A Multi-Agent Framework for Stock Trading

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Abstract
A requirement analysis for the portfolio management in the stock trading has presented a conduct viability and theoretical foundation for a stock trading system. The overall portfolio management tasks include eliciting user profiles, collecting information on the user's initial portfolio position, monitoring the environment on behalf of the user, and making decision suggestions to meet the user's investment goals. Based on the requirement analysis, this paper presents a framework for a Multi-Agent System for Stock Trading (MASST). The key issues it addresses include gathering and integrating diverse information sources with collaborating agents, and providing decision-making for investors in the stock market. We identify the candidate agents and the tasks that the agents perform. Agent communications and exchange of information and knowledge between agent has been described in this paper.
Key Words: Stock management, Multi-agent system, Decision support system, KIF, KQML.

1. Introduction and Background

The stock market is one of the most popular investing places because of its expected high profit. The Internet, Web, and other information technologies have brought in and will continue to have a dramatic effect on the stock market. Various types of financial information and stock trading become available to investors from the Internet. However, the information available from the Internet is disorganised and distributed over many server sites. The variety of data sources is dramatically increasing and constantly changing. Therefore, information becomes increasingly difficult for an individual investor to collect, filter, evaluate, and use for decision-making in stock trading. As a result, the problem of locating information sources, accessing, filtering, and integrating information in support of decision making has become a critical task.

In their analysis of the portfolio management domain, Decker *et al.* (1996) point out that the fundamental task is that of providing an integrated financial picture for the management of an investment portfolio over time, using the information resources already available over the Internet. Central to this task is the provision of the best possible rate of return for a specified level of risk, or conversely, to achieve a specified rate of return with the lowest possible risks.

Agent technology is especially suited to the issues that need to be addressed in designing computational systems for the portfolio management. Rus and Subramanian (1997) present a customisable architecture for software agents that capture and access information in large, heterogeneous, distributed electronic repositories. The key idea is to exploit the underlying domain structure at various levels of granularity to build high-level indices with task-specific interpretations. Information agents construct such indices and are configured as a network of reusable modules called structure detectors and segmenters. They illustrate their architecture with the design and implementation of smart information filters in two contexts: retrieving stock market data from Internet newsgroups and retrieving technical reports from Internet FTP sites.

Benos and Tzafestas (1997) present a methodology of studying the complex phenomena emerging in stock markets. Their methodology is based on the use of distributed multi-agent models with limited knowledge representation and reasoning capabilities that have proven to be a powerful modelling tool for complex biological systems. Unlike neural models, they report that their models allow a comparative and incremental evaluation of validity and relevance to the observed phenomena. The feasibility of their application for the modelling and study of stock market phenomena has been demonstrated with a simple example of a central agency that regulates the behaviour of the investors.

Bui and Lee (1999) propose a framework for building decision support systems using software agent technology to support organisations characterised by physically distributed enterprise-wide, heterogeneous information systems. Intelligent agents have offered tremendous potential in supporting well-defined tasks such as information filtering, data mining and data conversion. They propose a taxonomy of agent characteristics that can be used to help identify the type of agents needed to support different types of decision tasks. They advocate a goal-directed, behaviour-based architecture for building co-operative decision support using agents.

Delgado *et al.* (1999) investigate a hybrid learning system that combines different fuzzy modelling techniques. In order to implement the different methods, they proposed the use of intelligent agents, which collaborate within a multiple agent architecture. This approach, involving agents that embody the different problem solving methods, is a potentially useful strategy for enhancing the power of fuzzy modelling systems.

Even though there are several agent-based approaches reported in literature, which address the issues in the financial trading domain, the use of intelligent agents to support decisions has not been thoroughly explored and merits serious consideration. In current practice, portfolio management is carried out by investment houses that employ teams of specialists for finding, filtering and evaluating relevant information. Based on their evaluation and on predictions of the economic future, the specialists make suggestions about buying or selling various financial instruments. The current practice, as well as software engineering considerations, motivates our research in multiple agent systems for the stock management. A multiple agent system approach is natural for portfolio management because of the multiplicity of information sources and the different expertise that must be brought to bear to produce a good recommendation for a stock buy or sell decision.

In the rest of this paper, we present the requirement analysis for the task domain of stock management. Based on the requirement analysis, we propose a framework comprising of multiple task-specific agents that together will be capable of performing decision support in the stock trading. We present an analysis of how the agents communicate with each other and exchange information and knowledge by using an agent communication language based on KIF-KQML.

2. Requirement Analysis for Stock Management Systems

The overall task in the portfolio management, as stated by modern portfolio theory (Markowitz, 1991), is to provide the best possible rate of return for a specified level of risk. Sycara *et al.* (1996) pointe out that portfolio management has several components, which include eliciting (or learning) user profile information, collecting information on the user's initial portfolio position, and suggesting and monitoring stock allocation to meet the user's current profile and investment goals.

The stock market is a complex system. Stock price movements are affected by many financial and human factors. Two common analytical approaches are fundamental analysis and technical analysis. A fundamental analysis relies on the statistics of the macroeconomics data to arrive at an estimate of future business conditions. This includes factors such as interest rates, money supply, inflationary rates and foreign exchange rates, as well as the basic financial status of firms and the daily news. Taking all these into account, the analyst buys those stocks priced below his appraisal threshold. In contrast, a technical analyst pays more attention to historical financial time-series data. Predictions are made by exploiting implications hidden in past trading activities, and by analysing patterns and trends shown in price and volume charts. A technical analyst does not deal with what a firm sells or manufactures, or how it is capitalised. Both fundamental analysis and technical analysis can interpret stock price movements well. The former is usually adopted to predict the long-term stock trend, and the latter is better suited for the short-term stock price movements.

Besides these analytical approaches, artificial intelligence (AI) is widely used to develop new methodologies for time-series predication. Advanced trading systems employ neural networks, fuzzy logic, genetic algorithms, and expert systems. These have been widely used in finance for stock selection, stock forecasting, as well as profit and risk management with proven performance (Kuo, 1998; Saad *et al.*, 1998; Chou *et al.*, 1997; Lee and Kim, 1995).

Based on the discussion above, we desire the basic requirements for a stock trading management system that performs the following tasks:

- Collecting raw stock trading data – the daily opening price, highest price, lowest price, closing price, trading volume, and number of trades.
- Providing technical indicators such as charts analysis, Japanese candlesticks philosophy, and Dow theory. Technical indicators are a group of mathematical equations with simple trading algorithms (Achelis, 1995). Charts analysis is aimed at determining patterns and trends, for example, reversal patterns, hidden in price and volume charts (Qing, 1997). Japanese candlesticks can reflect the mass psychology in a stock market (Nison, 1991). Dow theory explains the financial market behaviour by means of primary, secondary and minor trends (Edwards and Magee, 1974).
- Collecting and updating the fundamental

information concerning the listed companies – such as amount of stock trading volume, after-tax profits, earnings per share, the percentage increase in earnings per share, number of common shares, new products or services, and new management.

- Finding, filtering and evaluating relevant news, reports, and analyst's comments from the environment (the Internet).
- Providing decision support for stock trading - combining technical analysis, fundamental analysis, and artificial intelligent technology, processing the input data, filtering out feasible stocks, and advising a list of stocks for buying, selling or holding.
- Identifying the investment behaviours of the institutional investors. Though the number of the institutional investors in the stock market is small, they play an influential role on the state of the stock market. For individual investors, one of the most essential conditions for success is to understand the investment behaviours of the institutional investors (Luo and Liu, 1999; Baldwin and Rice, 1997).
- Monitoring the status of the given stocks on behalf of users, reporting the technical indicators' status of the given stocks, notifying any abnormal change in trading volume and price according to the user's profile.
- Providing the profits and risks management - calculating profits based on the user's investment, reminding stop-loss for user's holding shares according to user's profile.

3. Organisational Structure of the MASST

We propose a user profile-centric framework as shown in Figure 1. This Multi-Agent System for Stock Trading (MASST) provides a unified environment in which several agents are integrated. These intelligent agents inter-operate to collect, filter, and fuse information from distributed, network-based information sources and to make suggestions to the investors.

The framework aims to provide a secure and private environment for registered users. There are three levels of privacy of the information held in a user profile:

- Public: the public information is available for all registered users.
- Restricted: the user can specify which individuals or groups are allowed to know about the restricted information. The user can exchange the information or opinions with specified users or groups in their common interest.
- Private: the private information is only available to the user's agents and will not be disclosed to other users' personal agents.

One of the key components in this framework is the User Profile Database (UPD), which is dynamic, changing and shared amongst agents within the system. Each user would have his or her own personalised interface agent and an individual user profile, while other agents in the system are shared by all users. The UPD should include information such as the username, password, the group that the user belongs to, the stock list that the user possesses, the stock list that the user is interesting in, trading strategies and styles (such as high risk or conservative), planned tasks, preferences and privacy settings. These agents are assigned to an individual user and must be able to learn a user's interests and behaviour autonomously and adapt to the changing needs of the user over time. The profile is centrally available to all the user's agents.

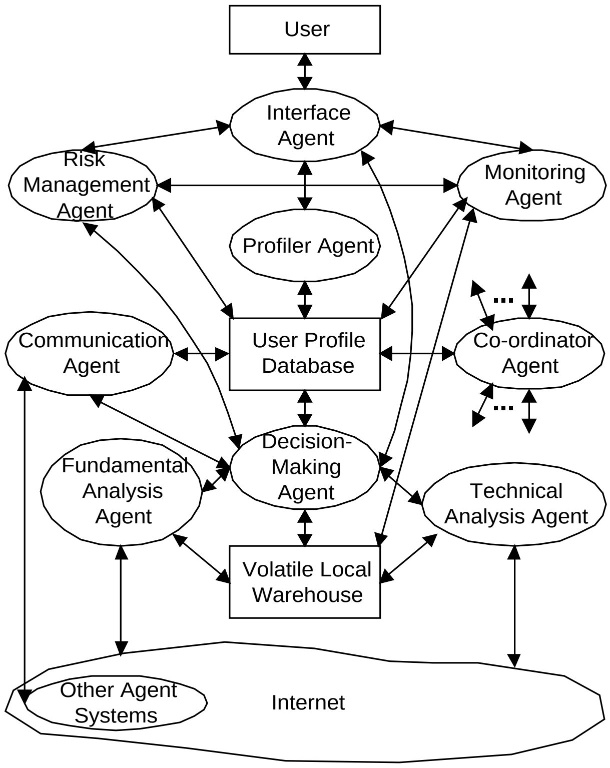

Figure 1. MASST Framework

The Volatile Local Warehouse (VLW) is the internal data resource and is continuously updated with relevant external information by the Technical Analysis Agent and the Fundamental Analysis Agent. The historic trading data, real-time trading data, technical analysis data, and fundamental analysis information are stored in the VLW, which is shared by all agents in the system.

The functions and relationships among the agents in MASST are as follows:

- Interface agent interacts with the user, receiving user tasks and specifications and delivering results.
- Profiler agent provides the mechanism by which a user’s profile is generated and maintained. The profiler agent interacts with the interface agent and monitoring agent to receive information from the user and the environment to determine the interests of the user.
- Monitoring agent monitors the status of the given stocks on behalf of users according to the user’s profile. This agent reports on the technical indicators’ status of the given stocks and notifies any abnormal change in trading volume and price.
- Communication agent allows the framework to interact or communicate with other agents or programmes developed by other developers.
- Risk management agent, on the basis of the user profile, interacts with the monitoring agent and decision-making agent to analyse the risk levels of user’s share holdings, report the profit status and suggest a stop-loss level for the holding shares.
- Co-ordinator agent is responsible for task decomposition and planning. The co-ordinator agent maintains a set of beliefs about the capabilities of all agents in MASST. It can decompose a given task into a number of subtasks and dispatch the subtasks to relevant agents to perform, in order to achieve its goals.
- Decision-making agent combines the outcomes of the technical analysis agent and the fundamental analysis agent, according to the investment strategies selected through the user profile. The decision agent will have three main functions: (1)
- to give a list of stocks advised for the next trading day to buy or sell; (2) to give suggestions for users holding shares to hold or sell; (3) to identify the investment behaviours of institutional investors in the given shares.
- Technical analysis agent retrieves and processes the raw stock trading data from the Internet, calculates various technical indicators, identifies various price and trading volume patterns, and gives the output to decision agent.
- Fundamental analysis agent gathers the macroeconomics data, fundamental financial status of the listed companies, opinions of the market commentators or experts, and some relative news. The fundamental analysis agent integrates this information and makes recommendations to the decision agent.

4. Communication and Knowledge Exchange in the MASST

There are four communications categories in the MASST framework: (1) Internal Agent – Internal Database; (2) Internal Agent – Internal Agent; (3) Internal Agent – External Data; and (4) Internal Agent – External Agent. Here we describe how agents communicate with each other in the framework.

Agents in the framework communicate with each other using the MASST Agent Communication Language (MASST-ACL) that is under development. MASST-ACL is based on Knowledge Query and Manipulation Language (KQML) and Knowledge Interchange Format (KIF). KQML provides the means for exchanging information and knowledge between heterogeneous software agents. KQML is both a message format and a message-handling protocol to support run-time knowledge sharing among agents. KQML allows agents to exchange information in spite of the potentially huge incompatibility across the different internal knowledge representation schemes used in different classes of agents (DARPA, 1993). KIF provides the knowledge-centric means for the interchange of knowledge among disparate programs. It has a declarative semantics (i.e. the meaning of expressions in the representation can be understood without appeal to an interpreter for manipulating those expressions). It is logically comprehensive (i.e. it provides for the expression of arbitrary sentences in the first-order predicate calculus). It provides for the representation of knowledge about knowledge (Genesereth, *et al.* 1994).

```
(ask if  :Language        MASST-ACL
         :Sender          DMA1
         :Receiver        FAA1
         :MessageID       DMA1-FAA1-2
         :Message-Seq     NULL
         :Reply-With      one-of
                          (low, medium, high)
         :Content         “?risk(stockX, medium-
                          term, return-level,
                          RETURN)”)
```

Figure 2: KQML performative example in MASST-ACL. The Decision-Making-Agent (DMA1) asks the Fundamental-Analysis-Agent (FAA1) about the risk associated with stockX over the medium-term for a given return-level.

A full implementation of KQML and KIF would be too complicated and unnecessary for this framework. Based on our preliminary work on decision support in other domains (Davis 2000, Chong and Liu 1999), a limited language set would be required. The MASST-ACL is a subset of KIF-KQML. It makes use of domain-specific performatives and associated structural components. The Sender and Receiver are identified in the message – each message in MASST-ACL requires a unique identifier. The communication sequence that any message is part of is referenced using the message sequence component. Figure 2 and 3 give examples of a message and its reply.

```
(reply :Language        MASST-ACL
       :Sender          FAA1
       :Receiver        DMA1
       :MessageId       FAA1-DMA1-2
       :Message-Seq     DMA1-FAA1-2
       :Content         “risk(stockX, medium-
                        term, return-level, low)”)
```

Figure 3: KQML reply example in MASST-ACL. The Fundamental-Analysis-Agent (FAA1) responds the Decision-Making-Agent (DMA1) message in figure 2, with a modified content that reflects FAA1 processing of the original message.

The message in figure 2 constitutes a new message sequence so that the Message-Seq component takes the NULL value. The Rely-with and Content components make use of KIF. The Rely-With component tells the receiving agent to couch its reply to the content of the request using one of the list of terms. As the content component makes use of the special token RETURN, the receiving agent is expected to reply with a message containing the original content modified by the receiver’s agent processing. Agent FAA1 is expected to reply by replacing RETURN in the content component with one of “low”, “medium” or “high”. Figure 3 shows the reply. In a full implementation of the decision support framework, the message shown in figure 2 would cause the Fundamental Analysis Agent to assess the risk with stockX over a medium-term period (as specified in the User Profile Database) for the expected return-level. This will cause the FAA to either search the Volatile Local Warehouse for information to enable it to perform the requested task or generate a message to update the VLW (or both). On acquiring this information, the FAA can perform its task and reply to the Decision-Making Agent as shown in figure 3.

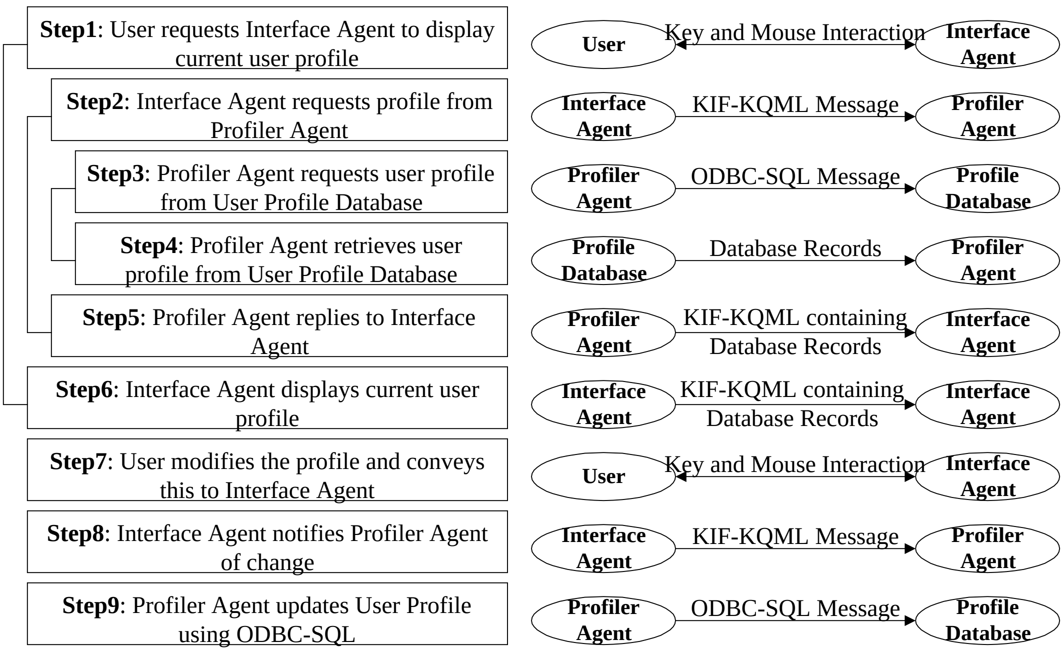

Figure 4: Agent interaction through ODBC-SQL and KIF-KQML communication to modify the user's profile. In a more sophisticated scenario the Interface Agent would request decision enabling information and knowledge from the Decision-Making Agent

Figures 4 and 5 show how the agents interact and communicate in response to a request to change the user profile. Figure 4 shows in fine detail the steps in updating the profile. Figure 5 shows the MASST framework response to the change in the profile. Here the user is using off-line information (from a previous interaction with the system) to modify the user profile. A more sophisticated scenario may require that the user be informed of changes to the stocks and commodities referenced within the user profile before making changes. Although these communication steps are shown as if they occurred in a serial fashion, they are asynchronous. For example in figure 5 step 9 can occur after step 3 while waiting for the results of steps 5,6,7,8 (or vice versa).

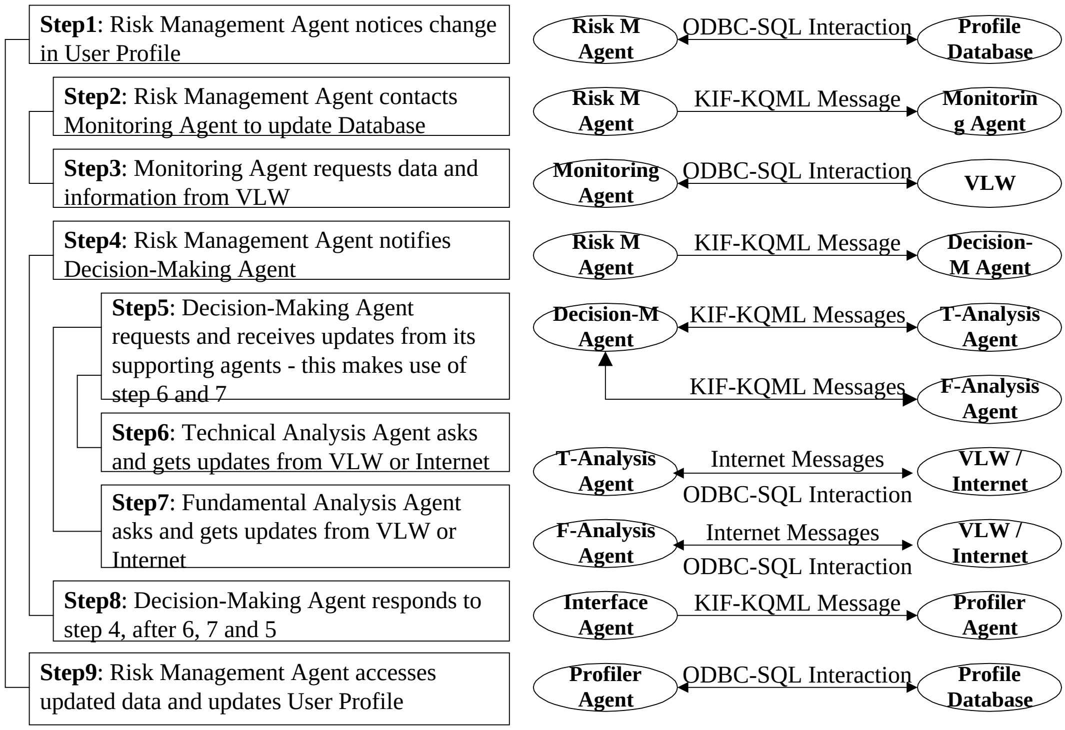

Figure 5: Agent interaction through ODBC-SQL and KIF-KQML in response to the modification of the user's profile. This occurs as a side effects of the steps shown in figure 4

5. Conclusion and future work

We have presented the framework of a multi-agent system for the management of stock trading through information access, filtering and integration. We described the various agent types that are necessary for supporting and seamlessly integrating information gathering from distributed internet-based information sources and decision support. We believe that such a flexible multi-agent architecture, consisting of reusable agent components, will be able to fit the requirements for systems used in stock trading. These requirements include locating, accessing, filtering and integrating information from disparate information sources, monitoring the environment and notifying the investors about events of particular interest in performing the user-designated tasks, and incorporating retrieved information into decision support tasks.

There are many online trading systems that provide basic technical analysis including charts analysis and trading data display in real-time. However, they do not provide intelligent decision-making support. The analysis is actually carried out by the users. They do not adopt the agent approaches and the programmes cannot be executed autonomously like an agent. However, these existing systems can be a useful information source (including the raw trading data, relevant news reports, and the comments from the market analysts) for our agent system. It is feasible for the system to interact with these existing systems.

Further work involves the design and implementation of each MASST agent. There are many difficult issues that need to be addressed. These include how to define the common ontology in the stock trading domain which every agent can share and understand the common domain concepts and how to represent the knowledge in the stock trading domain. The knowledge involved in our agent system includes both quantitative (such as the opening market index) and qualitative knowledge (such as macro-economic states, the opinions expressed in mass media) which can be used for decision support. The representation of the qualitative knowledge is one of the key issues for the future work.

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