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Expert system for predicting stock market timing using a candlestick chart

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Abstract

It has been one of the greatest challenges to predict the stock market. Since stock prices vary dramatically, it is important to determine when to buy and sell stocks in order to get high returns from stock investment. In this study, we have developed a candlestick chart analysis expert system, or a chart interpreter, for predicting the best stock market timing. The expert system has patterns and rules which can predict future stock price movements. Defined patterns are classified into five groups with respect to their meanings: falling, rising, neutral, trend-continuation and trend-reversal patterns. The experimental results revealed that the developed knowledge base could provide excellent indicators with an average hit ratio of 72% to help investors get high returns from their stock investment. Through experiments from January 1992 to June 1997, it was proven that the developed knowledge base was time- and field-independent.

Keywords: Expert system; Candlestick chart; Stock investment

1. Introduction

Determining stock market timing, when to buy and sell, is a very difficult problem for humans because of the complexity of the stock market. The Korean stock market has experienced dramatic changes since the late 1980s. The large number of stocks traded, and the changes in market environments have increased the complexity of the Korean stock market. Further, because financial and investment areas were opened to foreigners, the complexity of the stock market increased even more. As the Korean stock market has become larger and more complex, traders and investors in the stock market have come to need powerful assistants in their decision making. However, traders and investors are in great need of experts in the stock market; human capability in analyzing all the data could not satisfy our expectations. Thus, for better prediction of the stock market, expert systems which have scientific, organized and fast stock analysis methods have received special interest. Since the late 1980s, some researchers in finance and investment have begun to use other Artificial Intelligence (AI) technologies as well as expert systems for predicting the stock market.

AI techniques applied to stock market can be classified into four groups: neural networks, genetic algorithm, fuzzy logic and expert system. These methods have revealed excellent results over the traditional method, statistical analysis. But each method has its own advantages and disadvantages.

Neural networks have three major advantages: (1) nonlinearity, (2) robustness, and (3) adaptivity. But they also have disadvantages: (1) lack of explanation capability, (2) difficulty in designing models (Kamijo and Tanigawa, 1990; Park and Han, 1995; Yoda, 1994). Genetic algorithms (GAs) have potential benefits such as search, optimization, and machine learning. However, there are some problems such as lack of flexibility (Mahfoud and Mani, 1995; Goldberg, 1989). Fuzzy logic allows for the inclusion of trading rules provided by traders and provides for explanatory capability of the trading recommendation provided by the system. It can avoid reliance on quantitative data extremely. But there is no learning capability (Benachenhou, 1994; Man and Bolloju, 1995). Expert systems (knowledge-based systems) can explain market status, interpret patterns and be helpful to investors' decision making. The main shortcoming of knowledge-based systems is the difficulty in acquiring domain knowledge. However, expert systems can be more efficient than the other methods if they have high-quality knowledge which is organized and well formalized (Beckman, 1991; Yamaguchi, 1987; Yamaguchi and Tachibana, 1991; Yamaguchi and Tachibana, 1993).

Generally, there are two types of problems to be solved in stock investment: stock selection and stock market timing. Stock selection deals with selecting stocks which will give

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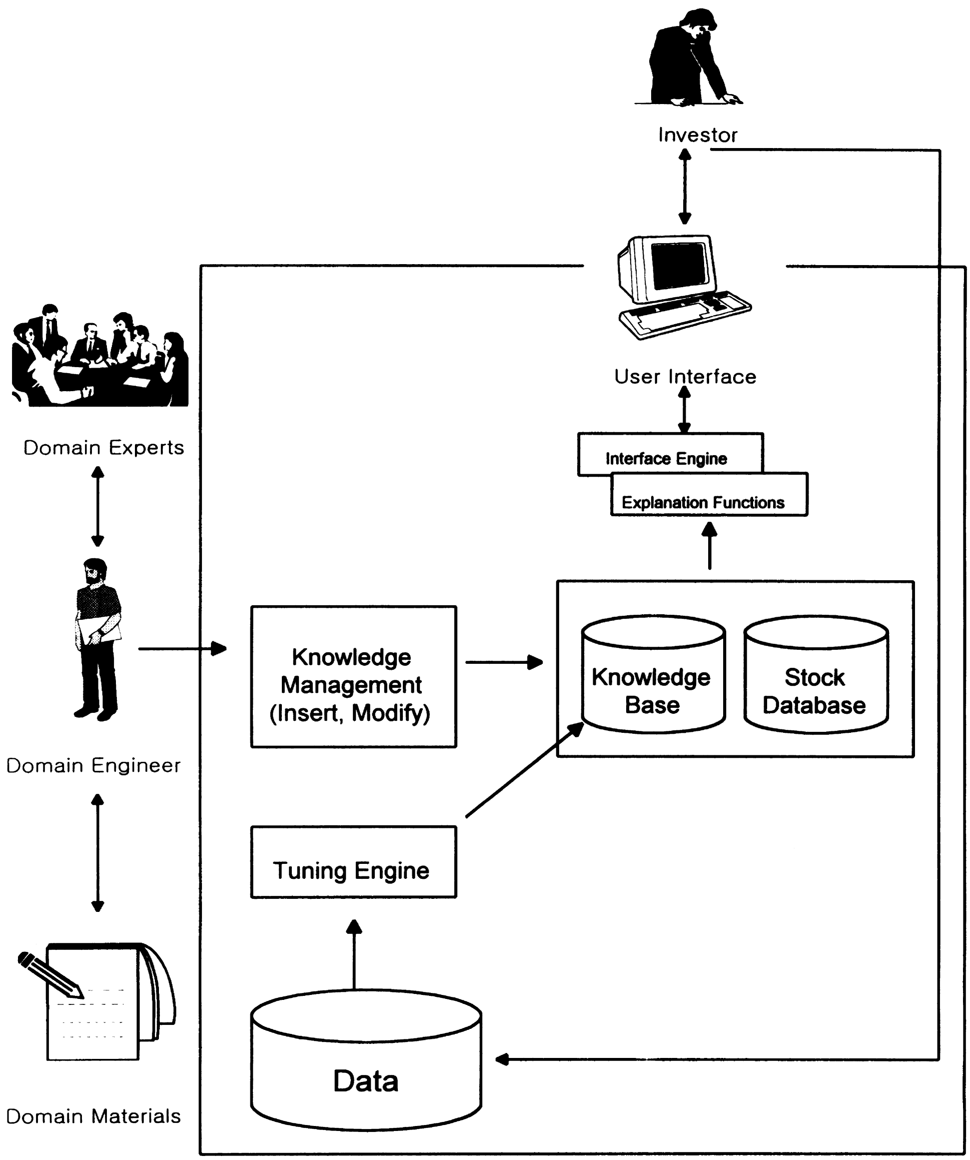

Fig. 1. The architecture of the expert system for predicting stock market timing.

us high returns. Stock market timing refers to determining the best time to buy and sell stocks, assuming that stock prices fluctuate repeatedly.

In this study, as an effort to improve the performance of determining the Korean stock market timing, the expert system which uses the knowledge on a candlestick chart analysis was developed. A candlestick chart is a Japanese-style chart used to visualize the stock price patterns. Using this candlestick chart, useful stock price patterns which could imply stock price movements were defined, and sales rules generated based on the patterns. With the patterns and the sales rules, the developed expert system performs the function of supporting stock investors to make the right decisions in determining the stock market timing.

The remaining sections of the article are organized as follows. In Section 2, the structure of the expert system presented in this study will be explained. Section 3 shows the experimental results for hit ratios according to defined rules, pattern sizes and companies. Section 4 compares this study with previous works and discusses several issues related with predicting the stock market timing based on stock price patterns. Section 5 is the conclusion.

2. System architecture and knowledge representation

2.1. System architecture

The basic architecture of the expert system for determining stock market timing is shown in Fig. 1. The developed expert system consists of five components. The function of each part is as follows:

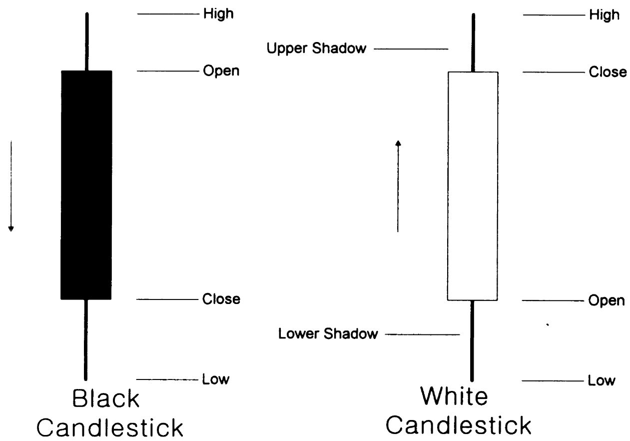

Fig. 2. The shape of a candlestick.

1. *User interface* is a window through which an investor can exchange information with the system.
2. *Inference engine* and *explanation function* provide automatic pattern recognition and interpretation of patterns. With the help of this information, investors can make a decision to buy or sell stocks.
3. *Knowledge base* is represented by rules from a knowledge engineer who collects and summarizes related knowledge and information from domain experts. This component is the key which determines the quality of this system; how well the knowledge base is organized and qualified determines the predicting power over the stock market. To construct a knowledge base for predicting stock market timing, meaningful stock price patterns which could indicate future price movements were observed in a candlestick chart and sales actions were added to sales rules according to the meanings of the patterns. *Stock database* is a database related to past stock performance.
4. *Case base* is collected from real invested results. It can be used to fine tune the knowledge in order to adapt to a dynamic situation.
5. *Tuning engine* adjusts the knowledge after analyzing recent market trends from the case base. In a dynamic situation, continuous knowledge-tuning is needed because old knowledge can no longer be useful.

2.2. Knowledge category

Generally, the type of knowledge in the stock market can be classified into three categories: expert's heuristic knowledge, technical knowledge and fundamental knowledge (Chu and Kim, 1993).

The following is an example of expert's heuristic knowledge: ''If oil prices decrease, then the paint, plastic, chemical fiber industry will improve.'' However, expert's heuristic knowledge is subjective and the performance different from experts to experts. More objective knowledge is needed to apply the information to real stock investment. In this study, the expert's heuristic knowledge is excluded to reduce the risk of an investment.

Technical knowledge is elicited by technical analysis such as chart analysis. A candlestick chart analysis was used in order to elicit technical knowledge in this study. A candlestick chart is a useful tool to visualize the stock prices so that investors can detect patterns which can be used to predict future stock price movements. As illustrated in Fig. 2, a candlestick consists of a rectangle and two shadow lines. The rectangle which is called the ''real body'' indicates the difference between the opening value and the closing value of a stock. If the real body of a candlestick shows that the opening value is higher than the closing value, the candlestick is called a ''white candlestick''. Inversely, if the closing value is higher than the opening value, the candlestick is called a ''black candlestick''. The white candlestick implies a rising signal of a stock price and the black candlestick implies a falling signal. The stock price patterns which are represented by the candlestick shapes give important clues to predict future stock price movements. Thus, the technical knowledge from a candlesticks chart was used as a key information to develop the expert system for predicting stock price movements in this study. The knowledge from a candlesticks chart analysis shows that ''if a certain pattern occurs, then the stock price will increase (or decrease)''. To elicit knowledge from candlestick charts, several aspects such as formalization of pattern definition, automatic recognition of patterns, rule generation based on the patterns and performance evaluation of the rules are to be considered (Chu and Kim, 1993).

The fundamental knowledge consists of information such as the numeric data and the categorical data obtained from periodical reports. The information is stored in the database, and can be used for knowledge generation and knowledge tuning which adjusts the knowledge to the dramatic changes of the stock market. In this study, the fundamental knowledge was excluded because this study concentrates on the prediction of stock price movements based on stock price patterns.

2.3. Knowledge representation

To formalize useful stock price patterns for predicting future stock price movements in a candlestick chart, one has to first observe the stock price patterns which occur frequently in a candlestick chart. Then the relationships between the observed stock price patterns and the price movements after one week are examined. Finally, if the price patterns and the price movements which have strong connections between them are elicited from examined results, a knowledge base for predicting stock market timing can be constructed. To represent the price pattern in a more organized and systematic way, the price patterns were classified into primitive and composite patterns. Primitive patterns which have relatively simple conditions and attributes were used in defining composite patterns. This means

```
PATTERN pattern_name
  IF      condition_A
  (AND    condition_B)
  (OR     condition_C)
  ...
  THEN PATTERN = pattern_name
         EXPLANATION = statement_A
```

Fig. 3. The syntax of a primitive pattern.

that composite patterns can have a hierarchy among patterns. In this study, notice that the pattern itself can be considered as the representation of a rule. According to the meaning of the pattern, a sales action to buy or sell stocks is added to pattern representation in order to define a sales rule. However, the conditions of a pattern can be conditions of a rule in the rule representation. Therefore, that patterns can have a hierarchy of patterns means that rules can also have a hierarchy of rules. In this article, pattern and rule will be used as interchangeable words. The main reason behind giving the patterns a hierarchy is to have flexibility in defining patterns, to overcome the difficulty in representing the changes of pattern definitions and to maintain the representations of patterns efficiently.

Figs. 3, 4 and 5 show how defined patterns are constructed. The syntax of a primitive pattern has the reserved words such as PATTERN, IF, AND, OR, and EXPLANATION, as illustrated in Fig. 3. If the input stock data are matched with ‘‘IF conditions’’ of a particular stock price pattern, the pattern is identified by the conditions. The EXPLANATION part gives the information about what the pattern really means. The primitive pattern itself has its own meaning and can be an important clue in predicting future stock price movements. For example, if condition_A, when the closing value of a stock price is lower than the opening value, is satisfied, the occurring pattern is identified as a *Black* pattern which indicates a falling signal.

A pattern can have a hierarchical structure as depicted in Figs. 4 and 5. That is, a pattern can be represented by the composition of simpler subpatterns, and the subpatterns can

```
PATTERN pattern_name
  IF pattern_A
  (AND pattern_B)
  (OR pattern_C)
  (AND condition_A)
  (AND condition_B)
  ...
  THEN PATTERN = pattern_name
         EXPLANATION = statement_A
```

Fig. 5. The syntax of a composite pattern.

be described by even simpler subpatterns. It means that bigger concepts are constructed by small concepts in a bottom-up approach, as illustrated in Fig. 4 in which a pattern is depicted as a rounded rectangle and a condition is depicted as a rectangle. For example, the *Bullish Harami* pattern has a *Big Black* and a *White* pattern as subpatterns. A *Big Black* pattern has a *Black* pattern as its own subpattern. The *Bullish Harami* pattern with the hierarchy implies a rising reversal signal which is different from the individual meanings of subpatterns, *Big Black*, *Black* and *White* patterns in the context of the various subpatterns.

The stock price pattern on a candlestick chart has the special feature that it has a dynamic nature. That is, two patterns having a similar shape can have different meanings according to how long the patterns keep their shapes. Therefore, the attributes that describe a primitive pattern should contain the duration of primitive as well as the special conditions. ‘Pattern size’ refers to the duration that a pattern can have. In this study, defined patterns can cover from one to five days. Patterns, as illustrated in Fig. 6, can have price shapes with different pattern sizes. For example, a *Big Black* pattern with a duration of 1 implies a falling signal, but a *Big Black* pattern, which is shown in the *Bullish Harami* pattern with a duration of 2, is part of the contextual meaning of the *Bullish Harami* pattern, thereby losing the *Big Black* pattern’s own meaning. Also, when a pattern has a long duration, the conditions of the pattern increase and the pattern can have more subpatterns.

As shown in Table 1, defined stock price patterns are

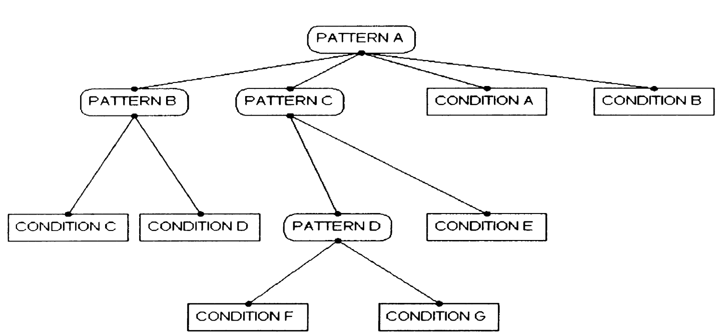

Fig. 4. The hierarchy of a composite pattern.

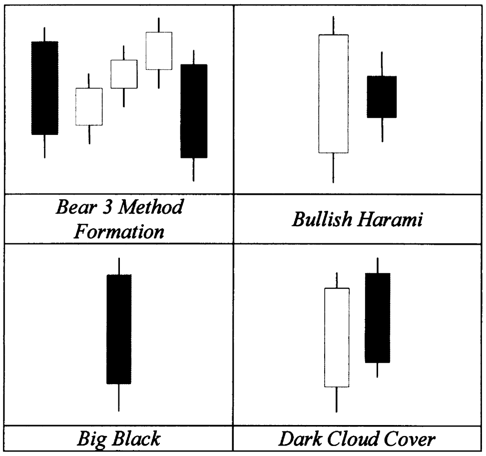

Fig. 6. Examples of patterns for predicting stock market timing.

classified into rising, falling, neutral, trend-continuation and trend-reversal. Trend-reversal patterns have the highest proportion among all the patterns. Neutral patterns are helpful in interpreting the stock market, but do not affect the final sales actions—whether to sell or buy stocks. As neutral patterns do not give information that suffices to judge whether a particular stock price will increase or decrease, sales rules depend on what the patterns actually mean. For example, when a *Big Black* pattern occurs and we have corresponding stocks, we have to make the decision to sell them because a *Big Black* pattern implies a falling signal.

Fig. 7 shows that defined rules in the knowledge base are based on predefined stock price patterns. It means that the corresponding sales rule has to be changed based on the change of meaning of the pattern. In order to determine an increasing or decreasing trend of a stock, a moving average line of closing values of stock prices was used. If the moving average line of closing values of a corresponding stock has a positive slope, it means that the stock price has an increasing trend. Otherwise, it means that the stock price has a decreasing trend.

3. Experimental results

The expert system for determining the stock market timing is implemented through an object-oriented PASCAL programming tool, DELPHI which could represent the hierarchy among patterns, design them efficiently, implement the user interface easily and reuse the codes efficiently. The test data set used for prediction covers the period from January 1992 to June 1997. From all the listings in the stock market, two companies from each area were selected at random. We have tried to experiment with the performance of the expert system for as long a period as possible in order to find the relationship between the defined rules and time. Throughout the five and half years of test data, the usefulness of defined rules was proven. The unit test data is a sequence of a code, a date, an opening price, a maximum price, a minimum price, a closing price, as well as up and down trends of a stock price.

As a method to evaluate the usefulness of the developed knowledge base, we observed the results that calculated the difference in price between the listed price at a sale point based on the defined rules and the listed price after one week. Generally, in the Korean stock market, the domain experts evaluate and analyze stock market movements using 6, 12, 25 or 75 d as a time unit. As the defined rules are designed for short-term forecasting of stock price movements, a 6-day stock market movement is used as the evaluation time unit in this study. The price difference after 6 d indicates whether the defined rule is successful or not. The hit ratio is defined as hit frequency/total frequency of a pattern. If the hit ratio of the pattern is above 51%, the rule for the pattern is regarded as useful and feasible knowledge. It means that investment according to the rule can result in a good profit.

Table 2 shows that 21 defined rules are very reliable. The average hit ratio of applied rules was about 72%. It implies that high returns can be obtained from investments according to developed rules for patterns. Even though 40 patterns

Table 1
The pattern classification according to the meanings of patterns

Pattern group	The number of defined patterns	Corresponding patterns
Falling	6	Bigblack, black, risingwindow, shavenbottom, 3 blackcrows, tweezerbottoms
Rising	5	Bigwhite, shavenhead, 3 whitesoliders, tweezertops, white
Neutral	3	Doji, dojistar, spinningtop
Trend-continuation	4	Bear3formation, bull3formation, fallingwindow, separatingline
Trend-reversal	22	Bearharami, bearharamicross, bullharami, bullharamicross, darkcloud, engulfingbear, engulfingbul, eveningdojistar, eveningstar, gravestondoji, hammer, hangingman, invblackhamme, invhammer, longleggeddoji, longlowershadow, longuppershadow, morningdojistar, moringstar, onneckline, piercinglie, shootingsta

```
RULE rule 1
    IF bigblack(1)
    AND 3whitesoldiers(2-4)
    AND bigblack(5)
    AND closev(1) < openv(2)
    AND openv(1) > closev(4)
    THEN PATTERN bear3formation
    SELL STOCKS

RULE rule 2
    IF bigwhite(1)
    AND black(2)
    AND closev(1) > openv(1)
    AND openv(2) < closev(2)
    THEN PATTERN bearharami
    SELL STOCKS

RULE rule 3
    IF black(1)
    AND bigwhite(2)
    AND openv(1) < closev(2)
    AND closev(1) > openv(2)
    THEN PATTERN engulfingbull
    BUY STOCKS
```

Fig. 7. Rules in the knowledge base.

were elicited and formalized through the knowledge acquisition, only 21 patterns were found in the test data set. However, if even small and compact rules can predict stock market timing efficiently, it is more desirable than larger and complex rules.

Frequencies of patterns are in reciprocal proportion to the pattern sizes (duration of patterns). That is, the patterns with longer pattern sizes occur less frequently than the patterns with shorter ones. However, test results in Table 3 show that the relationship between the predicting power and the pattern size (or pattern frequency) is not linear. It was expected that better performance could be obtained from patterns with longer pattern sizes. However, the test result (according to pattern sizes) implies that there is no linear relationship between pattern sizes and predicting power. However, neither too complex nor too simple patterns with adequate complexity have the best performance. That is, the patterns with pattern size 2 have better performance than the ones with pattern size 1 or 3. The complexity of a pattern depends on the pattern size because the patterns with the longer pattern sizes have more candlesticks, conditions and subpatterns.

The test results summarized in Table 4 show that there is no relationship between particular industrial fields and defined patterns. Most tested companies had similar pattern frequencies and hit ratios, regardless of particular industrial fields. The main reason for the field-independent feature of defined rules is that future stock price movements are judged not from field-dependent information, but only from stock price shapes.

Table 2
The hit ratio according to rules

Rule name	Pattern size	Total frequency	Hit frequency	Fail frequency	Hit ratio (%)
3blackcrows	3	25	17	8	68
3whitesoldiers	3	20	13	7	65
Fallingwindow	2	173	127	46	73.41
Risingwindow	2	265	182	83	68.68
Separatingline	2	896	592	304	66.07
Tweezerbottoms	2	2666	2072	594	77.72
Tweezertops	2	2848	2027	821	71.17
Black	1	2890	1975	915	68.34
Doji	1	666	481	185	72.22
Gravestondoji	1	98	69	29	70.41
Hammer	1	207	156	51	75.36
Hangingman	1	137	103	34	75.18
Invblackhammer	1	95	71	24	74.74
Invhammer	1	333	231	102	69.37
Longlowershadow	1	2056	1598	458	77.72
Longuppershadow	1	441	321	120	72.79
Shavenbottom	1	2699	1933	766	71.62
Shavenhead	1	2243	1667	576	74.32
Shootingstar	1	369	270	99	73.17
Spinningtop	1	6093	4274	1819	70.15
White	1	2537	1854	683	73.08

Table 3
The hit ratio according to pattern sizes

Pattern size	Total frequency	Hit frequency	Fail frequency	Hit ratio (%)
1	20 864	15 003	5861	71.91
2	6868	5000	1868	73.01
3	45	30	15	66.67
Sum	27 757	20 033	7724	72.17

4. Discussion

Recently, there have been some attempts to develop expert systems to assist investors and traders in the stock market. Most of them have simple rules or defined patterns using machine learning methods (Braun and Chandler, 1987; Zhu and Xiong, 1994). Also, some of the research has focused on neural networks. Relatively, there has not been much research using a candlestick chart in Korean domestic research despite the fact that the Korean stock market is similar to the Japanese stock market.

Kamijo and Tanigawa used a recurrent neural network for analyzing candlestick charts (Kamijo and Tanigawa, 1990). The triangle pattern in a candlestick chart indicates that a dramatic price change is about to begin. Sixteen triangles were elicited by domain experts from candlestick charts. The patterns were divided into two groups, 15 training patterns and one test pattern. In order to eliminate the bias due to difference in name and time span, the variation rate for the stock price calculated by exponential smoothing and disassociation from the average of high and low prices were utilized as normalized stock data. The test set of triangle patterns was accurately recognized in 15 out of 16 experiments. However, there is no explanation function about the stock market. They focused only on pattern recognition and did not consider sales decision-making. In practice, it does not suffice to give stock investors full information to help in real investments. In this study, the expert system for predicting stock market timing focuses not on triangle patterns but on various patterns which can actually happen in the stock market and can make various analyses possible. Also, the expert system can help investors make final sales decisions according to suggestions provided by the expert system.

There are two problems in determining the stock market timing based on pattern recognition. First, because several patterns can occur simultaneously, overall interpretation of them should be performed. After interpreting patterns, final decision-making should result in one choice. Second, as the stock market environments change dynamically, current knowledge can be no longer useful. Thus, knowledge needs to be fine-tuned periodically in order to maintain its continued usefulness in a dynamic situation.

Simultaneous occurrence of patterns which have opposite meanings from each other makes it difficult to make the right decision. Generally, pattern conflict can be resolved in two ways: Priority values and Meta-rules (Hopgood, 1993). Pattern conflict caused by simultaneous occurrence can be resolved by using priority among patterns. The method using priority values gives more reliable patterns higher priorities than the others. That is, the pattern with the highest priority can reflect the whole meaning of all patterns at any point in spite of simultaneous occurrence of the patterns. A pattern may have priorities based on hit ratios. However, the method using priority ignores the meanings of the other patterns with low priorities. Consequently, this method has the problem that the patterns with low priorities may not be useful in many cases, because only

Table 4
The hit ratio according to corresponding companies

Pattern size	Total frequency	Hit frequency	Fail frequency	Hit ratio (%)
A	1912	1416	496	74.06
B	1809	1336	473	73.85
C	1822	1308	514	71.79
D	1888	1313	575	69.54
E	1809	1312	497	72.57
F	1820	1276	544	70.11
G	1866	1386	480	74.28
H	1820	1318	502	72.42
I	1857	1382	475	74.42
J	1724	1193	531	69.20
K	1891	1395	496	73.77
L	1804	1223	581	67.80
M	1963	1361	602	69.33
N	1862	1369	493	73.52
O	1910	1445	465	75.65

the patterns with high priorities can survive in simultaneous occurrence of patterns.

Pattern conflict can also be resolved by using meta rules, ‘‘rules about knowledge’’ that control patterns and rules. Meta rules can provide an overall interpretation of the total patterns that occur and make new decisions based on this interpretation. But when the number of defined patterns is N, the number of meta rules needed amounts to 2^N. In practice, it is impossible to define meta rules for all the given combinations of all the patterns. Therefore, the proper trade-off between methods using meta rules and priority is needed to resolve pattern conflicts.

The automatic knowledge tuning method can be used in order to adapt to a dynamic situation. Knowledge base gained during the past few years can still be useful, but it often fails to predict the stock market timing accurately in practice. New knowledge can be generated to overcome this problem. However, new knowledge needs to be evaluated before using real investments. The evaluation procedure is very laborious and time-consuming. Even though new knowledge is generated from knowledge acquisition with high costs, after it is evaluated and added into the knowledge base it might often lose its usefulness. Meanwhile, knowledge tuning only has to adjust the conditions and parameter values of a pattern according to dynamic changes in situations. Thus, knowledge-tuning may be more effective and less costly than new knowledge which is elicited from domain experts.

5. Conclusion

In this study, we developed an expert system based on candlestick analysis to predict the timing of when to buy or sell stocks. To visualize the stock price movements, the candlestick chart was used and the knowledge base for predicting stock market timing constructed from various patterns which can imply future stock price movements. Through experiments over real stock investment data set during the past five and half years from January 1992 to June 1997, the usefulness of the developed expert system with an average hit ratio of 72% was proven. Also, the developed knowledge base has time-independent and field-independent features which means that the developed expert system can be applied and used regardless of particular time and industrial fields. However, the developed expert system has a limitation—the lack of an automatic machine learning from examples. Integrated systems with automatic learning algorithms may enhance the predicting power of this system. Finally, the development of an integrated trading system to combine stock selection and stock market timing is suggested for further research.

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