1m$.

In order to be close to the actual working scenario, we assume that both the human and cobot tend to the potential collision area simultaneously to complete the task of grasping the parts and stop $2s$ after reaching the possible collision area to simulate the process of getting the parts. Moreover, to increase efficiency, we assume that the human-cobot agents are on equal footing and can compete equally for the shared space.

In making decisions on the cobot actions using the MDP method, the algorithm’s weight selection for efficiency and safety is more similar to the weight ratio for both in the decision-making algorithm proposed in this paper, i.e., $w_E = (0.6, 0.3)$ $w_SE = (0.5, 0.4)$. We set the discount factor $\gamma_d$ at a fixed value in the MDP to a dynamic value, assigning a weight of 0.6 to safety $S_M$ and a weight of 0.4 to efficiency $E_M$. Since no bounded rationality factor is involved in the MDP, security is used as the probability in the state transfer matrix. The decision is obtained by solving the MDP using the value iteration method. The decision is obtained by solving the POMDP using the Q-Learning algorithm.

$$\gamma_d = 0.6 \cdot S_M + 0.4 \cdot E_M$$ (20)

$$S_M = \exp\left(-\frac{\Delta t_e^2}{2 \left(\frac{v_r-v_h}{2}\right)^2}\right)$$ (21)

$$E_M = \begin{cases} 1-t_s \cdot (t-t_s), & (t_s < t_s) \\ t_s \cdot (t-t_s), & (t_s \leq t \leq t_s) \\ 0, & (t_s < t) \end{cases}$$ (22)

We are particularly concerned with the following two scenarios.

1. When the cobot can reach the potential collision region at the original speed, the human arrives after the cobot reaches

\[
\mu_{SE} (S_{EP}) = \begin{cases} \frac{S_{EP} - S_{E0.3}}{0.5 - 0.3} (S_{E0.3} \leq S_{EP} < S_{E0.5}) \\ w_g \frac{S_{EP} - S_{E0.5}}{0.5 - 0.3} (S_{E0.5} \leq S_{EP} \leq S_{E0.8}) \\ w_g \frac{S_{EP} - S_{E0.8}}{S_{EP} - S_{E0.8}} (S_{EP} < S_{EP} \leq S_{P1}) \\ 0 (S_{EP} < S_{EP} , S_{EP} > S_{P1}) \end{cases}
\]

\[
u_{SE} (S_{EP}) = \begin{cases} w_g \frac{S_{EP} - S_{E0.5}}{S_{EP} - S_{E0.5}} + u_g (S_{EP} - S_{EP}) (S_{EP} < S_{EP} \leq S_{EP}) \\ w_g \frac{S_{EP} - S_{EP}}{S_{EP} - S_{EP}} + u_g (S_{EP} - S_{EP}) (S_{EP} < S_{EP} \leq S_{EP}) \end{cases}
\]
The experimental results indicate that the action decisions for accelerating through action, respectively. 838, 838, and 792 decisions for yielding, and 123, 23, and 1767 and 1643 yielding decisions were made by the MDP and POMDP methods, respectively, and the accelerated passing through decisions were made 4033 and 4157 times. For scenario 1, our proposed cobot action decision method made 1572 yielding decisions and 103358

FIGURE 9. Comparison of efficiency and safety results.

the target but before it finishes its grasping work and leaves the collision region. But the human can choose to accelerate to reach the potential collision area before the robot. At this time, to reduce the loss of efficiency, it is very likely that the human will take the accelerated way to reach the collision area first so that the cobot has to take a temporary yielding stop action and cause a significant increase in the risk of collision.

2. When the human can reach the collision area first with the actual speed, but the arrival time gap between the human and the cobot is not significant if the cobot accelerates before the human reaches the potential collision area to force the human to take a yielding pause action, not only to improve efficiency while ensuring the safety of the situation.

The experimental results of the three methods are shown in Fig. 8. The post-experiment statistics revealed a total of 5800 occurrences for scenario one, and for scenario two, a total of 861 occurrences. For scenario 1, our proposed cobot action decision method made 1572 yielding decisions and 4228 accelerated passing through decisions for the cobot, 1767 and 1643 yielding decisions were made by the MDP and POMDP methods, respectively, and the accelerated passing through decisions were made 4033 and 4157 times. For scenario 2, our method, MDP and POMDP methods made 738, 838, and 792 decisions for yielding, and 123, 23, and 69 decisions for accelerating through action, respectively. The experimental results indicate that the action decisions made by the MDP method and our method are biased toward conservative and aggressive, respectively, and the POMDP method is in between. To verify whether the action decisions made by our proposed method can improve efficiency and safety, we compared the efficiency and safety of the three methods for 10,000 experiments. To show the efficiency and safety more clearly in the figure, we averaged every 100 sets of data. We then plotted them in the figure to reflect the efficiency and safety comparison of the three methods. The experimental results are shown in Fig. 9. The results show that the MDP method is less efficient than our method and the POMDP method, while the efficiency of our method is slightly higher than that of the POMDP method. The three methods do not differ much in terms of safety, and the MDP method has the highest safety. In many scenarios, the cobot action decisions made by MDP yield, while the safety obtained by our method is similar to that of the POMDP method.

The effect of our method on the weighting factors can be determined by calculating the sensitivity of the weighting factors to determine within what range changing the weights will not change the ranking scheme of the IF set.

The results of the 10,000 sets of experiments generated by the Monte Carlo method show that our method can improve the smoothness and productivity of HRC and the safety of HRC in the overall experimental process compared to the MDP series method, which verifies the effectiveness of the algorithm. We designed simulation experiments to verify the accuracy of the human action intention model and human satisfaction with cobot decisions in real scenarios.

We present some of the experimental results of the Monte Carlo simulation experiments made by our method in the article’s attachment.

V. SIMULATION EXPERIMENT AND TURING TEST

To verify the accuracy of the human intention model and human satisfaction with cobot decisions in real scenarios, we designed the simulated experiment and Turing test. We use the simulated experiment to verify the prediction accuracy and the Turing test to test the satisfaction of the decision method with human intentions and whether humans can distinguish cobot decisions.

A. SIMULATION EXPERIMENT SETUP

To verify the effectiveness of the cobot action decision algorithm, we selected 20 sets of experimental scenarios obtained by the Monte Carlo method in the previous section that fit the two scenarios, and the three methods make different decisions. A total of 60 experiments were formed by using each of the three methods to make decisions. We built a cobot and human-like model in the RoboDK simulation environment to form visual animations of these 60 experiments. The human and cobot are on each side of the table, and both sides grasp the parts at the same position simultaneously. The experiments simulate HRC scenarios and collect the choices made by the experiment participants to ensure efficiency and avoid collisions.
First, we made an interactive video. In the first video, the person and the cobot move from the initial pose to the starting point and travel at a certain speed for a while. At the end of the first video, the option button of pass or yield pops up. Then, the experimental participants were asked to select the pass or yield button within 1 s. In the second video, different results appear according to the different choices of participants. After each experiment, participants recorded the results of this action selection and evaluated their satisfaction with the cobot’s action selection; we designed the satisfaction scale to be 0 to 5, corresponding from very dissatisfied to very satisfied. We recruited 42 people through voluntary recruitment to make their judgments on 20 scenes.

Each experiment record and satisfaction evaluation form can be viewed in the appendix. The interactive video can be viewed through https://www.bilibili.com/video/BV17Z4y117at?spm_id_from=333.337.search-card.all.click

B. Turing Test

To better test human satisfaction with the cobot’s decisions, we want to test whether the human can distinguish between the decisions made by the experimental participants for the cobot and the decisions made by the cobot through the method proposed in this study employing the Turing test. Our proposed method is human-like if the participants in the test cannot distinguish whether the cobot’s actions are made by a human or generated by our method.

To set up the Turing test, first, we propose a hypothesis: when a human and a cobot converge to the same target simultaneously, the experimental participants cannot distinguish whether the human or the cobot makes the cobot decision. Second, we randomly selected 5 of the 20 simulation experiments as group A and asked 10 participants to make decisions for each group of cobot actions. Each group of experiments took the most choices as the cobot action decisions. Five more experiments are randomly selected from the remaining 15, denoted as group B. The proposed algorithm is used to make decisions about the cobot’s actions in group B. Five more experiments are randomly selected from the remaining ten groups, denoted as group C, to randomly make decisions for the cobot’s actions. Again, ten experimental participants were re-recruited, informed of the testing procedure before the experiment, and reminded to note that a human decided for the cobot’s action in one of the three sets of experiments. At the beginning of the experiment, groups A, B, and C were randomly arranged. Participants were allowed to watch a video of the experiment; at the end of the experiment, each participant was asked to answer three questions, which were as follows.

1. Which groups of kobots do you think to act like a human?
2. After telling participants that group B is the decision made by the algorithm, do you think the cobot’s actions were more human-like or more like a computer program? On a scale from 5 (very human-like) to 1 (very computer-program-like).
3. How much do you trust a cobot like a group B when encountering a similar situation? From a score of 5 (very trusting) to 1 (very distrustful).
4. After the test was completed, aspects that were not considered by the robot were suggested for the robot’s improvement by reviewing the test process.

A total of 42 volunteers participated in our experiment, of which 32 participated in the simulation experiment, 29 males and three females. All ten volunteers, all males, participated in the Turing test. The participants were 22 and 28 years old and were asked about their age, gender, and experience with cobots and computer games. Most of the participants had some experience with computer games, and 35% had some knowledge of cobots.

C. Data Analysis

When the scenario presented in the paper arises, we hope to obtain the result that the cobot can accurately predict the human intention of passing through each time. The cobot makes accurate decisions by integrating the current situation to ensure safety, improve efficiency, and maximize human satisfaction. In the simulated experiments, participants did not make unified decisions about the actions in each experiment, so we take the conclusion of the majority of participants in each experiment as the standard.

For the simulation experiment, the sum \( n_s \) of the same decision as the standard decision action is added and divided by the total number of participants \( n_t \) to obtain the decision unity \( d_u \) of participants in each experiment, as shown in formula (23). Then the average value and standard deviation of the decision unity \( d_u \) of 20 experiments are obtained.

\[
\bar{d}_u = \frac{n_s}{n_t} \quad (23)
\]

For the standard human decision in each experiment, the cobot’s action decision should be opposite to the human action decision so that the collaborative task is smooth, efficient, and safe at the highest level. The number of times the cobot’s action decision is opposite to the human action decision in all 20 experiments is the correctness of the cobot’s action choice \( S \).

We counted the number \( n_o \) of cobot decisions opposite the standard human decision in each experiment. We calculated the percentage \( n_o \) in 20 experiments to obtain the degree of correctness \( S \) of the cobot action choice, as shown in equation (24). As for the prediction of human intention, only our method can obtain the human action intention among the three methods. We compare the IF set \( \mathbf{K} = (\mu_K (x), \nu_K (x)) \) of action intentions in passing through and yielding intentions, get the human action intentions in each experiment by ranking method, and compare the calculated action intentions collected from simulated experiments to predict accuracy.

\[
S = \frac{n_o}{20} \quad (24)
\]

We counted all participants’ mean and standard deviation for the unity of participant decision-making, the accuracy of
TABLE 2. Experiment result.

| Independent variable                        | Mean    | Standard deviation |
|---------------------------------------------|---------|--------------------|
| The participants’ decision uniformity $d_s$ | 81.76%  | 0.165824           |
| The accuracy of the cobot’s prediction of human intention $S$ | 85.62%  | 0.035345           |
| Satisfaction of IF set method               | 4.83    |                    |
| Satisfaction of MDP method                 | 4.21    |                    |
| Satisfaction of POMDP method               | 4.65    |                    |

TABLE 3. Confusion matrix.

| Actual | Through | Yield |
|--------|---------|-------|
|        | 8       | 3     |
|        | 3       | 6     |

the decision method in predicting human action intention, and human satisfaction with cobot decision-making for 20 experiments. The results are shown in Table 2.

Participants in the experiment made different judgments about the human-cobot state in the same scenario each time and had different perceptions of risk. Comparing the standard human decision, the average decision uniformity of the participants could only reach 81.76%. Then comparing the human action intention calculated by our method with the action decisions of all participants, it was found that the accuracy of human action intention predicted by our method could reach 85.62%.

While the recall is 72.72%, the accuracy is also 72.72%, and the specificity is 66.67%. From the results, the method of intuitionistic fuzzy set proposed in this paper has a higher accuracy for the intention of passing and yielding of humans. At the same time, the recall and precision are slightly lower. In the results, we pay special attention to recall and precision because safety is the performance we value most if a person has once created the intention to pass through. The recall and precision results show that our method can accurately predict the human’s intention to pass. In particular, when encountering the first type of situation, the advantage of the robot to choose avoidance decisions increases, thus increasing the gain in the gaming process and improving the security of safety.

Comparing the satisfaction obtained by the three methods, the IF set action decision method proposed in this paper has the highest satisfaction, reaching 4.83. After the experiment, we interviewed the experimental participants and most thought that the MDP method’s decision was somewhat conservative. In some scenes where the cobot could pass through, the decision made by the MDP method still did not pass through, which wasted the task time. The satisfaction obtained by the IF set method and the POMDP method were similar, and the experimental participants thought that the decisions made by both methods for cobot actions were more in line with human expectations of the cobot. We believe that the higher satisfaction for both our proposed method and the POMDP method is that both types of methods incorporate a human factor of limited rationality rather than simply calculating the gains in efficiency and safety. Such methods can more closely match the human cognitive process for such scenarios while targeting decisions more consistent with human bounded rationality characteristics.

Statistically, the results for questions 1, 2, 3, and 4 in the Turing test are as follows. For problem 1, group A is most often considered a human decision, accounting for 50%. It is closely followed by our proposed collaborative cobot action decision-making method, i.e., Group B is regarded as a decision made by humans, accounting for 40%. In contrast, group C accounted for only 10%. The results show that our proposed method has passed the Turing test, with a percentage of decisions considered to be made by humans greater than 30%. For questions 2 and 3, the mean scores are 4.4 and 4.3, respectively, demonstrating that the decisions made by our proposed method are human-like and receive a high level of confidence. For question 4, some participants suggested that the robot did not fully understand human intentions. There was not only passing, yielding, and hesitation in the human-robot collaboration process but also the intention of not actively participating, the neutral intention of only observing the cobot’s actions, and even the intention of refusing to cooperate with the cobot. For this small part of other intentions, we plan to make it one of our research directions in the future as well.

From the experimental results, our proposed method not only improves the robot’s efficiency and human satisfaction with the robot but also ensures the safety of HRC. We believe that the reason for this result is that the IF set gives not only the possibility of the human taking the intention to pass but also the possibility of yielding and hesitation. The IF set can better describe the human cognitive process and provide a more accurate human action intention for cobot decision-making.

VI. DISCUSSION

The paper focuses on proximity collaboration scenarios 1 and 2, which are an in-depth study of similar studies in the literature [14] that do not accurately predict scenarios. In such scenarios, once both parties involved in the action decide to pass, there is not enough time to take the avoiding action, and it is easy to collide and cause danger. The action choices of participants in this scenario often rely on bounded rational factors such as intuition and personality, and the action decisions of different participants are highly divergent internally, so how to better model human cognitive styles in this scenario is the key to solving this problem. However, previous studies lacked research on such situations and could not make predictions and decisions based on human cognitive styles. With the increasing popularity of HRC in both industrial and life scenarios, the frequency of such situations will increase, so it is necessary to model the human cognitive style in this situation.

We propose the cobot action decision-making method based on IF set and game theory for this problem.
We establish the human action intention IF set based on the efficiency and safety combined with the bounded rationality factor of humans and integrated simulation of a human cognitive process. We try to get more accurate human action intention prediction results through the human action intention IF set, which is the first innovation point of our research on such situations. We use the established cobot action decision-making method to decide on cobot actions. Our proposed robot action method can pass the Turing test, which illustrates the effectiveness of our method, and the experimental participants have high satisfaction with it, which is our second innovation point.

We compared our proposed method with MDP and POMDP methods in this paper, and our proposed method has higher satisfaction than MDP and POMDP methods. However, in the Turing test, the experimental participants did not score more than 4.5 for the human-like degree and trust degree of the actions made for the robot by the method proposed in this paper. We believe that the main reasons are:

1. The selection of parameters using CPT is based on the results of previous studies, but it is not necessarily suitable for the proximity HRC scenario mentioned in this paper. The selection for different parameters implies different human perceptions of efficiency in different scenarios, which eventually results in different cobot collision avoidance IF set \( \tilde{C} = \langle \mu_C(x), v_C(x) \rangle \) for robot action decisions, affecting the judgment of human action intentions and the formulation of robot action decisions.

2. We determined the importance weights of people for efficiency and comfort as \( w_E = (0.6, 0.3) \) and \( w_{SE} = (0.5, 0.4) \), respectively. Still, different people have different perceptions of efficiency and comfort, so this weight can significantly impact automated decision-making. After the experiment, we interviewed the experimental participants. We found that the five people who had experience collaborating with cobots thought that the speed and power of the cobots were limited. Even if the human arm and the cobot collided, it would not cause harm, so the cobot did not move too fast, or as long as it did not hit the head and other vital parts, they would not worry too much about the cobot’s harm to itself. They were more concerned whether the cobot’s efficiency can achieve the collaboration goal. In contrast, 4 out of 12 people with no experience thought that the cobot should stop as soon as the person made a passing motion and should not let the cobot reach the target first or even let the cobot approach the person. Most importantly, the experimental participants had different requirements for the cobot during the transition, from inexperienced to experienced, from more safety-oriented to more efficiency-oriented, but the transition laws were complex and not studied. The cobot’s action decisions cannot fully meet the requirements of people in the transition and adjustment phase, so this issue is also a future research direction for HRC.

3. The advantage of this paper is that, compared to decision methods such as MDP and POMDP, human intentions can be predicted while making decisions. The intuitionistic fuzzy set of human action intention proposed in this paper better reflects the human decision-making method in such scenarios, and the prediction of human intention, whether through or not, is more accurate. The safety of cobot action is ensured from the intention perception level. The disadvantage of this paper is that our proposed method does not perform to a high degree in terms of safety, efficiency, and human satisfaction, with a prediction accuracy of only 86% for human intentions. We believe this is related to the higher number of parameters that appear in the model, which need to correspond to the large number of model parameters that need to be adjusted to more closely match the action intentions of most people in different scenarios. The prediction accuracy of our proposed method does not reach 90%, and the decisive actions need to be improved in terms of safety, efficiency, and satisfaction.

4. However, the IF set can only represent affiliation, disaffiliation, and hesitation and do not represent neutral and rejected cognitions, so the model does not achieve more than 90% accuracy in predicting human action intentions. In our future work, we will optimize the model using picture fuzzy sets [25], [26] and similar improvement methods to improve the prediction model’s performance.

5. The simulation experiment is done in a laboratory environment using a computer game and cannot represent the choice of human responses in a natural setting. In a real industrial scenario, workers will be influenced by the impact of the work environment, task efficiency requirements, cobot actions, and other factors, which may produce different requirements for the cobot’s action decisions which is the future research direction of HRC.

VII. CONCLUSION

We design a cobot action decision-making method based on the IF set and game theory. The decision-making method integrates the three factors of human action intention, safety, and efficiency and provides an effective strategy for the cobot action decision. This method models human action intentions through CPT and IF set to reason about the human action intention in situations where there is no optimal trajectory for proximity HRC to achieve collision avoidance. The optimal action of the cobot is also calculated based on the IF set of two Nash equilibrium solutions for the human-robot scenario, similar to the static chicken game. Through experiments, it was found that the present method can achieve an accuracy of 85.22% in predicting human action intention. At the same time, the participants’ satisfaction with the cobot’s decision can reach a satisfactory level. Unlike the study in the literature [14], our study focuses more on situations where the human-cobot distance and speed are very close, with a high risk of collision. Also, different from the study in the literature [12], we consider the human as a boundedly rational agent and simultaneously consider the three action intentions of passing through, yielding, and hesitating. It is possible to predict human action intentions better and provide a reference for the cobot’s action decision-making.
We use the method to solve the decision-making problem for cobot actions when both humans and cobots compete for the shared space. We analyzed the bounded rational way of human cognition for efficiency and comfort and established the IF set of humans for efficiency and comfort, respectively. Using the method, we decide on the cobot’s action by comprehensively analyzing three factors: human action intention, safety, and efficiency.

Our method can depict the human cognitive process when a spatial conflict arises between a human and a robot in three states: passing, yielding and hesitating. In contrast, our method better describes the human cognitive process by considering the possibility of human intention and the hesitant intention that arises when a human encounters such a scenario. Therefore, compared with the MDP and POMDP methods, our proposed method can improve the efficiency of HRC and human satisfaction with the robot and ensure the safety of HRC. From the experimental results, our method can get the human action intention during the human-robot conflict with high accuracy, providing a reference for robot action decisions and planning.

**APPENDIX**

| Number | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Decision making | 11  | 12  | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  |
| Satisfaction |     |     |     |     |     |     |     |     |     |     |

Note: The satisfaction scale is 0 to 5, corresponding from very dissatisfied to very satisfied.

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