# Appendix: Planning with Multi-agent Belief using Justified Perspectives

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## 1 Complete semantics for justified belief

**Definition 1.1** (Complete semantics). The complete semantics for justified belief is defined as:

(a) 
$$(M, \vec{s}) \models r(\vec{t})$$
 iff  $\pi(s_n, r(\vec{t})) = true$ 

(b) 
$$(M, \vec{s}) \vDash \phi \land \psi$$
 iff  $(M, \vec{s}) \vDash \phi$  and  $(M, s) \vDash \psi$ 

(c) 
$$(M, \vec{s}) \vDash \neg \varphi$$
 iff  $(M, \vec{s}) \not\vDash \varphi$ 

(d) 
$$(M, \vec{s}) \models S_i v$$
 iff  $v \in \text{dom}(O_i(s_n))$ 

(e) 
$$(M, \vec{s}) \vDash S_i \varphi$$
 iff  $\forall \vec{g} \in \vec{S}_G, (M, \vec{g}[\langle O_i(s_n) \rangle]) \vDash \varphi$  or  $\forall \vec{g} \in \vec{S}_G, (M, \vec{g}[\langle O_i(s_n) \rangle]) \vDash \neg \varphi$ 

(f) 
$$(M, \vec{s}) \models K_i \varphi$$
 iff  $(M, \vec{s}) \models \varphi \wedge S_i \varphi$ 

(g) 
$$(M, \vec{s}) \models B_i \varphi$$
 iff  $\forall \vec{g} \in \vec{S}_G, (M, \vec{g}[f_i(\vec{s})]) \models \varphi$ 

where:  $\vec{S}_G \in \vec{S}$  is the set of all possible global states sequences and  $\vec{g}[\vec{s}] = g_1[s_1], \ldots, g_n[s_n]$ ; and, g[s] means function override: g[s](v) = s(v) when  $v \in \text{dom}(s)$  and g(v) otherwise; and  $s_n$  is the final state in sequence  $\vec{s}$ ; that is,  $s_n = \vec{s}(|\vec{s}|)$ .

#### 2 Ternary semantics for justified belief

**Definition 2.1** (Ternary semantics). The ternary semantics are defined using function T, omitting the model M for readability:

(a) 
$$T[\vec{s}, r(\vec{t})] = 1$$
 if  $\pi(s_n, r(\vec{t})) = true$ ;  
 $0$  if  $\pi(s_n, r(\vec{t})) = false$ ;  
 $\frac{1}{2}$  otherwise

(b) 
$$T[\vec{s}, \phi \wedge \psi] = \min(T[\vec{s}, \phi], T[\vec{s}, \psi])$$

(c) 
$$T[\vec{s}, \neg \varphi] = 1 - T[\vec{s}, \varphi]$$

(d) 
$$T[\vec{s}, S_i v] = \frac{1}{2} \text{ if } i \notin \text{dom}(s_n) \text{ or } v \notin \text{dom}(s_n)$$
  
  $0 \text{ if } v \notin \text{dom}(O_i(s_n))$ 

(e)  $T[\vec{s}, S_i \varphi]$   $= \frac{1}{2} \text{ if } T[\vec{s}, \varphi] = \frac{1}{2} \text{ or } i \notin \text{dom}(s_n);$  $0 \text{ if } T[\langle O_i(s_n) \rangle, \varphi] = \frac{1}{2};$ 1 otherwise

(f) 
$$T[\vec{s}, K_i \varphi] = T[\vec{s}, \varphi \wedge S_i \varphi]$$

(g) 
$$T[\vec{s}, B_i \varphi] = T[f_i(\vec{s}), \varphi]$$

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where  $s_n$  is the final state in sequence  $\vec{s}$ ; that is,  $s_n = \vec{s}(|\vec{s}|)$ .

## 3 Proof for $KD45_n$

Now, we give the theorem and proof for  $KD45_n$  properties.

**Theorem 3.1.** The following axioms hold, making this a  $KD45_n$  logic:

K (Distribution):  $B_i \varphi \wedge B_i (\varphi \to \psi) \to B_i \psi$ 

D (Consistency):  $B_i \varphi \rightarrow \neg B_i \neg \varphi$ 

4 (Positive Introspection):  $B_i \varphi \to B_i B_i \varphi$ 

5 (Negative Introspection):  $\neg B_i \varphi \rightarrow B_i \neg B_i \varphi$ 

*Proof.* Based on the definition of  $B_i$ ,  $M, \vec{s} \vDash B_i \varphi$  is equivalent to  $M, f_i(\vec{s}) \vDash \varphi$ . From this, axiom K is:  $M, f_i(\vec{s}) \vDash \varphi$  and  $M, f_i(\vec{s}) \vDash (\varphi \to \psi)$  imply  $M, f_i(\vec{s}) \vDash \psi$ , which holds trivially. For the axiom D, when  $M, f_i(\vec{s}) \varphi$  holds, then it must be that  $M, f_i(\vec{s}) \neg \varphi$  does not hold.

Axioms 4 and 5 are more involved. The value of a variable from  $f_i(\vec{s})$  depends on two values: lt and  $\vec{s}$ , which are, respectively, the last time the variable was seen by agent i and the input perspectives. The lt depends only on the function  $O_i$ . Since  $O_i(s) = O_i(O_i(s))$ , the lt of  $f_i(\vec{s})$  and  $f_i(f_i(\vec{s}))$  for each state and each variable are the same.

Now, note that the retrieval function R returns the value v = e if v is in the state  $s_{lt}$  (the first line of R), the value of each variable in  $f_i(s)$  is the same as its in  $f_i(f_i(s))$ . Therefore,  $f_i(s) = f_i(f_i(s))$ .

Given that axiom 4 is equivalent to  $M, f_i(\vec{s}) \models \varphi$  implies  $M, f_i(f_i(\vec{s})) \models \varphi$ , this holds trivially.

For axiom 5,  $M, f_i(s) \nvDash \varphi$  is equivalent to  $M, f_i(f_i(s)) \nvDash \varphi$ . Based on the definition of  $B_i$ ,  $M, f_i(f_i(s)) \nvDash \varphi$  gives  $M, f_i(s) \nvDash B_i \varphi$ . Then, based on the definition of  $\neg$ , we have that  $M, f_i(s) \nvDash B_i \varphi$  is equivalent to  $M, f_i(s) \vDash \neg B_i \varphi$ . Therefore, axiom 5 holds.

### **4** Experiment Results for Coin example

	Parameters				Performance					
	Agt	d	$ \mathcal{G} $	P	Gen	Exp	Calls	TIM	E(s) Total	Goal
C01	2	1	1	1	3	2	2	0.0	0.0	$B_a coin = head$
C02	2	1	1	2	7	18	7	0.0	0.0	$B_a coin = tail$
C03	2	1	1	2	5	12	7	0.0	0.0	$B_a coin = head \wedge B_b coin = head$
C04	2	2	1	4	43	126	61	0.0	0.0	$B_a coin = head \wedge B_b coin = tail$
C05	2	3	2	4	46	135	58	0.0	0.0	$B_a coin = head \land B_b coin = tail \land B_b B_a coin = head$
C06	2	2	2	6	414	1239	533	0.5	0.7	$B_a B_b coin = tail \wedge B_b B_a coin = head$

Table 1: Experimental results for coin domain