Assessing the *HI-ness* of Virtual Heritage applications with Knowledge Engineering

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Abstract. This paper explores the use of Knowledge Engineering to measure the nature of Hybrid Intelligence (HI)—where humans and machines collaborate toward a shared goal—within an existing application. We assess the level of HI by examining the synergy between humans and machines—stronger HI corresponds to greater synergy in collaboration. The findings provide insights into the effectiveness of Knowledge Engineering in identifying HI aspects within existing applications, as well as the potential for quantifying and improving HI in such applications. This abstract is based on the published paper [1].

Keywords: Virtual Heritage · Knowledge Engineering · Hybrid Intelligence · Human-Computer Interaction

Virtual Reality (VR) has demonstrated its effectiveness in crafting immersive, personalized, and interactive museum experiences [2, 3]. The integration of virtual agents as guides or companions within these VR environments holds significant promise for enhancing user engagement and satisfaction by facilitating personalized interactions and communication [4, 5]. To fully harness the potential of AI technologies in VR, it is essential to understand the dynamics of human-agent interactions. Virtual Heritage applications exemplify Hybrid Intelligence (HI), where multiple actors collaborate, adapt to each other's strengths and limitations, and utilize diverse data and methods to achieve common goals [6]. In these contexts, humans and artificial agents complement each other's limitations. To assess the level of HI in such scenarios, this paper proposes using Knowledge Engineering [7]. Knowledge Engineering involves the elicitation, structuring, formalization, and operationalization of the information, knowledge, and tasks pertinent to knowledge-intensive applications. Historically, methods such as CommonKADS [8] have aided engineers in defining the structure of complex applications. Recently, adaptations of CommonKADS have been employed to identify typical tasks, inputs/outputs, and knowledge roles in Hybrid Intelligence applications, referred to as the application's *Knowledge Model* [9]. We suggest that the HI Knowledge Model (HIKE) can serve as an analytical tool to measure the HI-ness of existing applications.

Consider a scenario where a virtual agent interacts with a user, Sarah, by capturing her gaze, facial expressions, and speech inputs through multimodal analysis. The agent uses this information to infer Sarah's interests and dynamically tailors its interactions accordingly. For instance, the agent might highlight specific objects in a painting

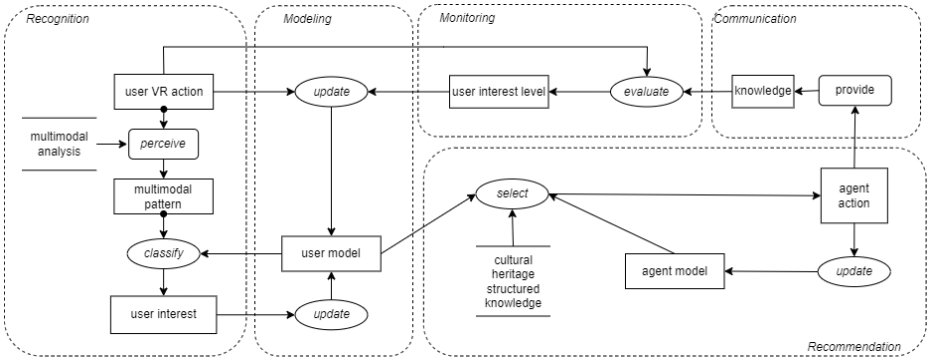

Fig. 1: Task Decomposition of scenario

to guide Sarah's attention, provide additional cultural context, or recommend related artworks. We represent this scenario using processing workflows, following the recommended UML notation[3] (see, Figure 1).

To assess HI-ness, we categorize tasks into two types: **Weak HI** and **Strong HI**. Weak HI tasks involve minimal collaboration toward a shared goal, while strong HI tasks exhibit high synergy within the human-agent team. For example, the **Modeling** task, which involves storing user actions, interests, and agent responses, primarily focuses on data storage and retrieval. This task shows minimal collaboration, indicating *Weak HI*. Similarly, the **Recognition** task, where the agent recognizes user interests and updates the user model, also falls into the *Weak HI* category, as it relies on data-driven interactions rather than true collaboration. Enhancing these weaker tasks could involve integrating mechanisms for the agent to seek user clarification or confirmation when it is uncertain about decisions regarding user interests or mental state. Such mechanisms, coupled with clear explanations, can improve decision-making strategies in future interactions. In contrast, the **Recommendation** task, where the agent selects actions based on both user and agent models, exemplifies *Strong HI*. Here, the agent's actions adapt to the user's preferences, demonstrating high synergy.

HIKE serves not only as an analytical tool but also as a method for recommending adaptations and improvements. For example, the **Communication** task, which involves conveying knowledge to the user, and the **Monitoring** task, where the agent evaluates user interest post-interaction, tend to be *Weak HI* due to one-way information transfer. However, communication can be strengthened when the agent transparently conveys its capabilities and limitations (e.g., "I can only answer factual questions" or "I'm unfamiliar with that fashion style"), promoting *Team Awareness*, a key aspect of HI [10]. By calculating the proportion of Strong HI tasks relative to the total number of tasks, we can gain an indicative assessment of the extent to which our application qualifies as Hybrid Intelligence.

[3] UML notation: ovals represent inferences, rounded rectangles denote transfer functions, full squares indicate dynamic inputs/outputs, horizontal lines mark static inputs/outputs, dotted arrows show lists, and dashed boxes signify more general tasks.

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