Journal of King Saud University – Computer and Information Sciences (2014) 26, 218–227

King Saud University

Journal of King Saud University – Computer and Information Sciences

www.ksu.edu.sa
www.sciencedirect.com

Wavelet low- and high-frequency components as features for predicting stock prices with backpropagation neural networks

Salim Lahmiri *

ESCA School of Management, 7, Abou Youssef El Kindy Street, BD Moulay Youssef, Casablanca, Morocco

Received 21 January 2013; revised 13 September 2013; accepted 4 December 2013
Available online 14 December 2013

KEYWORDS

Stock prices;
Discrete wavelet transform;
Approximation and detail coefficients;
Backpropagation neural networks;
Forecasting

Abstract This paper presents a forecasting model that integrates the discrete wavelet transform (DWT) and backpropagation neural networks (BPNN) for predicting financial time series. The presented model first uses the DWT to decompose the financial time series data. Then, the obtained approximation (low-frequency) and detail (high-frequency) components after decomposition of the original time series are used as input variables to forecast future stock prices. Indeed, while high-frequency components can capture discontinuities, ruptures and singularities in the original data, low-frequency components characterize the coarse structure of the data, to identify the long-term trends in the original data. As a result, high-frequency components act as a complementary part of low-frequency components. The model was applied to seven datasets. For all of the datasets, accuracy measures showed that the presented model outperforms a conventional model that uses only low-frequency components. In addition, the presented model outperforms both the well-known auto-regressive moving-average (ARMA) model and the random walk (RW) process.

1. Introduction

Forecasting stock markets has long been investigated by researchers and professionals. Indeed, a large number of computing methods for stock prediction have been proposed in the literature (see Atsalakis and Valavanis (2009) and Bahrammirzaee (2010) for surveys). However, due to non-stationary, high volatility clustering and chaotic properties of the stock market prices, the prediction of share prices is always considered to be a difficult and challenging task. Recently, multi-resolution techniques such as the wavelet transform (Mallat, 1989; Daubechies, 1992) have been successfully applied to both engineering problems (De and Sil, 2012; Rikli,

* Address: Department of Computer Science, University of Quebec at Montreal, 201 President-Kennedy, Local PK-4150, Montreal, Québec H2X 3Y7, Canada. Tel.: +1 5149876516.
E-mail addresses: slahmiri@esca.ma, lahmiri.salim@courrier.uqam.ca.

Peer review under responsibility of King Saud University.

Production and hosting by Elsevier

1319-1578 © 2013 Production and hosting by Elsevier B.V. on behalf of King Saud University.
http://dx.doi.org/10.1016/j.jksuci.2013.12.001

2012) and financial time series studies (Li et al., 2006; Huang and Wu, 2008, 2010; Hsieh et al., 2011; Huang, 2011; Wang et al., 2011; Kao et al., 2013; Lahmiri, 2013) because of its powerful feature extraction capability. The wavelet transform is a signal processing technique that simultaneously analyzes the time domain and the frequency domain. In particular, the wavelet transform decomposes a time series into subsequences at different resolution scales. In particular, it decomposes given data into high and low-frequency components. At high frequency (shorter time intervals), the wavelets can capture discontinuities, ruptures and singularities in the original data. At low frequency (longer time intervals), the wavelet characterizes the coarse structure of the data to identify the long-term trends. Thus, the wavelet analysis allows us to extract the hidden and significant temporal features of the original data.

Li et al. (2006) applied the discrete wavelet transform to decompose the Down Jones Industrial Average (DJIA) index time series and to extract features derived from approximation coefficients such as energy, entropy, curve length, non-linear energy and other statistical features. Finally, a genetic programming algorithm was used for forecasting purposes. They concluded that the wavelet analysis provides promising indicators and helps to improve the forecasting performance of the genetic programming algorithm. Huang and Wu (2010) used a discrete wavelet transform to analyze financial time series, including the National Association of Securities Dealers Automated Quotations (NASDAQ, United States), Standard & Poors 500 (S & P 500, United States), Cotation Assistée en Continu (CAC40, France), Financial Times Stock Exchange (FTSE100, United Kingdom), Deutscher AktienindeX (DAX30, Germany), Milano Italia Borsa (MIB40, Italy), Toronto Stock Exchange (TSX60, Canada), Nikkei (NK225, Japan), Taiwan Stock Exchange Weighted Index (TWSI, Taiwan) and the Korea Composite Stock Price Index (KOSPI, South Korea). A Recurrent Self-Organizing Map (RSOM) neural network was used for partitioning and storing the temporal context of the feature space. Finally, a multiple kernel partial least squares regression was used for forecasting purposes. The simulation results indicated that the presented model achieved the lowest root-mean-squared forecasting errors in comparison with neural networks, support vector machines or the traditional general autoregressive conditional heteroskedasticity (GARCH) model. Hsieh et al. (2011) applied the wavelet decomposition to analyze the stock price time series of the Dow Jones Industrial Average Index (DJIA), London FTSE-100 Index (FTSE), Tokyo Nikkei-225 Index (Nikkei) and Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX). Then, they used a recurrent neural network (RNN) to perform the forecasting task. The Artificial Bee Colony algorithm (ABC) was adopted to optimize the RNN weights and biases. The authors concluded that the proposed system is highly promising based on the obtained simulation results. Huang (2011) combined wavelet analysis with kernel partial least square (PLS) regression for stock index forecasting, including the NASDAQ (US), S & P 500 (US), TSX60 (Canada), NK225 (Japan), TWSI (Taiwan), and KOSPI (South Korea), CAC40 (France), FTSE100 (UK), DAX30 (Germany) and the MIB40 (Italy). The DWT was employed to identify financial time series characteristics, and the PLS was used to create the most efficient subspace that maintains maximum covariance between inputs and outputs. In terms of the forecasting errors, the empirical results showed that the DWT-PLS model outperformed traditional neural networks, support vector machines and GARCH models. Wang et al. (2011) used wavelets to transform the Shanghai Stock Exchange (SCE) prices into multiple levels of decomposition. Then, for each level of decomposition, the backpropagation neural network (BPNN) was adopted to predict SCE prices while using low-frequency coefficients. The authors found that the BPNN with fourth decomposition level low-frequency coefficients outperforms a BPNN that uses past values of the original data. Lahmiri (2013) applied discrete wavelets to decompose the S & P 500 price index. The low-frequency coefficient time series were extracted, and out-of-sample predictions of the S & P 500 trends were conducted. Support vector machines (SVM) with different kernels and parameters were used as the baseline forecasting model. The simulation results reveal that the SVM with the wavelet analysis approach outperforms the SVM with macroeconomic variables or technical indicators as predictive variables. The author concluded that the wavelet transform is appropriate for capturing the S & P 500 trend dynamics.

To predict future stock prices, previous studies have used only approximation coefficients in an attempt to work with de-noised data. However, working with approximation decomposition coefficients is useful only in capturing major trends in the data. Indeed, approximation coefficients capture major trends of a time series whereas detail coefficients capture only deviations in the time series. As a result, choosing approximation coefficients as predictive inputs is not appropriate when capturing the overall characteristics of the original data. To take full advantage of the wavelet transforms, detail coefficients should also be used as predictors of future stock prices because detail coefficients are suitable for detecting local hidden information, such as abrupt changes, outliers and short discontinuities in stock prices. We argue that these features could improve the forecasting accuracy of machine learning methods.

In summary, wavelet transforms decompose a signal at different dilations, to obtain those approximation coefficients that represent the high-scale and low-frequency components and the detail coefficients that represent the low-scale and high-frequency components. From the viewpoint of feature extraction, high-frequency components are a complementary part of low-frequency components; in this way, they can capture the missing features that frequency components do not capture. Combining the two frequency components (two types of features) could provide better accuracy in the prediction of future stock prices.

To examine the effectiveness of high-frequency coefficients obtained from wavelet transforms in the prediction of stock prices, artificial neural networks (NN) are adopted in this study as the main machine learning approach for forecasting prices. Indeed, they are very popular as nonlinear stock market forecasting models because the behavior of share prices is nonlinear (Atsalakis and Valavanis, 2009; Bahrammirzaee, 2010; Wang et al., 2011). Artificial neural networks are nonlinear methods that can learn from patterns and capture hidden functional relationships in given data even if the functional relationships are not known or are difficult to identify (Zhang et al., 1998). In particular, they are capable of parallel processing information when there is no prior assumption about the model form. In addition, artificial neural networks are adap-