A Comparison of Architectures for Autonomous Multi-Agent Communication*

Alison Cawsey, Julia Rose Galliers, Steven Reece and Karen Sparck Jones

Computer Laboratory, University of Cambridge, New Museums Site, Cambridge CB2 3QJ, England
{ac,jrg,ar,kpj}@uk.ac.cam.cl

Abstract. We present an empirical comparison of alternative architectures for managing negotiation between autonomous agents, focussing on the ability of a set of agents to resolve conflicts. We contrast a blackboard-based architecture with an actor-based architecture and show how features of the way expertise is distributed should influence the choice of architecture. In our problem domain the actor architecture is shown to involve less effort than, and be as effective as, the blackboard one.

1 Introduction: Multi-Agent Theory and Application

This paper presents an empirical approach to the selection of a multi-agent architecture given a particular problem domain. The work forms part of an ongoing project concerned with multi-agent communication and focussed on how a set of autonomous agents can resolve conflicts [3]. Galliers [5] presents a formal framework accommodating an agent’s preferences for belief change in communication, and allowing true agent autonomy given the presence of conflicts. This model of autonomous belief revision has been computationally implemented, providing a preference ordering among sets of conflicting belief which allows an agent to decide how and whether to take on communcicated information.

However, Galliers’ model of communication is a very general one, and leaves open how to organise the communication between a whole set of agents. In this paper we compare (through computational implementation and testing) two alternative architectures for multi-agent communication, by measuring how effective each is at resolving conflicts.

The overall theory of communication can apply both to negotiation between modules in a distributed system, and between system and user. Our chosen project domain is one where we can study both of these, since negotiation between system and user is vital (as neither has all the information needed to complete the task), and distributed models have been proposed for the system’s internal processing. We are developing a model of an information retrieval intermediary who aids the user in deciding on appropriate literature searches. Automating the intermediary is a difficult but important task, requiring many sorts of knowledge, of user capabilities and needs, subject domains, literature searching techniques, etc.

2 System Architecture

Several authors have proposed models of the intermediary based on a number of interacting functional experts [1]. Belkin et al. analysed dialogues between human intermediaries and users and abstracted details of the individual functional experts that seem to be required for information retrieval. They attempted to test their model using humans to simulate the expert sub-functions, and trying different protocols for communication between them [2]. They suggested that a blackboard-based communication protocol has most promise, but their results are inconclusive and it is not clear whether their human simulation could be followed computationally. In our research we are using a subset of the functional experts proposed by Belkin, and exploring communication between experts through computational implementation.

Our basic architecture consists of a set of communicating agents, each with their own beliefs, and able to revise their beliefs in the face of inconsistent information. Within this basic framework we can vary the channels of communication between agents, and are exploring two main alternatives, based on simple actor and blackboard architectures. In the actor-based architecture agents communicate directly to other specific agents, while in the blackboard-based architecture all communications are placed on a common message-board, accessible by all.

We have implemented a simple information retrieval expert allowing us to explore both the general theory and

---

*This research is supported by grant 90/CS42 of the UK Tri-Council Initiative on Cognitive Science and Human-Computer Interaction.

---

1 In fact, each agent has an identical copy of this message board, as agents reside on a separate machines.
of agent communication and alternative system architectures. Each functional expert in the system is an autonomous agent, acting in parallel with the others\(^2\), and having several different interrelated tasks. These include drawing new inferences from existing beliefs, reasoning about preferences among alternative inconsistent sets of beliefs, and communicating with the other agents. Communication between agents is motivated primarily by conflict—either internal conflict (where an agent is uncertain about some proposition, having reasons to believe both the proposition and its negation), or external conflict (where two agents disagree). But agents will also communicate when they have new results, potentially useable by other agents.

Four message types are used in inter-agent communications, allowing agents to inform, ask questions, and ask for and give justifications. Knowledge in the system is typed, with agents knowing what types of knowledge are useable by them (i.e., their area of expertise). In the actor architecture agents also know the types of knowledge useable by other agents, so they can direct their communications appropriately.

3 Comparison: Data and Methods

In our architecture comparison we aim to identify the particular features of a problem domain which make one architecture preferable to another. To do this effectively we started with a domain-independent evaluation where relevant features of a set of agents could be systematically varied. We could thus explore the relationship between problem type and preferred architecture. In this first stage of evaluation, our agents were initialised with particular general properties, but with their individual beliefs and justifications randomly chosen by the system. The general properties of the agent set which we have varied are:

- The total number of agents in the system: we varied this from 2 to 6.
- The spread of areas of expertise. This was defined in terms of the types of knowledge useable by agents: we tried both fully overlapping areas of expertise, with all agents able to reason about all types of knowledge, and distinct areas, where agents had their own private useable knowledge types (though with some overlap).
- The accuracy of their knowledge of other agents areas of expertise, expressed in terms of the types of knowledge useable by other agents: we tried two extremes, namely completely accurate knowledge, or inaccurate (in fact, random) knowledge.

We defined a particular problem type in terms of the number of agents, the spread of areas of expertise, and the accuracy of knowledge of areas of expertise. But as the latter would only be relevant when the expertise was not fully overlapping, we had 15 problem types altogether, with 2-6 agents and accurate distinct, inaccurate distinct and fully overlapping areas of expertise.

Given a problem type, we created artificial agent dialogue scenarios by generating random sets of beliefs consistent with the problem type, and assigning them to the agents. (These beliefs might be inconsistent, and the agents have to reason about which are preferred and 'really' believed.) Communication was 'kicked off' by having one expert communicate all its preferred beliefs. This would lead to new communications as other agents drew new inferences or tried to deal with apparent conflict.

To evaluate the different architectures we measured the effectiveness and the effort involved for dialogues given different architecture and problem type pairs. For each architecture and for the 15 problem types, we created 50 random dialogue scenarios, and so measured the properties of 1500 dialogues in all. On average, the agents started off with each having 5 beliefs, while the number of messages passed in a dialogue ranged from 2 to 70. The test situations are thus much simpler than real ones would be, but are still rich enough for a useful first architecture evaluation.

We measured dialogue effectiveness in two main ways. As part of our theory of communication emphasises the importance of conflict resolution and negotiation, our primary measure concerned the number of conflicts resolved. However, we also measured the amount of useable information communicated between agents.

We measured effort in terms of the number of messages passed between agents, and the time taken to run the dialogue to completion. In the blackboard cases the system would count each reading of an item on the blackboard as a message. But as the precise way of counting messages depends on the blackboard implementation, strict comparisons between the number of messages for blackboard and actor cannot be made.

4 Results

We first consider the effect of the problem type on the effort involved. Figure 1 illustrates the ratios of effort for actor (A) against blackboard (B) architectures, given distinct areas of expertise and accurate knowledge of other agents areas, but different numbers of agents. (The standard error in the results was approximately 7\%). The figure shows that as the number of agents increases the relative effort involved for the blackboard model gets worse, as every agent examines the messages of every other agent. We would

---

\(^2\)Implemented as separate UNIX processes, communicating via socket based IPC.
5 Conclusion

Our results show how the preferred architecture should depend on features of the problem domain. In particular, if knowledge is well distributed, with each agent having distinct types of knowledge they can reason about, and having accurate models of the areas of expertise of other agents, an actor model is appropriate, especially where large numbers of agents are involved. This is in fact true for our present information retrieval application. However, if there is more overlap in the areas of expertise, or if the agents have only limited knowledge of each others expertise areas, then the blackboard model may be more appropriate. We expect this to be a general result, providing a basis for the selection of architectures for future distributed systems in other domains.

For our application the results conflict somewhat with Belkin et al's simulation conclusions. This was partly due to the different way they counted messages for the blackboard case (where each message posting was counted, but not each reading). However, we should explore further whether our conclusions have been influenced by the particular, artificial nature of our dialogues.

These experiments are just the first stage in developing a distributed model of an information retrieval intermediary, and in testing a general theory of communication. They demonstrate a particular empirical methodology for the development of agent architectures, appropriate for a wide range of projects. In our own work the next stage is to develop a more realistic information retrieval system, working with an actor architecture.

References