Exploring Shared Reality and Consciousness Alignment through Model Predictive Control

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Argument Against Shared Reality

1. Individual Perception

Let S_i and S_j be two conscious systems. Each system S_i has a perception function P_i which maps external stimuli E to internal perceptions I_i:

$$P_i : E \to I_i$$

Given that P_i is influenced by system-specific factors (e.g., cognitive biases, history, and internal states), we have:

$$P_i(E) \neq P_j(E) \quad \text{for} \quad i \neq j$$

Thus, each system interprets the same external stimuli E differently, resulting in distinct internal perceptions I_i and I_j.

2. Nature of Information Exchange

The exchange of information between systems S_i and S_j is constrained by the speed of light c. Let d_{ij} be the distance between S_i and S_j. The time t_{ij} for information to travel between the systems is given by:

$$t_{ij} = \frac{d_{ij}}{c}$$

During this time delay, both systems continue to evolve. Let t be the current time, and $I_i(t)$ be the internal state of S_i at time t. By the time S_j receives the information $I_i(t)$, the internal state of S_i has evolved to $I_i(t + t_{ij})$:

$$I_i(t + t_{ij}) \neq I_i(t)$$

This temporal gap ensures that the information received by S_j is always outdated.

3. Probabilistic and Subjective Nature of Consciousness

Conscious decisions involve probabilistic elements. Let D_i be the decision function of system S_i, incorporating probabilistic behavior ω:

$$D_i(\omega) : E \to O_i$$

Where O_i represents the possible outcomes. Due to the probabilistic nature, the outcome O_i is not deterministic, and the state of S_i remains uncertain to S_j:

$$P(O_i) \neq 1 \quad \text{for any specific} \quad O_i$$

As both S_i and S_j continuously make decisions and evolve, their states are in constant flux.

4. Thought Experiments and Examples

Consider two astronauts, A and B, on different planets separated by distance d. The communication delay t_{AB} ensures that:

$$I_A(t + t_{AB}) \neq I_A(t)$$

Similarly, during human interactions, let M_i and M_j be the messages exchanged between systems S_i and S_j. The subjective interpretation functions F_i and F_j map these messages to internal states:

$$F_i(M_j) \neq F_j(M_i)$$

Conclusion

Due to the finite speed of information transfer, subjective perception, and the probabilistic and evolving nature of consciousness, a truly shared reality R between systems S_i and S_j is unattainable:

$$R_i \neq R_j$$

Each conscious system experiences a unique and dynamic version of reality, ensuring that their realities remain fundamentally distinct and personal.

Alignment of Conscious Realities

1. Perception and Reality Functions

Let $R_A(t)$ and $R_B(t)$ be the subjective realities of conscious systems A and B at time t:

$$R_A(t) = P_A(E_A(t))$$

$$R_B(t) = P_B(E_B(t))$$

where P_A and P_B are the perception functions, and $E_A(t)$ and $E_B(t))$ are the external stimuli.

2. Desired Reality of B

Let D_B be the desired reality of system B:

$$D_B = \{S_1, S_2, \ldots, S_n\}$$

3. Alignment Function

Define an alignment function $A_{AB}(t)$:

$$A_{AB}(t) = f(R_A(t), D_B)$$

where f quantifies the alignment between $R_A(t)$ and D_B.

4. Decision Process

Information Exchange

System B communicates D_B to system A through message M_B.

Adjustment Mechanism

System A modifies its reality based on M_B:

$$R'_A(t) = \alpha_A(R_A(t), M_B)$$

where α_A is the adjustment function.

Maximizing Alignment

System A aims to maximize $A_{AB}(t)$:

$$\max_{R'_A(t)} A_{AB}(t)$$

Conclusion

By receiving information about D_B and adjusting its reality R_A accordingly, system A can align its reality with the desired reality of system B to the extent possible, given the subjective nature and dynamic evolution of each system's consciousness.

Model Predictive Control-based Framework for Aligning Realities

1. Prediction Model for B

Let $\hat{R}_B(t+k|t)$ be the predicted state of system B at time $t+k$, given information available at time t:

$$\hat{R}_B(t+k|t) = f_B(R_B(t), u_B(t))$$

where f_B is the prediction model of B's state.

2. Objective Function

Define the objective function J that system A aims to optimize:

$$J = \sum_{k=0}^{N-1} \|R_A(t+k) - \hat{R}_B(t+k|t)\|^2$$

where N is the prediction horizon.

3. Optimization Problem

System A solves the following optimization problem to find the optimal control actions $u_A(t)$:

$$\min_{u_A} J$$

subject to the dynamics of A's state and any constraints.

4. State Dynamics

Update A's state based on the chosen control actions:

$$R_A(t+1) = f_A(R_A(t), u_A(t))$$

where f_A represents the state dynamics of system A.

Conclusion

By predicting the future state of system B and optimizing its control actions, system A can align its reality with the desired outcome. This MPC-based approach allows system A to proactively influence its own state to achieve a specific reality before receiving information from system B.