Using KADS to Design a Multi-Agent Framework for Stock Trading

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Abstract: A requirement analysis for a portfolio management in stock trading is presented. This provides a 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. A KADS-based analysis of the processes within the framework is described in this paper.

Keywords: Multi-agent system, Knowledge-based system, Stock trading, Decision-making, KADS.

1 Introduction

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 and will continue to have a dramatic effect on the stock market. Various types of financial information and stock trading have 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 increasing dramatically 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 and accessing information sources and 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 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 for 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) investigated 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, these 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, using KADS methodology (Schreiber *et al.* 1993), we identify the overall organisational process that the system will support, present the KADS process model which consists of process decomposition, process distribution, and process glossary. According to the process model, we propose a framework comprising of multiple task-specific agents that together will be capable of performing decision support in stock trading. We present an analysis of how the agents exchange information and knowledge, and the processes the system must support.

2 KADS – Knowledge Acquisition and Document Structuring

KADS is knowledge engineering methodology in which the main concern is with the two phases of analysis and design. The central theme is that of modelling the behaviour of the intended knowledge-based system, the context within which it will work and the framework for more general requirements and constraints.

KADS is a structured approach to the development of knowledge based systems and as such is to be seen in contrast to unstructured approaches such as rapid prototyping. According to KADS, development of a knowledge-based system is to be seen as a modelling process, during which models of the acquired knowledge at different levels of abstraction are developed.

KADS identifies three levels of models. At the process level, the process model identifies the tasks involved in the domain, the nature of data flows and stores, and the assignment of ownership of tasks and data stores to agents. At the system level, the co-operation model describes in detail the interactions between the system and external agents, and how the internal agent interact. The co-operation model can be used to separate the user task model and the system task model. It allows a full description of the knowledge wholly internal to the system. The expertise level corresponds to an expertise model. This divides the task of describing the expertise level of the system into a number of supportive tasks. The four-layer framework for expertise consists of the domain, inference, task and strategic layers. The domain layer is comprised of static or slowly changing knowledge describing concepts, relations, and structures in the domain. The inference layer reformulates the domain layer in terms of the different types of inferences that can be made. The task layer defines knowledge about how to apply the knowledge in these two layers to problem-solving activities in the domain. The strategic layer defines how to select appropriate problem-solving capabilities for specific types of task.

Within this framework knowledge engineering becomes a structured search for appropriate task, inference and knowledge models. This is performed through the use of analysis (the process of generating abstract descriptions of the inference patterns) and design and coding (a process of implementing the details of those patterns).

3 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) points 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 in this case).
- 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.

4 Scoped Organisational Context

MASST is a middle layer agent system situated between the demand side of information (i.e. investors in stock market) and the supply side of information (i.e. the Internet). The major functions of MASST include:

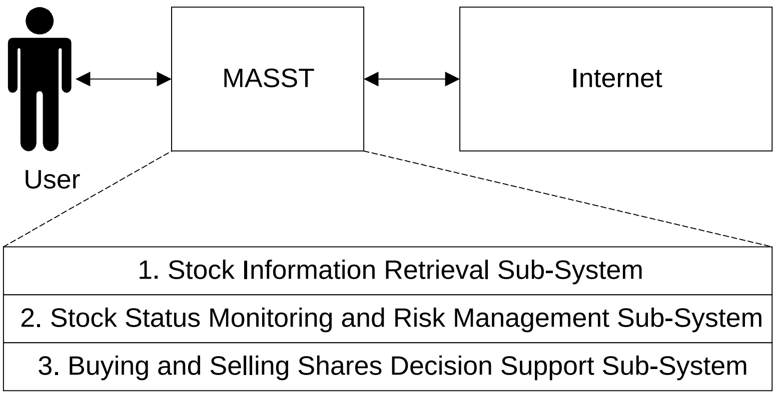

Figure 1. MASST Scoped Organisational Context

- Stock Information Retrieval – this function is not unique to our system. Nowadays many online brokers and commercial stock analysis software can provide this function. Thus our research does not focus on this field. Our system will provide this function because it is a basic requirement of the investors (users). MASST will provide four categories information retrieval: (a) trading history and current quotations, such as the information of Opening Price, Highest Price, Lowest Price, Current Price, Trading Volume for the selected stock on given trading date. (b) browsing stock technical analysis charts, such as price movement chart (for example Candlestick Chart), trading volume chart, and various technical indicators chart. (c) listed company's fundamental data and financial health information retrieval, such as total amount of stock trading volume, after-tax profits, earnings per share, annual earnings increases, number of common shares, new products or services, new management, and the market news. (d) market statistics information retrieval, such as the list of top ten shares of maximum trading volume in the given trading day(s), the list of top ten shares of maximum price upward (or downward), the list of top ten of the lowest Price-Earning Ratios.

- Stock Status Monitoring and Risk Management – MASST will automatically monitor the market status of the shares that the user holds and is interested. The share's market status includes the listed company's fundamental financial status and status of the share's technical indicators. Based on the share's market status, MASST will also automatically and promptly report any abnormal status to users. The abnormal status includes: (a) price fluctuation abnormal; (b) trading volume abnormal; (c) technical indicator's status abnormal, (d) price chart pattern abnormal, and (e) some break news relating to the given shares. Furthermore, MASST will provide the profits and risks management which including calculation of profits/risk ratio based on shares' market status and user's investment, reminder the stop-loss level for user's holding shares according to the user's profile.
- Buying and Selling Shares Decision Support – From the investors' perspective, the most important and concerned issues for investment in stock market are buying share issue and selling share issue. Which share is the best one to buy? What time is the right time to buy the share? And what is the right time to sell your holding shares? It is difficult (maybe impossible) to find an accurate and simple answer for these kind of questions. Every investor has his/her own buying and selling share strategies and rules. MASST will give the buying and selling decision support based on the behaviour rules defined by investors themselves. Combining with human knowledge and machine knowledge, using agent and AI technologies, MASST aims to reduce investors' work overload in the process of stock analysis and investment decision-making.

5 Process Decomposition and Distribution

In this section, the further detail analysis will be carried out for the three major functions of MASST mentioned above. The tasks and data stores associated with the decomposed process will be assigned to different agents.

Figure 2 shows the augmented form of the process of Stock Information Retrieval Sub-System, in which the process decomposition with tasks and data stores are assigned to Interface Agent (in green), Technical Analysis Agent (in grey), and Fundament Analysis Agent separately (in yellow). Figure 3 shows the process glossary definitions of some notations and data entities used in Figures 2, 4, 5, 6, 7 and 8.

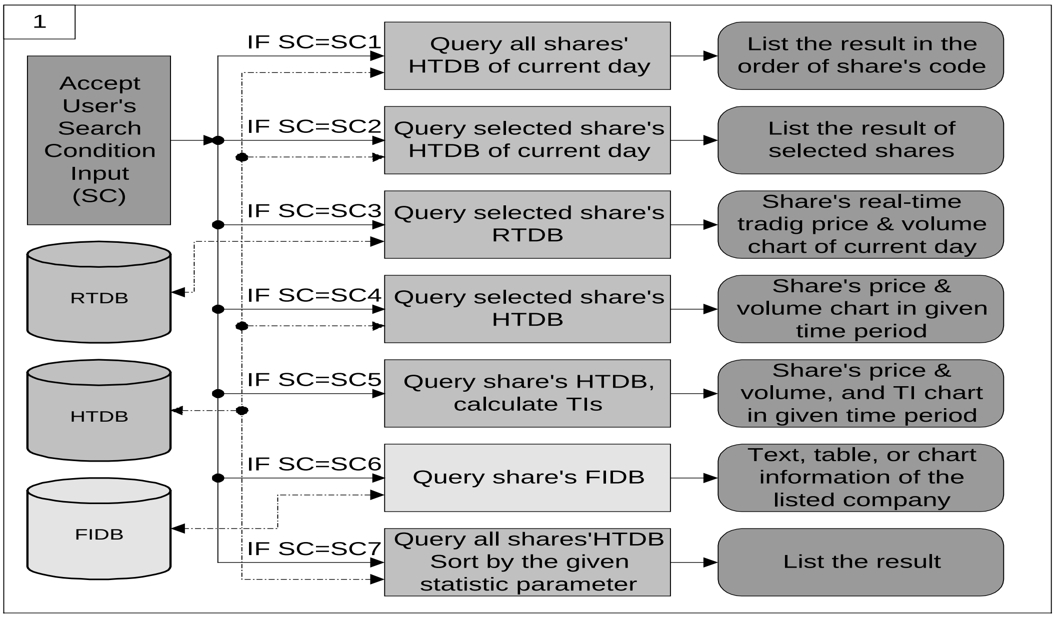

Figure 2. Stock Information Retrieval Sub-System. Tasks assigned to Interface Agent (in green), Technical Analysis Agent (in grey), and Fundament Analysis Agent (in yellow)

The History Trading Database (HTDB) holds every share's day-trading raw data, the data fields include Opening Price, Highest Price, Lowest Price, Close Price and Trading Volume. Every trading day's data is a record in the data form. Every share has a form in the database. Real-time Trading Database holds every share's real-time trading data in a trading-day. The data fields include Opening Price Highest Price, Lowest Price, Current Price, Current Trading

Volume, Accumulating Trading Volume, Current Bid Price and Volume, Current Ask Price and Volume. Fundamental Information Database (FIBD) holds listed company's fundamental data and financial health information, such as total amount of stock trading volume, after-tax profits, earnings per share, annual earnings increases, number of common shares, new products or services, new management, and the market news, etc. FIDB consists of text files that contain the listed company's fundamental information. There are several decades of Technical Indicators (TIs) which are used in stock technical analysis, such as MACD (Moving Average Convergence/Divergence), RSI (Relative Strength Index), MFI (Money Flow Index). The MASST can provide users with most of the technical indicators in common use.

A ::= B		*means 'A is defined in terms of B'*
A + B		*means 'A and B'*
A | B		*means 'A or B'*
SC	**::=**	**Search Condition**
SC1	::=	Market-Name | Market-Code
SC2	::=	SC1 + Share-Name | Share-Code
SC3	::=	SC2 + Real-Time-Chart
SC4	::=	SC2 + Day-Chart | Week-Chart | Month-Chart + Period
SC5	::=	SC4 + Technical-Indicator(s)
SC6	::=	SC2 + Fundamental-Data
SC7	::=	SC1 + Statistic-Parameter
HTDB	::=	History Trading Database
RTDB	::=	Real-time Trading Database
FIDB	::=	Fundamental Information Database
TI	::=	Technical Indictor
UPDB	::=	User Profile Database
BSRDB	::=	Buying and Selling Rules Database which are defined by users

Figure 3. Process Glossary Definitions

5.1 Stock Status Monitoring and Risk Management Sub-System

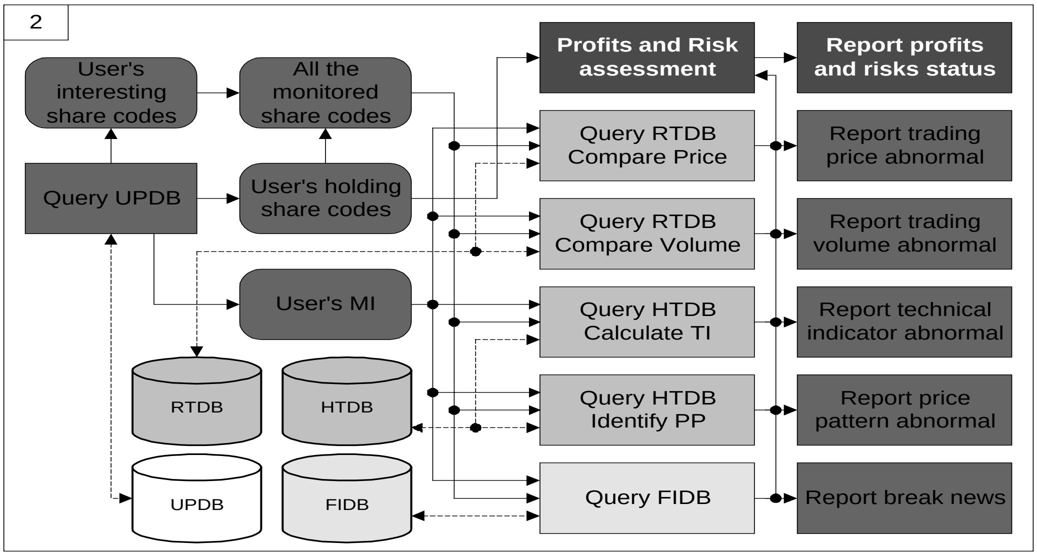

Figure 4. Stock Status Monitoring and Risk Management Sub-System. Tasks in lilac assigned to Monitoring Agent. Tasks in red assigned to Risk Management Agent. Others as per figure 2.

Figure 4 shows the Stock Status Monitoring and Risk Management Sub-System's process decomposition with tasks and data stories assigned to agents. Both user held and user-interested (but not held) share codes are stored in User Profile Database (UPDB). The Monitoring Agent can get all the monitored share codes by requesting UPBD every trading day. MASST provides the five kinds of abnormal status' monitoring functions described above. The user must define what the abnormal status is. For example, if the user wants MASST to monitor the selected shares' price abnormal status, the user should define what price level is the abnormal price (appraisal threshold) for each share. The user can deliver monitoring tasks by giving the Monitoring Instructions (MI) which are any combinations of these five functions and related abnormal status definitions. User's Monitoring Instructions are also stored in UPBD. Monitoring agent will interact with Technical Analysis Agent and Fundamental Analysis Agent in order to complete the monitoring tasks assigned by user, and the reports of abnormal status will be presented to user through Interface Agent. Risk Management Agent will continuously assess the profits status and risk level of user's holding shares by interacting with Monitoring Agent.

5.2 Buying and Selling Share Decision Support Sub-system (BSSDSS)

The overall architecture of BSSDSS is shown in Figure 5. This sub-system is, in fact, the intelligent stock selection and assessment decision support system. The stock market is a complex system. 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.

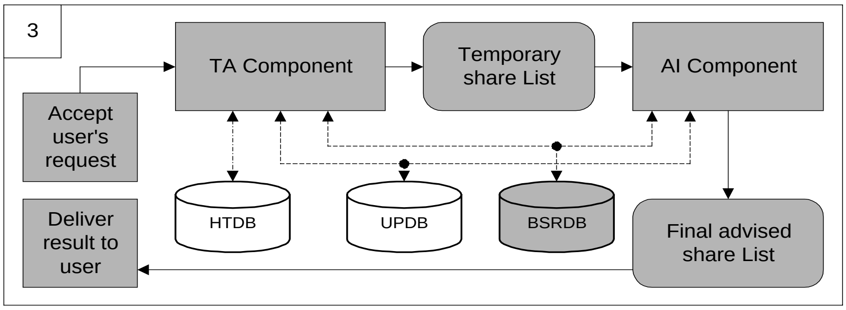

Figure 5. Overview Architecture of BSSDSS. Tasks in blue assigned to the Decision Making Agent.

There are two main components in our BSSDSS. A Technical Analysis (TA) component is responsible for pre-processing the market raw trading data, filtering out feasible shares and advising a list of shares for buying or selling. The second component is the Stock Selection (SS) component, which plays the role of an experienced trader to refine the advised share list produced by the TA component. Thus, the activities of BSSDSS can be divided into two major stages. In first stage, the TA component pre-processes the raw trading data of each given stock and gets a temporary share list with the highest potential. In the second stage, the AI component makes its own judgement of the market based on financial data and combines it recommendation with the output of the TA component to give a final list of shares advised for the next trading day.

5.2.1 Technical Analysis (TA) Component

Figure 6 shows the TA Component in detail. There are six main functional blocks in the TA Component including risk assessment, number of trades assessment, correlation between the particular stock and the market assessment, stock trend assessment, stock price assessment, and trading time assessment.

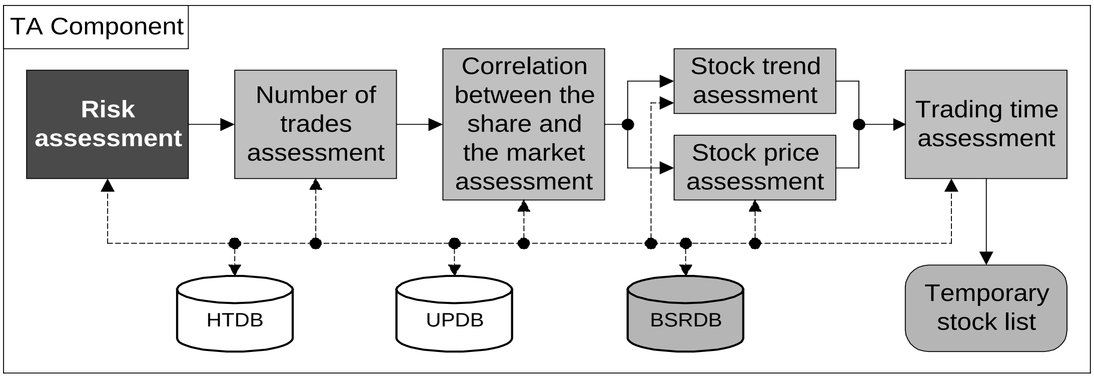

Figure 6. TA Component

The Risk Assessment block takes risk evaluation. Risk evaluation is the first thing investors have to do when they invest in any financial market. BSSDSS throws out the relatively high-risk shares in order to keep the profit/risk ratio under control. The number of trades assessment block will measure the average number of trades in a short trading period. The number of trades reveals the popularity of the stock. If the average number of trades for a stock is too small, the stock can easily be controlled by institutional investors. It is better to avoid these stocks because most of the technical indicators are based on mass psychology and cannot work well for these stocks. The correlation between an individual stock and the market trend assessment block will take into account the relative stock trend as compared with the weighted stock price index. In those relatively small stock markets, the money supply is limited. A major trader who invests a lot of money in the market can dominate some stocks price. BSSDSS judges this condition by evaluating the price movement between the given stock and weighted stock price index. If the price of the given stock moves against the weighted stock price index for more than half of the trading days in a given trading period, BSSDSS throws it out.

The stock trend assessment block measures the current stock trend and assumes the trend will continue. Hence, if a stock is on an up trend, BSSDSS marks it with a buying tag. Conversely, if the stock in on a down trend, the stock is marked with a selling tag. BSSDSS throws out stocks which have no significant trend.

The stock price assessment block evaluates the stock's value, and assumes the stock price will reverse if it is too high, or too low. BSSDSS puts a selling tag on the overvalued stocks, or a buying tag on the undervalued stocks, and throws out the rest. The trading time assessment block determines whether it is a good time to trade or not. BSSDSS suggests to buy (sell) those stocks with buying (selling) trading signals and buying (selling) tags.

5.2.2 The Stock Selection Component

The stock selection component finalises the list of selected stocks based on fuzzy decision rules. It plays the role of an experienced trader to double-check the stocks picked by the TA component. It is built upon fuzzy rules in the form of induction trees. There are two induction modules in this component, namely, a buying induction module and a selling induction module. Figure 7 shows the functional blocks of this component. The fuzzy pre-processor block first transforms numerical input data to symbolic attributes with fuzzy degrees. Then BSSDSS uses the buying and selling induction module to abstract matching rules for buying and selling decisions. Finally, the inference engine combines the suggestion of the TA component and the consequence of two induction modules and then outputs the final suggestion by voting.

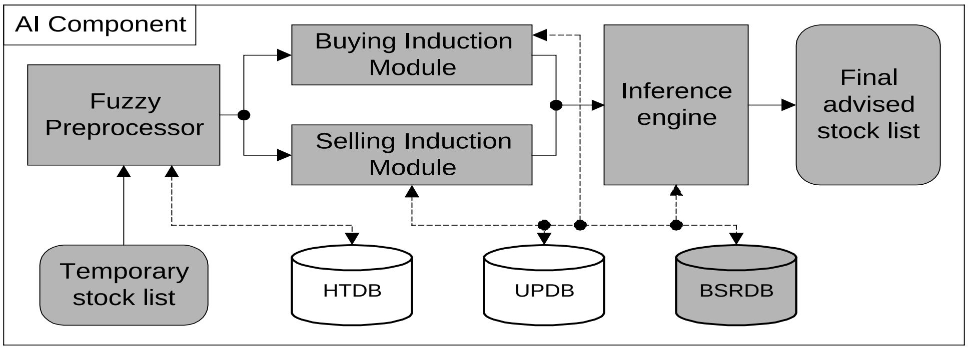

Figure 7. The stock selection Component

6 MASST Framework

Based on the process analysis above, we are implementing the MASST framework as shown in Figure 8. MASST provides a unified environment in which a number of agents are integrated. These intelligent agents inter-operate to collect, filter, and fuse information from distributed, network-based information sources and to make buying and selling decision suggestions for investors in their daily stock trading. 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 (UPDB), which is dynamic, changing and shared amongst agents within the system. Each user would have his or her own personalised interface agent, an individual user profile and BSRBD, while other agents in the system are shared by all users. The UPDB 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, monitoring instructions, 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.

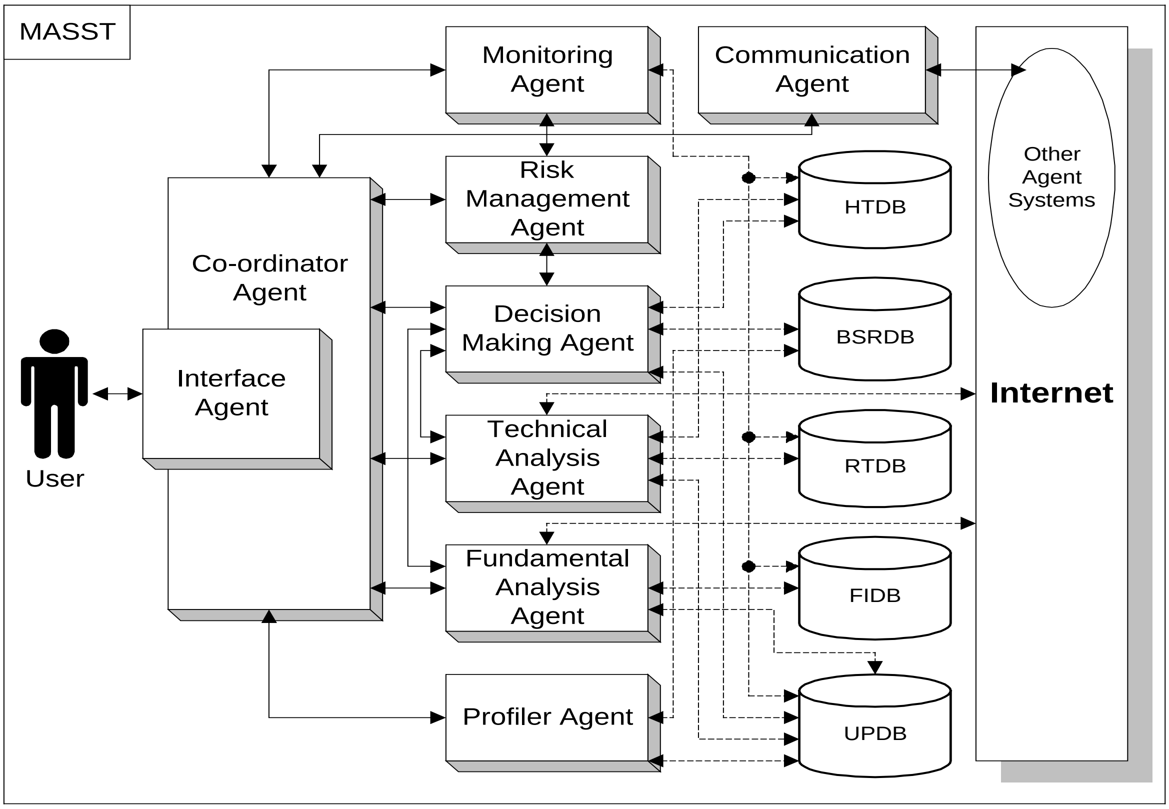

Figure 8. MASST Framework

The HTBD, RTDB, FIDB combine to form a volatile local warehouse which is the internal data resource and is continuously updated with relevant external information by the Technical Analysis Agent and the Fundamental Analysis Agent. 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. Interface agent pass user's tasks to and get returns from co-ordinator agent.
- 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.
- Profiler agent provides the mechanism by which a user's profile and BSRDB are generated and maintained. The profiler agent interacts with the co-ordinator 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. This is a reserved interface to other systems.
- 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.

- 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's BSRBD. The decision agent will have two main functions: (1) to give a list of stocks advised for the next trading day to buy; (2) to give suggestions for users holding shares to hold or sell.
- Technical analysis agent retrieves and processes the raw stock trading data from the Internet, store the raw data to relevant database (HTDB, RTDB), 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, put these information into FIDB. The fundamental analysis agent integrates this information and makes recommendations to the decision agent.

7 Conclusion and Future work

This paper describes the design of a mulit-agent framework (a knowledge-based system) for stock trading which would assist investors in decision-making of investment that would meet the investor's requirements. The development of this framework is to be guided by KADS methodology. It has been shown that the contribution of KADS is most influential and pervasive during the knowledge acquisition and analysis stages. KADS is therefore considered to be a valuable tool in the hands of KBS developers. Its greatest strengths lie in the provision of a structure, which can be used as a starting point for system development.

In this paper 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 approach and the programmes cannot be executed autonomously. 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 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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