Stock Index Pattern Recognition:
A Combined Approach using Case Based Reasoning and Dynamic Time Warping Technique

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Abstract

in this paper, we study the problem of recognizing the temporal patterns of KOSPI 200 stock index futures sampled at 5-minute intervals. Our approach, based on the Dynamic Time Warping technique, consists of a search for the optimal path of the underlying time series patterns by minimizing the accumulated distances. Moreover we develop a trading model which yields the promising improvements in the recognition performance of financial time series. A new investment decision model is constructed by hybridizing CBR and DTW. Experimental results are reported to verify the performance gains of DTW for recognizing the fragments of time series. Preliminary results indicate that the predictions can be used in intraday futures trading. Although many practical considerations including transaction cost have not been fully considered, DTW may be useful in predicting the reversal of trends in financial time series.

Purpose

The studies performed here focused on the recognition of the underlying patterns of noisy stock market index. The aim is to detect a profitable temporal pattern(such as rising of stock index) that can indicate an important clue to the trends and directions of future changes in stock index. With increasing demands for intraday market prediction, the pattern detection systems are strategically exploited for superior performance in day futures trading. Finding pre-stored profitable patterns or time series fragments is an interesting sub-problem within the context of discovering higher-level relationships for investment analysis. In futures trading with technical analysis, general market forecasting and investment positioning can be programmed or modeled with the aid of pattern recognition technique. For recognizing specified patterns from a time sequence of stock index, it is indispensable to investigate and to explore more refined and efficient optimization algorithm.

The challenge of knowledge discovery research in futures market and financial area is to develop methods for extracting valuable information from streams of underlying assets. This paper presents a pattern detection algorithm based on dynamic programming and non-linear time alignment. To develop rapid and effective model for finding the patterns of stock index, DTW(Dynamic Time Warping) algorithm used in speech recognition fields is introduced. Also, CBR is used for predicting a market timing from the meta-level case base. This mixed approach presented utilizes dynamic programming to search local or global optimal path with several constraints. This implementation is novel in that CBR is used in determing the positions during the day trading and Dynamic Programming algorithm is effectively employed.

The proposed approach is compared to the result of CBR. The concepts and development procedures are discussed through a practical application involving the recognition of stock index patterns.

Background

Pattern recognition techniques have been poorly used in discovering the potentially useful patterns for investment decision process. Recently, Korean futures market, opened in 1996 and traded the KOSPI 200 stock index futures, has witnessed a tremendous growth of interest in the field of temporal pattern recognition. As a early study, a recurrent neural network was applied to triangle pattern recognition for all companies listed in Tokyo Stock Exchange. That experiment revealed that the given test pattern was accurately recognized in 15 out of 16 experiments, and that the number of the mismatching patterns was 1.06 per firms on the average in 16 experiments[Kamijo et al, 1990].

A variety formulations of the DTW problem,

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especially as applied to speech recognition, have been proposed[Sakoe and Chiba(1978), Myers and Labiners(1980)]. DTW technique uses a dynamic programming approach to align the time series and the specific template,i.e, reference patterns so that some distance measure is minimized. Berndt and Clifford [1996] conducted several pattern detection experiments for searching DJIA patterns and for various social science times series data.

It is generally agreed that the introduction of DTW algorithms as a method of registering two time series patterns is one of the major breakthroughs that have made patterns recognition more practical for a wide range of conditions. The importance of this class of methods has been manifest in a variety of areas including financial market. Generally DTW algorithms, as a variant of a dynamic programming procedures have showed that distinct improvements in recognition performance over simple linear time alignment.

CBR is hereby explored for their feasibility in predicting the investment decisions such as sell/buy the market. In many problem, it is observed that CBR is good at serving as a strategic planner and modifying the decision reacting to situation changes. On the other hand, the performance of DTW often suffers before it is not possible to formulate a robust DP- problem, due to limited search strategies and several types of restrictions to constrain the search spaces. To overcome the limitations of DTW, this study has tried to integrate DTW with the multistrategy learning using CBR.

Methodology

The problem of recognizing words in continuous human speech seems to include many of the important aspects of pattern detection in time series. Successful recognition strategies are based on the ability to match words approximately in spite of wide variations in timing and pronunciation.

Dynamic Time Warping Algorithm

DTW algorithm is to find the optimal warping path $w(n)$ which minimize the accumulated distance D between test and reference patterns, subject to a set of path and endpoint constraints. More detailed implementation procedure is shown in Figure 1. Warping curve is determined as the solution to the optimization problem,

$$D* = \min_{w(n)} \left[\sum_{n=1}^{NT} d(T(n), R(w(n))) \right] \qquad (1)$$

where $d(T(n), R(w(n)))$ is the distance between frame n of the test pattern, and frame $R(w(n))$ of the reference pattern. The basis behind most DTW algorithms is the realization that the solution to the optimization problem (1) is equivalent to finding the "best" path through a finite grid. Figure 2 depicts the warping function and the time registration between reference pattern and test time series. A simple recursive technique, which defines the minimum accumulated distance function $D_A(n,m)$ as the accumulated distance from the initial grid point $n=1, m=1$ to the grid point (n,m) has been used to the best warping path in the plane. With monotonicity and local continuity constraints, the recursion can be expressed as

$$\begin{aligned} D_A(n,m) = d(T_n, R_m) + \min[& D_A(n-1), m) \\ & g(n-1,m), D_A(n-1,m-1), \\ & D_A(n-1,m-2)] \end{aligned} \qquad (2)$$

where,

$$\begin{aligned} g(n-1,m) &= 1 \qquad if\; w(n-1) \neq w(n-2) \\ &= \infty \qquad if\; w(n-1) = w(n-2) \end{aligned}$$

the iteration of (2) is carried out over all valid m, for each value of n sequentially from $n=1$ to $n=NT$, and final desired solution is given as

$$D* = D_A(NT, NR) \qquad (3)$$

Dynamic programming equation or D must be recurrently calculated in ascending order with respect to coordinate m and n, starting from initial condition at (1,1) up to (NT, NR). The optimal warping path $w(n)$ is determined by backtracking from the endpoint. For most word-recognition or financial applications, the warping path need not be computed, only the accumulated distance $D*$ is required.

In order to implement DTW algorithm, several factors must be specified including slope constraint forms and distance measures. These conditions can be realized as the restrictions on warping function or points($m = w(n)$). Specifically endpoint and global constraints on the path, local path continuity, i.e, directions and the slope of the path are considered.

Case Based Reasoning for multistrategy learning

Case Base Reasoning is a recent approach to problem solving and learning that has got a lot of attentions over the last few years. Instead of relying solely on general knowledge of a problem domain, or making associations along generalized relationships between problem descriptors and conclusions, CBR utilizes a similar past case previously experienced, concrete problem situations[Aamodt et al. 1996].

In its simplest form, CBR involves four steps: performs situation assessment to determine the most relevant features, retrieves a relevant prior cases, compares the cases to new situation, saves a new case to base future reasoning[Leake,1996].

Reuse and representation of the specific domain knowledge involves integration of the case based method with other methods. The main goal of domain knowledge is to provide a more effective strategic supports. From this point of view, the multistrategy learning module may be served as a meta-level planner to enhance the prediction accuracy of the recognized pattern. To this end, CBR module is used to predict the market timing forecasting by retrieving the nearest neighbor in the case base prepared.

Case Study

Experiment outline

The case study involves the detection of informative patterns on each 5 minute closing price for KOSPI 200 stock index. We undertake this case study to determine the feasibility of applying DTW technique to futures day trading with technical analysis. A number of experiments are conducted to compare the performance of various investment strategies. Our experiments are fulfilled with the stock index's intra-day data for contiguous period of 10 months. This KOSPI 200 series are used to run the experiments based on the templates drawn from technical analysis[Pring, 1985].

The templates(reference patterns) are fixed in length of 60 trading minutes. Well-known 12 technical patterns constitute the templates such as panic reversal, double top, head and shoulders pattern and so forth. In Figure 3, the reference patterns are summarized for both right and reversal one. Normalization method will be used for eliminating the bias due to differences in time span and scale. Line-up and alignment of the template of Head and Shoulder is displayed in Figure 4 on near 11:00 ,7 Aug, 1997

To evaluate the proposed system as a day trading tool for long/short strategies, we used its predictions to buy or sell the market and analyzed their performance using cumulative returns. In the simulation, we repeatedly pretend that the beginning of a day is current starting time for a day trading. Since the system uses a binary classification pattern; Top or Bottom form, so it needs a sell or buy value to predict. These values are generated by the template that has the minimum accumulated distance between reference pattern and test patterns.

Closing time was set to 2:35 p.m. in a day, and the prediction must be completed before 2:00 p.m. We then apply these predicted values to long/short the KOSPI 200 index futures for only one transaction a day. Therefore the system has no more investment in the same day. To estimate the recognition capability of the test patterns, we do not use transaction costs and margin requirements. And assume that at the closing time of each day we completely liquidate our positions, so that a realized return is daily assessed on our invested position.

To implement DTW, Symmetric DP- algorithm is utilized with the slope condition $p = (m / n) = 0.1$, which showed best word-recognition performance [Sakoe and Chiba, 1978]. Time registration is done within 12 frames or 1 hour. In CBR implementation, the nearest neighbor is retrieved from the case base that not contained time series data of the trading day.

Results

Below we discuss the results, examining the pattern recognition accuracy of the integrated DTW technique. The strategy is daily buying or selling depending only on the decision of the proposed investment model. We choose the capital weighted market index as a proxy for a passive investment.

Figure 5 shows the cumulative returns of both DTW techniques and CBR, along with the returns to the KOSPI 200 stock index. The trading model, which is started on 11, July 1997, yields encouraging results. The cumulative return of DTW based investment model is 29.34% better than -53.4% of passive (buy and hold)strategy. With the meta-level prediction by CBR, DTW based model gives 11.97% lower total gains than DTW solely, but the profits is still positive, higher than -3.07% of CBR. It is suspected that simple DTW algorithm yields higher returns than mixed model with CBR and shows quite stable results. On the other hand, The hit rate of DTW technique in Table 1 is 66.7%, which is signigicantly better than random walk. Especially the model performed better on bearish technical patterns. This encouraging results state clearly that the use of DTW pattern recognition technique in contact with a trading model can improve the forecast of the reversal of trends. Table 2 shows the recognition performance of DTW techniqueis by technical patterns. In particular, simply or steep shaped patterns such as

Spike V or Rouding/Saucer are effectively recognized by the model.

From the results shown in Figure 6, it can be observed that the performance by cumulative returns tends to decrease as the slope constraint grows. In this study, the slope constraint condition with the most simple form $p = 0$, is determined as a optimal point. The difference with the results of Sakeo and Chiba is due to the fact that time series are generated from noise financial market.

Future Works

Genetic Algorithm for optimizing local path

In many problem, it is observed that GAs are good at locating fit regions quickly. DTW technique has some shortfalls regarding constraints and search strateties. Some attempts need to improve the recognition accuracy of simple DTW algorithm due to the high cost of mismatching patterns. Searching local optimal paths using GA may be one of such implementations. Each gene of the individual represents an point in all possible warping paths and contains information about the partial accumulated distance and alignment. New integrated model may be powerful for identifying best fit regions and locating the optimal solutions of these regions quickly by hybridising GA and DTW. GA for match process is applicable to extend the search space and to eliminate the mismatching patterns.

Conclusion

A new method for recognizing the patterns in time series was established by registering the non-linear time frames. Preliminary results indicate that the DTW algorithm may be useful in pattern recognition on financial domain. Also, the multistrategy learning model designed does work to a certain extent. But more precise reference patterns must be explored and various window sizes testing are necessary to make that DTW algorithm make futures trading more profitable and practicable. Surprisingly, it is also found that CBR doesn't work for predicting the time series data and intraday data well. Consequently, other pertinent tools or integrated models should be considered and included into the investment decision process. It is hoped to develop a method for optimizing the local path and to eliminate the mismatching patterns as suggested in future works.

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Figure 1. Dynamic Time Warping Algorithm

Optimal Path problem

Find the sequence $m_S = w(n_1), w(n_2), \ldots, w(n_Q) = m_Q$ with $\sum_{n=1}^{NT} d(T(n), R(w(n))) =$ minimum

Initial Condition: $D(0,m) = \begin{cases} \infty & m \neq m_S \\ 0 & m = m_S \end{cases}$

Loop over the level n=1, ..N
    Loop over the state m=1,.. Q
        evaluate recurrence relation
            $D(n,m) = \min\{D(n-1,m^*) + d(m^*,m) : m^* = 1, \ldots Q\}$
        and store decision in a backpointer array
            $B(n,m) = \operatorname{argmin}\{D(n-1,m^*) + d(m^*,m) : m^* = 1, \ldots Q\}$
    Loop control
Loop control

Construct the optimal sequence $m(0), m(1), \ldots, m(n), m(N)$ by backtracking
The decision store in $B(n,m)$ from (N, m_Q) to $(0, m_s)$

m_S - start state
m_Q - destination state
$D(n,m)$ - partial accumulated cost
m^* - preceding state which is unknown in general
$B(n,m)$ - additional backpointer array

Figure 2. Warping Function and Time Registration

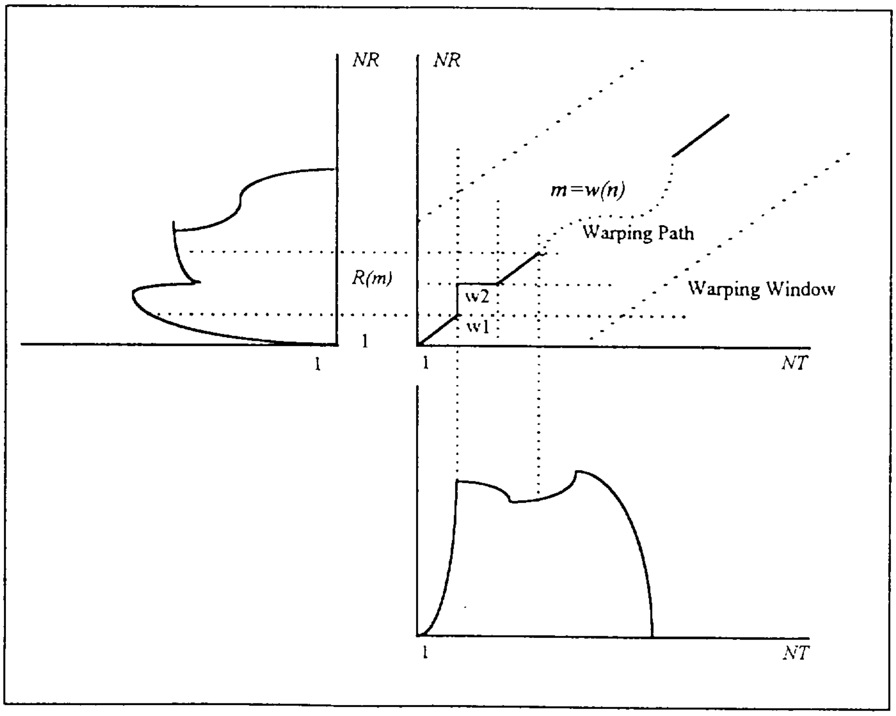

Figure 3. Templates used for searching KOSPI 200 Stock Index

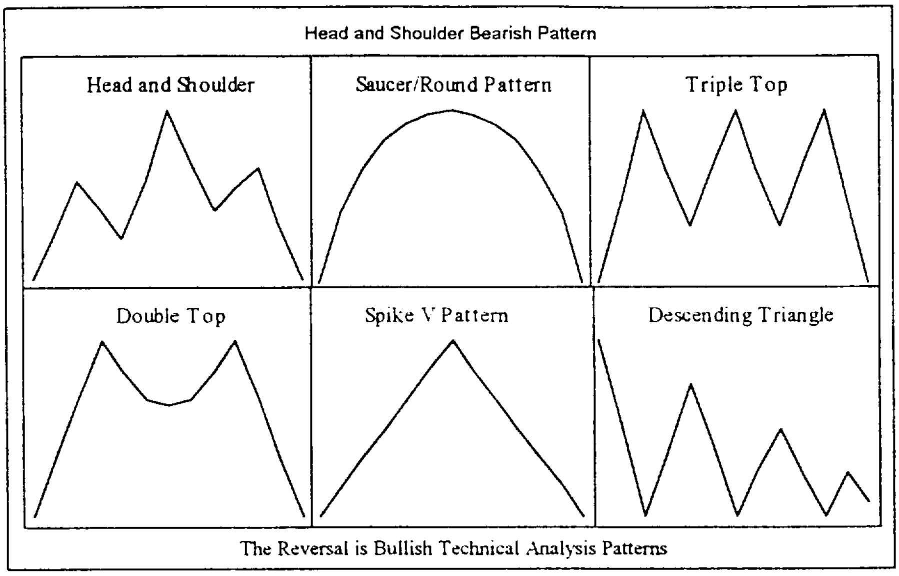

Figure 4. Times Series and Reference Pattern alignment anchored near 11:30 on 7, August 1997

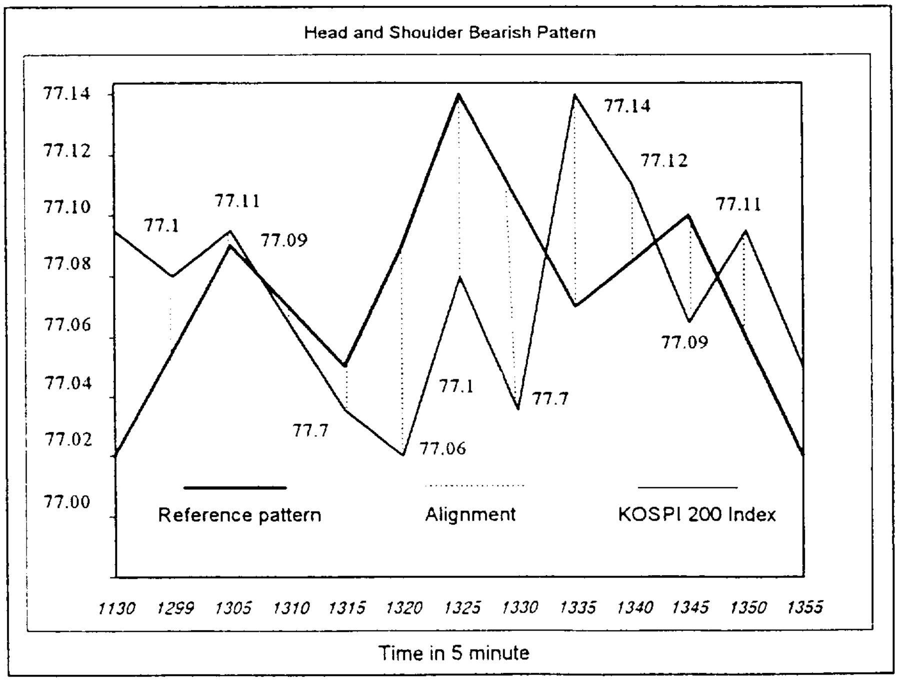

Figure 5. Passive Investment and Active Trading by DTW and CBR

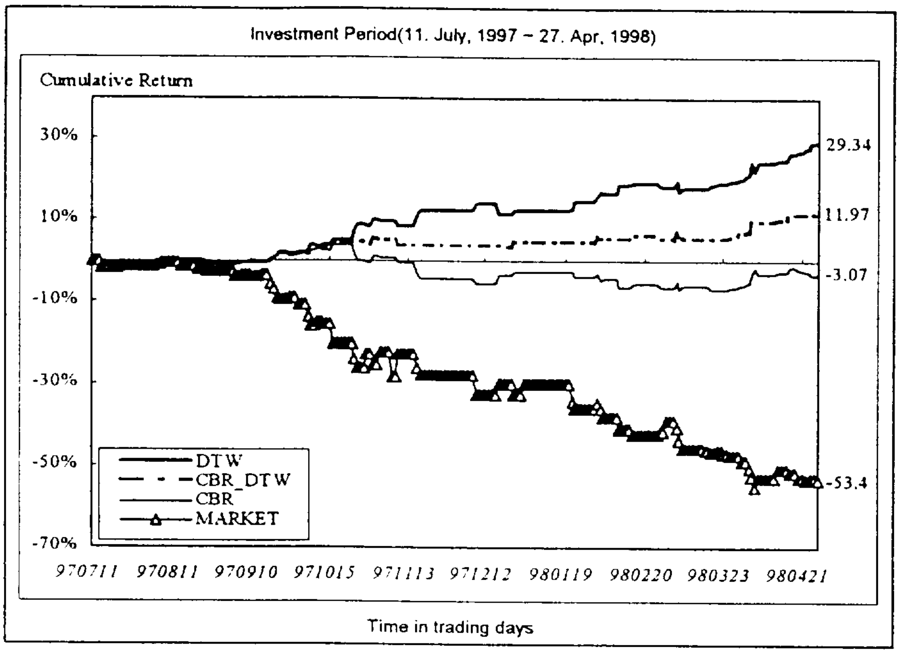

Table1. Hit rate of Trends Reversal Prediction by DTW

MARKET TRENDS \ HIT RATE	Number of Patterns	Hit Rate(%)
Bearish Technical Patterns	35	79.6
Bullish Technical Patterns	9	20.4
Total Accuracy Rate	44/66 = 66.66%	

* The 66 positions excluded the 169 hold strategies are evaluated during the period of 235 trading days

Table2. DTW Recognition Performance by Technical Patterns

MARKET TRENDS \ HIT RATE	Pattern Name	Hit Rate(%)
Bullish Technical Patterns	Ascending Triangle	4.5
	Sauce/ Round shape	13.6
	Spike V shape	2.3
Bearish Technical Patterns	Head and Shoulder	2.3
	Ascending Triangle	22.7
	Double shape	2.3
	Sauce/ Round shape	29.5
	Spike V shape	22.7

Figure 6. Slope variation experiment results by DTW