Trend Detection Using Auto-Associative Neural Networks : Intraday KOSPI 200 Futures

Junmyung Lee, Sungzoon Cho and Jinwoo Baek

Department of Industrial Engineering
Seoul National University
San 56-1, Shillim-Dong, Kwanak-Gu, 151-744, Seoul, Korea
E-mail : basara@snu.ac.kr, zoon@snu.ac.kr, baekhana@snu.ac.kr

Abstract — *This paper reports the results of a new neural network based trend detector. An auto-associative neural network was trained with the "trend" data obtained from the intra-day KOSPI 200 future price. It was then used to predict a trend. Simple investment strategies based on the detector achieved a one-year return of 31.2 points with no leverage.*

1. Introduction

Technical analyses use certain stock chart patterns and shapes as signals for profitable trading opportunities [12]. The general goal of a technical analysis is to identify any regularity in the time series of prices by extracting nonlinear patterns from noisy data. Technical analysts concentrate on forming a specific pattern. The human eye can perform this signal extraction.

Recent breakthroughs in computer technology and numerical algorithms give rise to many methods in financial engineering. On the other hand, technical analysis has survived over the years because pattern recognition is one of the few repetitive activities where computers do not have an absolute advantage[7]. Efforts to automate the pattern recognition process have been reported but their monetary performance left a lot to be desired [3].

In this paper, a neural network based trend detector is proposed using an auto-associative neural network. An auto-associative neural network (AANN) is basically a neural network whose input and target vectors are the same. The proposed detection process is as follows First, the trend data is identified in the historical database. Second, the trend data is used to train the AANN. Third, the trained AANN is used as a trend detector.(see Figure 1).

This mechanism has been used in previous studies[2]. In this paper, the AANN was used in the intra-day KOSPI 200 future price data. The intra-day price data has more chances than the daily price data. It is expected to make a profit more stable. In a previous study[14] the returns were more volatile when low frequency data was used. Moreover, the intra-day price data is expected to have some differences when compared to the daily price data. Compared to the daily price data, the intra-day price data is expected to reflect a larger information-gap between investors.

In section 2, a definition of "trend" is given. In section 3, it is shown how to detect a trend using an auto-associative neural network. Experimental methods and results are reported in sections 4 and 5, and concluding remarks are given in section 6.

2. Definition of Trend

The definition of a Trend in the financial market is ambiguous and subjective. In order to obtain a training data set, a Trend pattern needs to be defined.

The period in which $X(t+1) - X(t)$ is positive or negative consecutively for more than 15 minutes is identified with $X(t)$ defined as follows:

$$X(t) = \frac{1}{11}\sum_{i=t-5}^{t+5} C_i$$

where C_i is the price at the i th minute. If $X(t+1) - X(t)$ is consecutively positive, it is called an Up-Trend. Conversely, if $X(t+1) - X(t)$ is consecutively negative, it is called a Down-Trend.

3. Auto-Associative Neural Network as an Trend Detector

A pattern classification method such as a neural network is an ideal candidate for a trend detection problem. The detection problem can now be formulated as a 2-class problem. A neural network is trained with both trend data and non-trend data. The network tries to classify new input data or current situations as a trend or a non-trend. One problem with this approach is an inability to collect a sufficient amount of non-trend data. This is a well-known problem of partially-exposed environments in pattern classification where there is little or no training data from the on class. The related problems include counterfeit bank note detection and typing pattern identity verification [1].

An Auto-Associative Neural Network (AANN) has been used in many partially-exposed environments [1]. An AANN is basically a neural network whose input and target vectors are identical [6]. An AANN should reproduce an input vector at the output with the least error [4].

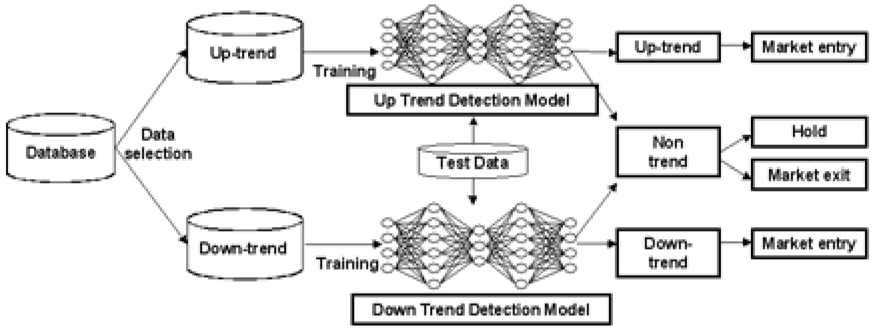

Figure 1. Detection Process framework

Let F denote an auto-associative mapping function, x_i an input vector and y_i an output vector. Network F is then usually trained to minimize the mean square error given by the equation:

$$E = \sum_{i=1}^{N} \left\| x_i - y_i \right\|^2 = \sum_{i=1}^{N} \left\| x_i - F(x_i) \right\|^2$$

Historical financial data has particular trends and characteristics, which tend to repeat themselves. The financial situations that correspond to the trend are assumed to have unique characteristics. If the core information can be incorporated into the network input variables, then the unique characteristics can be captured by the subspace of the AANN embodied by the transformation at the hidden layers. Once the AANN is trained with trend data, any trend data that shares a common characteristic will result in a small error at the output layer while the non-trend data will result in a large error at the output layer. With an appropriate threshold, the AANN can be used to detect the occurrence of the trend.

4. Data Collection and Neural Network Training

The Korea Composite Stock Price Index 200 (KOSPI 200) future price data from Jan 1999 to Dec 2001 was used for these experiments. The KOSPI 200 is a type of a market-value weighted index, which is similar to the S&P 500 futures index [13]. The base date is May 1, 1999 with a base index of 100. The KOSPI 200 futures index is based on the KOSPI 200.

For neural network training, technical indicators such as the VR, RSI and MACD were used as the input variables (for more details regarding the technical indicators, see reference [11]). Using the technical indicators can reduce the number of input variables effectively, while maintaining the historical information. Reducing the number of input variables helps to prevent overfitting [8].

Figure 2 displays the intra-day KOSPI 200 future data of a typical day used in the training of this experiment. The AANN used has a 4-layer structure containing hidden layers with a nonlinear transfer function (the tangent sigmoid was used). The Levenberg-Marquardt algorithm was employed to minimize the sum of the square error function. The experiments were performed using Matlab 5.3 software.

5. Results

Table 1 shows the mean and standard deviation of the distances between the input vectors and output vectors. Up-trend data has a clearly smaller mean (0.21) than non up-trend data (0.461) with the up-trend model. On the other hand, down-trend data has a clearly smaller mean (0.38) than non down-trend data (0.56) with the down-trend model. These results indicate that there is a chance for profit. Let Su(i) and Sd(i) denote a directional signal (1,0,-1) for minute i for up-trend and down-trend model, respectively. Then we combine them to produce the system signal S(i) for minute i based on the simple rule (in Table 2). A simple trading strategy based on S(i) and current position is given in Table 3.

Table 1. The means and standard deviations of the distance between the input and output

Up-Trend Model

Measurements	Up-trend	Non Up-trend
Mean	0.21	0.46
Standard Deviation	0.15	0.31

Down-Trend Model

Measurements	Down-trend	Non Down-trend
Mean	0.38	0.56
Standard Deviation	0.20	0.27

Table 2. Combination Signal from the Up-trend and Down-trend Model

$S_u(i)$ / $S_d(i)$	1	0
0	S(i) is 1	S(i) is 0
-1	Close Position	S(i) is -1

A stop loss is employed with a threshold, θ_{stop}, to manage the investment risk. Three stop loss methods were used in these experiments.

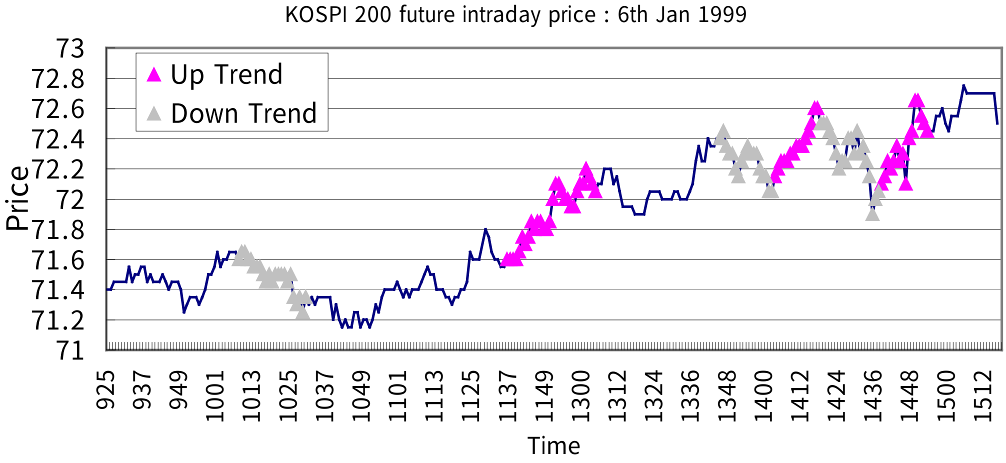

Figure 2. Up Trend and Down Trend in KOSPI 200 future intraday price

Table 3. Simple trading strategy based on a Trend signal

Current Position / $S(i)$	Long position	No position	Short position
1	Hold long position	Take a long position	Take a long position
0	Hold long position	Hold no position	Hold short position
-1	Take a short Position	Take a short position	Hold short position

The Minute Losscut(MLC) means a stop loss level set on the basis of a minute before the price. The Entry Losscut(ELC) means the stop loss level set on the basis of the entry price. The High-TPE Losscut (HLC) means the stop loss level set on the basis of the previous peak profit level.

Table 4. Result of Validation for Trade parameter

		ELC								
		0.4			0.5			0.6		
		MLC 0.3	MLC 0.35	MLC 0.4	MLC 0.3	MLC 0.35	MLC 0.4	MLC 0.3	MLC 0.35	MLC 0.4
H	0.5	42.4	41.3	40.75						
L	0.6	45.6	44.3	43.1	50.95	48.55	47.85			
C	0.7	43.65	42.1	42.3	48.65	46.1	47.05	44.7	44.25	44.35

The optimal values of the stop loss levels were found from the 2000 KOSPI 200 future intra-day price data (Table 4). The cumulative total point earned (TPE) is plotted in Figure 3 and 4, without and with transaction cost of 0.01%, respectively, usually charged in a Korean brokerage firms on online trading. A yearly profit of more than 30 points (approximately 40% rate of return) was returned without the cost. But, a disappointing 70 point loss is registered when the cost is considered. The main cause of the loss is the excessive number of trades, or 7055 trades in 2001 alone.

6. Conclusions

In this paper, a neural network based trend detector was proposed. For these experiments, a definition of "trend" was given and the trend data was selected from the intra-day Korea Composite Stock Price Index 200 future price for 12 months (Jan 1999 – Dec 1999). Two auto associative neural networks were trained with the data obtained and the signals of these models were combined. The model was then tested on an out-of-sample period from Jan 2001 to Dec 2001 without retraining. A simple investment strategy based on the detector achieved a single year profit of 31.2 points.

There were several limitations in this work. First, the trend detection leads to a market entry signal. It is more important to find a way to give a market exit signal. Although, the up-trend and down-trend model can reinforce each other, it is not a complete solution. Therefore, some stop loss methods were used as the exit signal. Commission is another limitation of this work. Without commission, the AANN provides significant profit. However, too much trading and commission results in an overall loss. This kind of system can be useful to brokerage firms since they do not pay the transaction cost.

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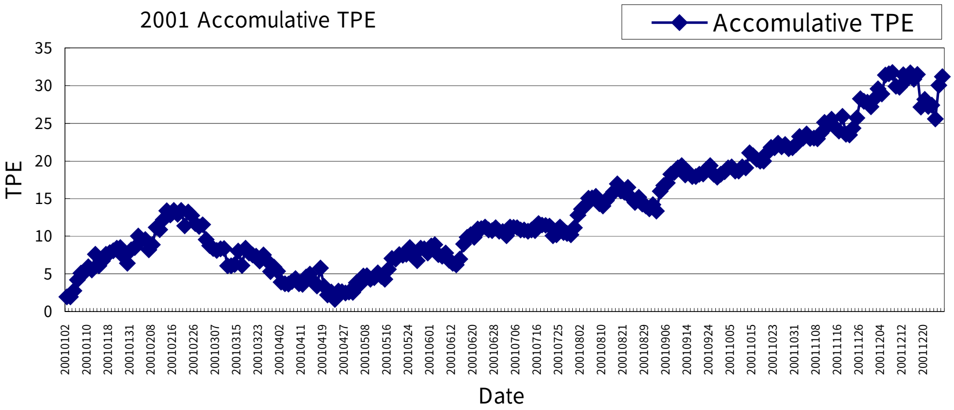

Figure 3. Accumulated total point earned for 2001, without the transaction cost

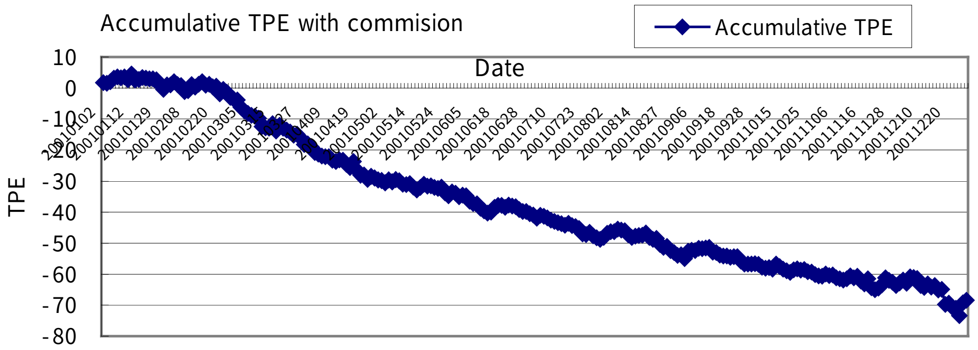

Figure 4. Accumulated total point earned for 2001, with the transaction cost

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