Design and Implementation of Candlestick Chart Retrieval Algorithm for Predicting Stock Price Trend

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Abstract—**Advances in data mining techniques are now making it possible to analyze a large amount of stock data for predicting future price trends. The candlestick charting is one of the most popular techniques used to predict short-term stock price trends, i.e., bullish, bearish, continuation. While the charting technique is popular among traders and has long history, there is still no consistent conclusion for the predictability of the technique. The trend of stock prices often continues after intervals of several days because stock prices tend to fluctuate according to announcements of important economic indicators, economic and political news, etc. To cope with this kind of stock price characteristics, this paper focuses on a dynamic programming algorithm for retrieving similar numerical sequences. To be specific, the well-known Longest Common Subsequence (LCS) algorithm is revised to retrieve numerical sequences that partially match. The proposed algorithm also handles a relative position among a stock price, 5-day moving average, and 25-day moving average to take into account where the price occurs in price zones. Experimental results on the daily data of the Nikkei stock average show that the proposed algorithm is effective to forecast short-term trends of stock prices.**

Keywords— Stock price prediction; Technical analysis; Candlestick charts; Longest common subsequence algorithm for numbers; Multi numerical attributes; Nikkei stock average.

I. INTRODUCTION

Stock market prediction techniques play a crucial role to bring more people into market and encourage markets as a whole. Fundamental analysis and technical analysis are two popular approaches to successful stock trading [1].

Fundamental analysis combines economic, industry, and company analysis to derive a stock's current fair value and forecast future value. Traders apply this approach over a long period of time, e.g., months, quarters. Because of this analyzing processes, most investors believe that fundamental analysis is mainly suitable for long-term prediction.

Technical analysis is a study of market action, primarily through the use of charts for the purpose of forecasting future price trends [2]. Technical analysis is based on the following three premises:

1. Market action discounts everything: a stock's price reflects all relevant information such as economic, fundamental and news events,

2. Prices move in trends: prices trend keep directionally, i.e., up, down, or sideways, for a certain period,

3. History repeats itself: the repetitive nature of price movements is mainly attributed to market emotions like fear or excitement that often repeat themselves.

One of the important types of technical analysis is candlestick chart patterns [2]. The candlestick chart patterns provide short-term predictions for traders to make buy or sell decisions. While most of techniques use statistics of stock prices, the candlestick charting technique focuses on patterns among several days of candlesticks formulated by opening, high, low, and closing prices within a specific time frame, such as minute, hour, day or week. Dozens of candlestick chart patterns are identified to be signals of bullish/bearish reversals and continuations. These patterns consist of a single candlestick or a combination of multiple candlesticks. In fact, the technique acts as a leading indicator with its capability to provide trading signals earlier than other technical indicators based on statistics. It is also used by some real time technical service providers [3] to provide quick signals for market's sentiments.

The candlestick charting technique probably began sometime after 1850 [2]. Despite of its long history and popularity, mixed results are obtained in the studies on candlestick charting. Negative conclusions to the predictability of candlesticks are reported [4]-[6], while positive evidences are provided for several candlestick chart patterns in experiments using the U.S. and the Asian stock markets [7]-[10].

It is also pointed out that candlestick chart pattern recognition is subjective [2][7][11]. The candlestick chart patterns are often qualitatively described using words and illustrations. The studies [6][7] adopt definitions using a series of inequalities with different parameters that specify candlestick patterns. Numerical definitions of candlestick patterns are still controversial issues.

In addition, they don't occur in time series in a strict sense because stock price fluctuation continues after intervals of several days depending on announcements of important economic indicators, economic and political news, etc. Because of these characteristics, the candlestick chart patterns are deemed to bring controversial results on predictability regarding future market trends even sort-term prediction.

The aim of the study is to estimate the predictability of candlestick patterns for future stock price trends. The proposed algorithm is applied to the daily Nikkei stock average (Nikkei 225) in the experiments. Daily historical stock prices are used because we plan to relate chart patterns to economic and political news in the future study.

The contributions of this paper are as follows:

(I) The Longest Common Substring (LCS) algorithm [12], which is a kind of dynamic programming algorithms, is improved to cope with candlestick patterns containing several intervals,

(II) The proposed model utilizes tolerances for multiple attributes that specify candlestick charts, so it can retrieve similar candlestick charts in terms of upper and lower tolerance bounds,

(III) The proposed model uses relative position among a stock price, 5-day moving average, and 25-day moving average to decide whether the price occurs in high or low price zones,

(IV) The proposed model uses slopes of the moving averages to identify their trends,

(V) The proposed model devises a graphical representation to make evaluation of the retrieval results easy to depict the predictability for short-term trends.

The remainder of the paper is organized as follows. Section II gives backgrounds of the candlestick chart. Section III describes a model for retrieving similar candlestick charts. An augmented dynamic programing technique is used to implement the proposed model. Section VI presents experimental results on both the uptrend and downtrend of stock prices. Section V gives some of the most related work. Section VI concludes the paper with our plans for future work.

II. CANDLESTICK CHART AND PATTERNS

This section introduces the formation of a candlestick. Candlestick patterns are a combination of one or more candlesticks [2]. Samples of well-known candlestick chart patterns are shown. Because the candlestick patterns are described in natural language and illustrations, there are criticisms on their use for trend prediction by a computer.
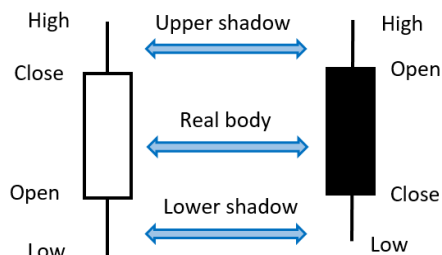
A. Formation of Candlestick

A daily candlestick line is formed with the market's opening, high, low, and closing prices of a specific trading day. Figure 1 represents the image of a typical candlestick. The candlestick has a wide part, which is called the "real body" representing the range between the opening and closing prices of that day's trading.

If the closing price is above the opening price, then a white candlestick with black border is drawn to represent a bullish candlestick. If the opening price is above the closing price, then a filled candlestick is drawn. Normally, black color is used for filling the candle to represent a bearish candlestick.

The thin lines above and below the body represent the high/low ranges. These lines and are called "shadows" and also referred to as "wicks" and "tails." The high is marked

by the top of the upper shadow and the low by the bottom of the lower shadow.

(A) Bullish candlestick   (B) Bearish candlestick

Figure 1. Candlestick formation

B. Samples of Candlestick Patterns

Dozens of candlestick patterns are identified and become popular among stock traders [2][3]. These patterns have colorful names like *morning star*, *evening star*, *three white soldiers*, and *three black crows*.

Figure 2 shows the *morning star* pattern which is considered as a major reversal signal when it appears in a low price zone or at a bottom. It consists of three candles, i.e., one short-bodied candle (black or white) between a preceding long black candle and a succeeding long white one. The pattern shows that the selling pressure that was there the day before is now subsiding. The third white candle overlaps with the body of the black candle showing a start of a bullish reversal. The larger the white and black candle, and the higher the white candle moves, the larger the potential reversal. The opposite version of the *morning star* pattern is known as the *evening star* pattern which is a reversal signal when it appears in a high price zone or at the end of an uptrend.
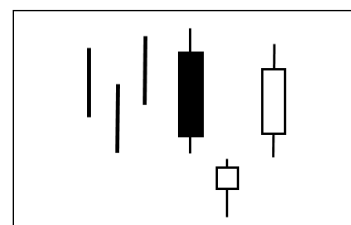

Figure 2. Morning star pattern

Figure 3 shows the *three white soldiers* pattern which is interpreted as a strong indication of a bullish market reversal when it appears in a low price zone. It consists of three long white candles that close progressively higher on each subsequent trading day. Each candle opens higher than the previous opening price and closes near the high price of the day, showing a steady advance of buying pressure. The opposite of the three white soldiers pattern is known as the *three black crows* pattern which is interpreted as a bearish signal of market trend.
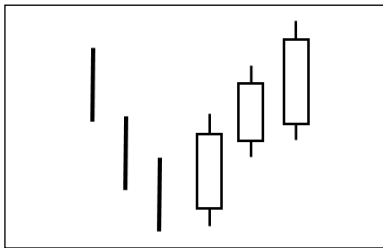
Figure 3. Three white soldiers pattern

C. Criticism of Candlestick Patterns

The major criticism of the candlestick chart patterns is that the patterns are qualitatively described with words, such as "long/short candlesticks," "higher/lower trading," "strong/weak signal," supported by some illustrations [2]. What percentage of price change does "long/short" mean? Without modeling the candlestick patterns in a way that a computer can process and performing experiments comprehensively, arguments on the effectiveness of chart patterns would not come to an end.

Since it is highly possible that the existence and predictability of candlestick patterns depends on stock markets, this study focuses on the Nikkei stock average (Nikkei 225) as the first stage of study. This paper proposes a model for retrieving similar candlestick charts based on a data mining algorithm using dynamic programing technique to handle candlestick patterns including several intervals that suggest unpredictable price trends.

III. PROPOSED MODEL FOR RETRIEVING CANDLESTICK PATTERNS

This section describes a model for retrieving similar candlestick charts. A dynamic programing technique is used to implement the proposed model.

A. Parameters Featuring Candlestick Patterns

As a preliminary stage of study, experiments only using the closing prices and the length of real bodies are conducted. The experiments simply correspond to the conditions of the candlestick chart patterns [2]. The results are discouraging. Although mined stock price sequences are similar before the specified period of the reference date, trends of the sequences after the reference date are seemed to be random. Analyses of the results show that the randomness occurs due to the relative position among the stock price, the 5-day moving averages, and the 25-day moving averages.

Based on the results of the preliminary experiments, we propose the model for retrieving similar candlestick charts. Figure 4 depicts the model that consists of the six parameters as follows:
(1) Change of prices w.r.t previous closing price,
(2) Length of candlestick body,
(3) Difference from 5-day moving average,
(4) Difference from 25-day moving average,
(5) Slope of 5-day moving average,
(6) Slope of 25-day moving average.

The proposed model is unique because it uses two moving averages and their slopes, while the previous studies [4]-[12] do not deal with them. Relative position among a stock price, 5-day moving average, and 25-day moving average is significant to identify the zone where the candlestick pattern under consideration occurs, which is vital information for applying the candlestick pattern. The slopes of the moving averages are also important to identify their trends, e.g., an uptrend, a downtrend or a sideway (flat).
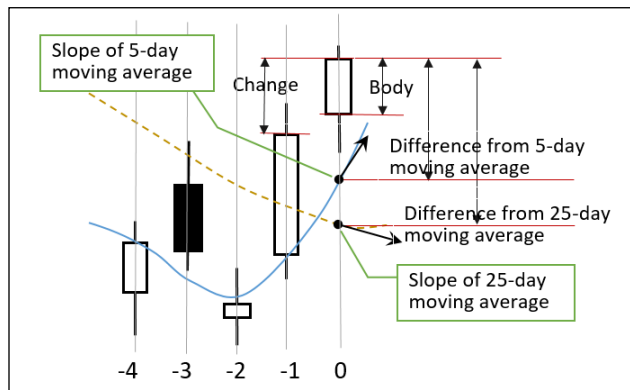

Figure 4. Candlestick pattern retrieval model

B. nLCS: LCS for Numerical Subsequences

Another issue of retrieving candlestick chart patterns is that stock prices can move continued after a few days of intervals because stock prices can vary according to important economic indicators, political news and actions, etc. The detection of similar candlestick chart patterns is essentially the detection of a set of numerical sequences that partially match the numerical sequences corresponding to a chart pattern under consideration.

The Longest Common Subsequence (LCS) algorithm is originally developed for character strings [12]. Finding the LCS between two strings is described as follows. Given two strings, find the longest character subsequence that presents in both of them. Characters of the subsequence appear in the same relative order, but not necessarily contiguous. Figure 5 depicts the LCS of the two strings "246612" and "3651." Since elements of sequences are interpreted as characters that require an exact match, the LCS is "61."
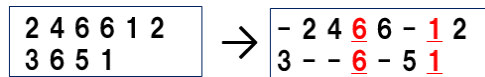

Figure 5. The LCS of two character sequences, "246612" and "3651"

It is rather easy to improve the LCS algorithm to deal with numerical sequences (nLCS) by interpreting each element as a number and using a tolerance given by a user. If the difference of two numbers is not greater than the given tolerance, then the two numbers are regarded as the same. For example, let the tolerance be set to one, and the two number sequences be "246612" and "3651." The nLCS are "2661" and "3651" as shown in Figure 6.
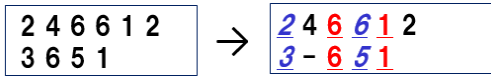
Figure 6. The nLCS of the two number sequences
"246612" and "3651" for the tolerance of one

The LCS and nLCS are formally defined as follows.

LCS algorithm: Let the input sequences be X[1 … m] of length m and Y[1 … n] of length n. Let D[i, j] denote the length of the longest common subsequence of X[i] and Y[j] for $0 \leqq i \leqq m$ and $0 \leqq j \leqq n$.

A) If either sequence or both sequences are empty, then the LCS is empty, i.e., D[i, 0] = 0 and D[0, j] = 0.

B) If X[i] and Y[j] match (X[i] = Y[j]), then the LCS is become longer than the previous sequences by one, i.e., D[i, j] = D[i−1, j−1] + 1.

C) If X[i] and Y[j] do not match (X[i] ≠Y[j]), then the LCS is the maximum of the previous sequences, i.e., max(D[i−1, j], D[i, j−1]).

The value of D[m, n] is the LCS of the sequences X[1 … m] and Y[1 … n]. The actual LCS sequence can be extracted by following the matrix D[i, j].

nLCS algorithm: The nLCS algorithm is derived from the LCS algorithm by replacing the match condition (X[i] = Y[j]) with ((X[i] − Y[j]) $\leqq$ diff) where diff is a tolerance given by a user.

C. nLCSm: LCS for Subsequences with Multi Numerical Attributes

The idea of deriving the nLCS from the LCS can be further extend to the multi numerical attributes to obtain the nLCS for subsequences with multi numerical attributes (nLCSm).

nLCSm algorithm: Let p $(1 \leqq p)$ denote the number of numerical attributes. Let C_q $(1 \leqq q \leqq p)$ denote the match conditions for the qth numerical attribute. The nLCSm is derived by replacing the match condition of the nLCS, i.e., ((X[i] − Y[j]) $\leqq$ diff), with $(C_1 \wedge ... \wedge C_q \wedge ... \wedge C_p)$.

D. nLCSm and candlestick pattern retrieval

Given the candlestick pattern model with six parameters as depicted in Figure 4, the nLCSm algorithm can be applied to implementing the model by assigning match conditions C_1 to C_6 for each candlestick as follows.

C_1: if a difference between closing price change of a given candlestick and that of a candidate candlestick is within the change tolerance (*change_tol*), then C_1 is true.

C_2: if a difference between body length of a given candlestick and that of a candidate candlestick is within the body tolerance (*body_tol*), then C_2 is true.

C_3: if a difference between a closing price and a 5-day moving average is within the tolerance (*av5diff_tol*), then C_3 is true.

C_4: if a difference between a closing price and a 25-day moving average is within the tolerance (*av25diff_tol*), then C_4 is true.

C_5: if a slope of a 5-day moving average is within the given tolerance (*slope5_tol*), then C_5 is true.

C_6: if a slope of a 25-day moving average is within the given tolerance (*slope25_tol*), then C_6 is true.

The 5-day moving average is calculated by the latest five days' closing prices. Because these prices are just a sample of larger population of closing prices, the sample standard deviation or *Bessel's* correction [2] is adopted as a measure of threshold to decide whether a given 5-day moving average is within an expected distribution.

The tolerance of 5-day moving average *av5diff_tol* is statistically dependent on the change tolerance *change_tol*. In the proposed retrieval model, *av5diff_tol* and *av25diff_tol* are calculated by the following formulas as defaults according to the definition of the sample standard deviation.

$$av5diff\_tol = change\_tol / \text{SQRT}(4) = change\_tol / 2 \qquad (1)$$

$$av25diff\_tol = change\_tol / \text{SQRT}(24) = change\_tol / 4.899 \qquad (2)$$

Thus, there are essentially four independent parameters in the proposed model, which still causes difficulties in setting parameters. Assuming that each parameter has 5 ranges of values representing, for instance, very high, high, the same level, low, and very low. The candlestick patterns of one candlestick have 5 to the power 4, i.e., $5^4 = 625$ cases of parameters. The patterns composed of two candlesticks have $5^{(4*2)} = 625*625 = 390,625$ cases. The patterns of tree candlesticks have 244,140,625 cases. These cases mean very wide varieties of candlestick charts leading difficulties even in setting parameters for retrieving a specific candlestick chart pattern.

IV. EXPERIMENTAL RESULTS

The predictabilities of the *morning star* pattern and the *evening star* pattern are evaluated through experiments. The experiments are conducted on the daily historical stock prices of Nikkei stock average (Nikkei 225) of 2,420 business days from Jan. 4, 2008 to Nov. 15, 2017.

A. Data Conversion

The stock prices are converted to the ratio of closing prices to reduce the effects of highness or lowness of the stock prices. The formula below is used for calculating the ratio of prices in a percentage.

$$R_i = (CP_i − CP_{i+1})*100 / CP_i \quad (1 \leqq i \leqq n) \qquad (3)$$

CP_i indicates the closing price of the i-th business date. CP_1 means the closing price of the current date. R_1 is the ratio of the closing price of the current date CP_1 and the difference between CP_1 and CP_2, i.e., the closing price of the date before the current date. The similar calculations are performed to opening, high, and low prices. In addition, the 5-day and 25 day moving averages, and their slopes are calculated before the experiments. The number of data valid, i.e., n in effect is 2,396 (=2,420−24) because the 25-day averages can't be calculated to the last 24 days.

B. Experiments on Morning Star Pattern

Figure 7 shows the candlestick chart of the Nikkei 225 in which a strong uptrend starts on Sept. 11, 2017. The candlesticks ending on Sept. 11, 2017 form a *morning star* pattern. The first experiment is performed on the three candlesticks surrounded by a dotted rectangle in Figure 7.
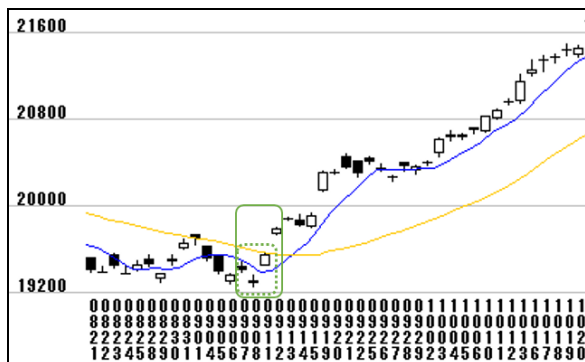

Figure 7. Candlestick chart around Sept. 11, 2017

Table I shows a list of the retrieved business dates, the number of matched days or nLCSm. The ratio of nLCSm is calculated by dividing the nLCSm by the period of three. The parameters used for the experiment are as follows: *change_tol*=1.600, *body_tol*=1.600, *av5diff_tol*=0.800, *av25diff_tol*=0.327, *slope5_tol*=0.050, *lope25_tol*=0.020.

TABLE I. RESULTS CONCERNING MORNING STAR PATTERN ON SEPT. 11, 2017

Date	Match	Ratio of nLCSm
20170911	3	1.000
20170802	2	0.667
20170726	2	0.667
20160825	2	0.667
20160525	2	0.667
20150707	2	0.667
20140502	2	0.667
20131111	3	1.000

The three candlesticks that end on Nov. 11, 2013 totally match those on Sept. 11, 2017. It is not surprising that the chart pattern on Nov. 11, 2013 in Figure 8 draws a similar trend as Sept. 11, 2017 in Figure 7.
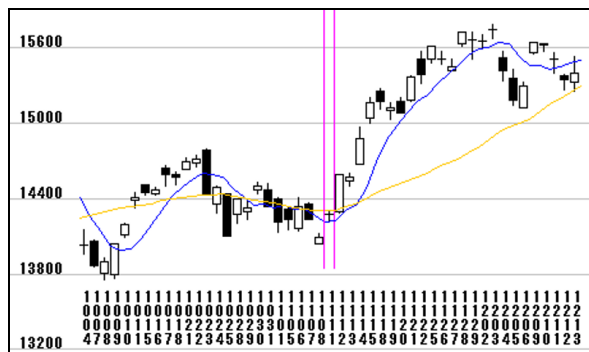

Figure 8. Candlestick chart around Nov. 11, 2013

Figure 9 shows overlapped closing prices whose business dates are listed in Table I for graphically representing the future stock trend. All reference dates are aligned on the origin to make the comparison easy. The thick black line represents the closing price sequences of the reference date, i.e., Sept. 11, 2017. Thin solid lines represent the closing price sequences of business dates listed in Table I except for the reference date. The thick light blue line indicates the average of the candlestick charts plotted by thin solid lines.

Three out of the seven closing price sequences suggest an uptrend, while two out of the seven suggest downtrend. The others suggest sideways. It can be reasonable to say that no trade judgments, i.e., indecision, should be made based on the results of retrieval.
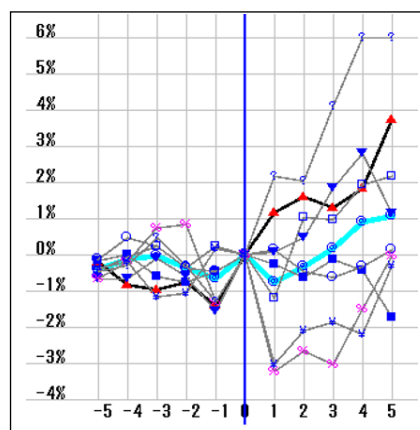

Figure 9. Overlapped closing prices representing for future stock trend

C. Experiments on Morning Star Pattern with Confirmation

Four candlesticks enclosed by a solid rectangle in Figure 7 show the *morning star* pattern plus one confirmation day. Table II summarizes the result of the experiment on four candlesticks ending on Sept. 12, 2017.

TABLE II. RESULTS CONCERNING MORNING STAR PATTERN ON SEPT. 11, 2017 PLUS ONE CONFIRMATION DAY

Date	Match	Ratio of nLCSm
20170912	4	1
20160829	3	0.75
20150519	3	0.75
20141030	4	1
20140523	3	0.75
20120118	3	0.75
20110622	4	1
20091016	3	0.75

Figure 10 shows overlapped closing prices whose business dates are listed in Table II for representing the future stock trend. Five out of seven closing price sequences suggest an uptrend, while the other two out of seven ones suggest keeping the same price level. This result may well be noteworthy for traders to identify buying opportunities with expectation of approximately 2.5% profits on average in the next five days.
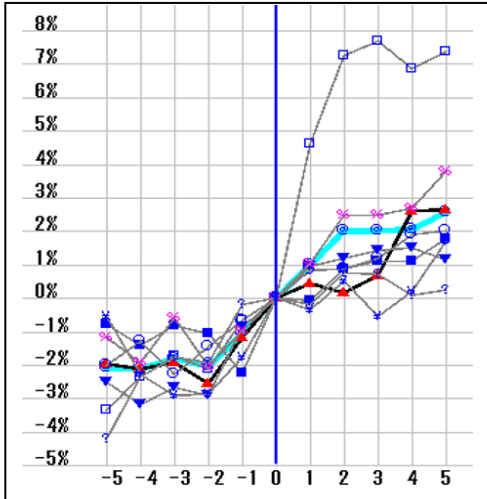
Figure 10. Overlapped closing prices for representing future stock trend

D. Experiments on Evening Star Pattern

Figure 11 shows the candlestick charts with respect to an *evening star* pattern ending on June 6, 2017. The patterns consist of four candlesticks enclosed by a solid rectangle in Figure 11.
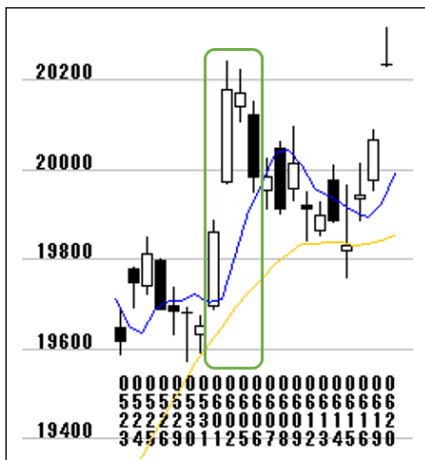

Figure 11. Candlestick chart around June 6, 2017

Table III summarizes the result of the experiment on the pattern. The parameters used for the experiment are as follows:

change_tol=1.320, *body_tol*=1.3200, *av5diff_tol*=0.660, *av25diff_tol*=0.269, *slope5_tol*=0.050, *slope25_tol*=0.020.

TABLE III. RESULTS CONCERNING EVENING STAR CHART PATTERN ON JUNE 6, 2017

Date	Match	Ratio of nLCSm
20170606	4	1
20170315	3	0.75
20150811	3	0.75
20150129	4	1

Figure 12 shows overlapped closing prices whose business dates are listed in Table III. Figure 12 generally suggests a downtrend of the future stock price. However, two closing price sequences and that of June 6, 2017 predict a dip in stock prices of approximately 1%.
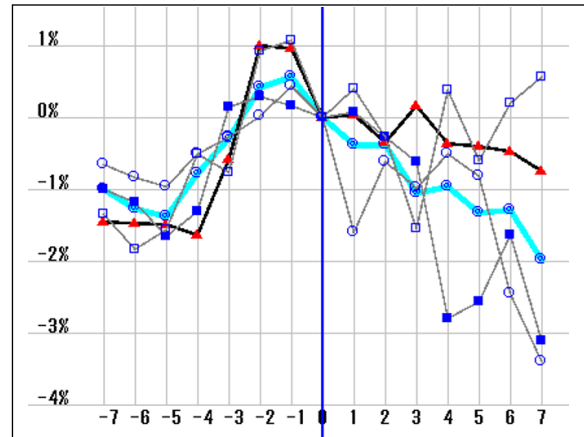

Figure 12. Overlapped closing prices concerning June 6, 2017

The closing price on June 6, 2017 (Figure 11) shows sudden drop, but is still above the 5-day and 25-day moving averages. Many traders know that there are two possible price trends at this position of prices, i.e., continuing downtrends and/or bargain-hunting after several days of stock price decline. The proposed algorithm seems to be successful in retrieving both possible price trends.

V. RELATED WORK

Some studies [4]-[6] find that the candlestick charting is useless based on the experiments using the stock exchange markets' data in the U.S., Japan and Thailand. Tharavanij, Siraprapasiri, and Rajchamaha [6] investigate the profitability of bullish and bearish candlestick patterns consisted of one-day, two-day, and three-day candle sticks. The candlestick patterns are defined by a set of inequalities defined by opening, high, low, and closing prices. These inequalities are originally proposed by Goo, Chen, and Chang [7] who report positive results in Taiwan markets. Based on experiments using stock data in the Stock Exchange of Thailand, they conclude that any candlestick patterns cannot reliably predict market directions even with filtering by well-known stochastic oscillators [2].

Other studies conclude that applying certain candlestick patterns is profitable at least for short-term trading [8]-[11]. Chootong and Sornil [8] propose a trading strategy combining price movement patterns, candlestick chart patterns, and trading indicators. A neural network is employed to determine buy and sell signals. Experimental results using stock data in the Stock Exchange of Thailand show that the proposed strategy generally outperforms the use of traditional trading methods based on indicators. Zhu, Atri, and Yegen [9] examine the effectiveness of five different candlestick reversal patterns in predicting short-

term stock movements using two Chinese stock data. The results of statistical analysis suggest that the patterns perform well in predicting price trend reversals.

Lu, Chen, and Hsu [10] apply candlestick trading strategies to the U.S. market data with several trend definitions. They find three-day reversal patterns are profitable when the transaction cost is set at 0.5%.

One of the obstacles of candlestick charting is the highly subjective nature of candlestick pattern [2] since the candlestick patterns are defined using words and illustrations. Tsai and Quan [11] propose an image processing technique to analyze the similarities of the candlestick charts for stock prediction instead of using numerical inequality formulas. The experimental results using the Dow Jones Industrial Average (DJIA) show that visual extraction of contents and similarity matching of candlestick charts are suitable for predicting stock movements.

The studies [4]-[10] translate these candlestick verbal and visual descriptions into numeric formulas in order to be used in an algorithm. However, they fail to consider zones where the candlestick patterns in focus occur. The interpretation of candlestick patterns depends on the price zone, e.g., high, low, neutral. For example, the *morning star* pattern generally suggests a bullish trend when it occurs in a low price zone. However, the morning star pattern is deemed to be less bullish when it occurs in a high price zone than it occurs in a low price zone.

Most importantly, the studies [4]-[10] do not discuss neutral candlesticks or intervals that often take place in charts because stock prices depend on important economic and political news and events.

VI. CONCLUSIONS AND FUTURE WORK

This paper proposes a model for retrieving similar candlestick charts with six parameters that feature candlestick charts. A numerical sequence version of the Longest Common Substring (LCS) algorithm is devised to implement the proposed model because partial matching of candlesticks plays a significant role to retrieve similar candlestick patterns. Results of experiments using the Nikkei stock average show some positive evidences regarding the prediction of future market trends.

As for the future work, we are planning to improve the proposed model by augmenting available parameters including the upper and lower shadows. The augmentation allows the model to examine various shadow sensitive patterns known as the *hammer*, *dragon fly* patterns [2]. As

the current study is limited to a Japanese stock market, it is suggested that future researches may focus on different stock markets from other countries for further analyses of candle stick patterns.

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