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A variational mode decompoisition approach for analysis and forecasting of economic and financial time series

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ABSTRACT

The empirical mode decomposition (EMD) has been successfully applied to adaptively decompose economic and financial time series for forecasting purpose. Recently, the variational mode decomposition (VMD) has been proposed as an alternative to EMD to easily separate tones of similar frequencies in data where the EMD fails. The purpose of this study is to present a new time series forecasting model which integrates VMD and general regression neural network (GRNN). The performance of the proposed model is evaluated by comparing the forecasting results of VMD-GRNN with three competing prediction models; namely the EMD-GRNN model, feedforward neural networks (FFNN), and autoregressive moving average (ARMA) process on West Texas Intermediate (WTI), Canadian/US exchange rate (CANUS), US industrial production (IP) and the Chicago Board Options Exchange NASDAQ 100 Volatility Index (VIX) time series are used for experimentations. Based on mean absolute error (MAE), mean absolute percentage error (MAPE), and the root mean of squared errors (RMSE), the analysis results from forecasting demonstrate the superiority of the VMD-based method over the three competing prediction approaches. The practical analysis results suggest that VMD is an effective and promising technique for analysis and prediction of economic and financial time series.

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1. Introduction

Huang et al. (1998) introduced an adaptive technique called empirical mode decomposition (EMD) to represent nonlinear and nonstationary signals as sums of components with amplitude and frequency modulated parameters. In particular, it is a multiresolution technique to perform the joint space-spatial frequency decomposition of a signal empirically by successive removal of elemental signals, the intrinsic mode functions or IMF, which represent the oscillatory modes of the original signal going from high- to low-frequency ranges. The obtained IMFs can then serve to represent the signal. The intrinsic mode function is complete, adaptive and almost orthogonal. The main advantage of using the EMD technique is that the input signal is analyzed without need to convolve it with a basis function as done for Fourier and wavelet transforms. In addition, the method is data driven and, thus, self-adaptive. These features make EMD suitable for nonlinear and nonstationary data analysis. Because of its attractive features, it was applied in diverse scientific areas of signal processing; including mechanical engineering (Ricci & Pennacchi, 2011), signal de-noising (Li, Wang, Tao, Wang, & Du, 2011, Lahmiri and Boukadoum, 2014a, 2015a), speaker identification (Wu et al, 2011), biomedical image analysis (Ai, Wang, & Yao, 2011, Lahmiri & Boukadoum, 2014b, 2015b), DNA sequence analysis (Zhang et al, 2012), and machinery fault diagnosis (Cheng, Yang, & Yang, 2012).

The EMD has also received a large attention in analysis of economic and financial data for forecasting purpose. For instance, it was employed in modeling and predicting crude oil price (Zhang, Lai, & Wang, 2008; Zhang, Yu, Wang, & Lai, 2009), stock market (Cheng et al, 2014), electricity price (An, Zhao, Wang, Shang, & Zhao, 2013, Lisi & Nan, 2014), and foreign exchange rate (Lin, Chiu, & Lin, 2012, Premanode & Toumazou, 2013).

More recently, a new multiresolution called variational mode decomposition (VMD) was introduced by Dragomiretskiy and Zosso (2014) as an alternative to the EMD algorithm to overcome its limits. For instance, drawbacks of the EMD include lack of exact mathematical model, interpolation choice, and sensitivity to both noise and sampling (Dragomiretskiy & Zosso, 2014). The VMD is an entirely non-recursive variational model where the modes are extracted concurrently (Dragomiretskiy & Zosso, 2014). In particular, the VMD model searches for a number of modes and their respective center frequencies, such that the band-limited modes reproduce the input signal exactly or in least-squares sense (Dragomiretskiy & Zosso, 2014). In sum, the VMD has the

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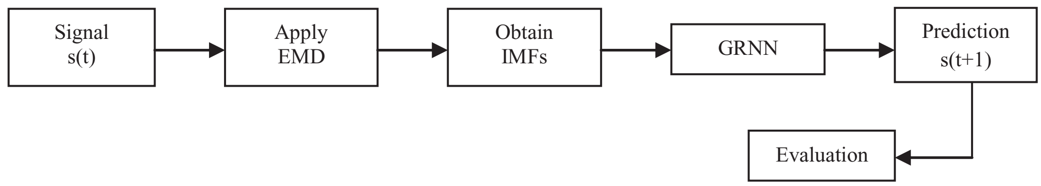

Fig. 1. EMD-based system.

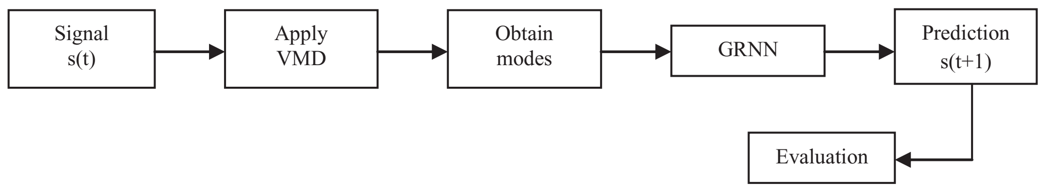

Fig. 2. VMD-based system.

ability to separate tones of similar frequencies contrary to the EMD (Dragomiretskiy & Zosso, 2014). Using simulated harmonic functions, Dragomiretskiy and Zosso (2014) found that the VMD as a denoising approach outperforms the EMD. The VMD was found to be effective in biomedical signal denoising (Lahmiri & Boukadoum, 2014c, 2015c) and also was applied in analysis of international stock markets (Lahmiri, 2015d). However, there is a need to explore the effectiveness of the VMD against the EMD in modeling and forecasting economic and financial data. Indeed, modeling and forecasting economic and financial data is crucial for government to set economic policy and for companies to manage portfolios and control risk.

The objective of this study is to explore the usefulness of the VMD in extracting economic and financial time series features (components) for prediction purpose. In particular, we compare the performance of the EMD and VMD based approach in terms of forecasting accuracy of four economic and financial data: West Texas Intermediate (WTI) (crude oil), Canadian/US exchange rate, US industrial production (IP), and the Chicago Board Options Exchange NASDAQ 100 Volatility Index (VIX).

Finally, the performance of each approach will be assessed by virtue of statistical performance measures they are the mean absolute error (MAE), mean absolute percentage error (MAPE), and the root mean of squared errors (RMSE). The general regression neural network (GRNN) (Specht, 1991) will be used for training and testing the EMD and VMD extracted patterns. The GRNN is chosen since it provides fast learning and convergences to the optimal regression surface as the number of samples becomes very large (Polat & Yildirim, 2008). In this work, a feedforward neural network (FFNN) (Haykin, 2008) trained with past observations and the well-known autoregressive moving average (ARMA) process will also be considered as baseline models for comparison purpose.

The remaining of the paper is organized as follows. In Section 2 briefly introduces the empirical mode decomposition, the variational mode decomposition, and the general regression neural network. The obtained simulation results are provided in Section 3 while Section 4 concludes.

2. Methods

Two main prediction systems are designed, evaluated, and compared. In the first system, the EMD is applied to the original data (signal) to obtain its intrinsic mode functions (IMFs). Then, they will be fed to the GRNN for forecasting purpose. Similarly, in the second system the VMD is applied to the original data (signal) to obtain its variational modes. Then, the latter will be fed to the GRNN for forecasting purpose. The two forecasting systems are described in Figs. 1 and 2 respectively. The EMD, VMD, GRNN, and statistical performance measures are described next.

2.1. Empirical mode decomposition

The key feature of the EMD is to decompose a signal into a sum of functions such that each of them has the same numbers of zero crossings and extrema, and is symmetric with respect to its local mean (Huang et al., 1998). These are the so called Intrinsic Mode Functions (IMFs). The IMFs are found at each scale going from fine to coarse by an iterative procedure called sifting algorithm. For a signal s(t), the EMD decomposition is performed as follows (Liu, Xu, & Li, 2007):

(a) Find all the local maxima, $M_i, i = 1, 2, \ldots,$and minima, $m_k, k = 1, 2, \ldots,$in $s(t)$.

(b) Compute by interpolation -for instance a cubic Spline- the upper and lower envelopes of the signal: $M(t) = f_M(M_i, t)$ and$m(t) = f_m(m_i, t)$.

(c) Compute the envelope mean $e(t)$ as the average of the upper and lower envelopes: $e(t) = (M(t) + m(t))/2$.

(d) Compute the details as:$d(t) = s(t) - e(t)$.

(e) Check the properties of $d(t)$:(e.1) If $d(t)$ meets the conditions on number of extrema and symmetry stated previously, compute the *i*th IMF as $IMF(t) = d(t)$ and replace s(t) with the residual $r(t) = s(t) - IMF(t)$.

(e.2) If $d(t)$ is not an IMF, then replace $s(t)$ with the detail: $s(t) = d(t)$.

(f) Iterate steps (a) to (e) until the residual $r(t)$ satisfies a given stopping criterion.

In the end, $s(t)$ is expressed as follows:

$$s(t) = \sum_{j=1}^{N} IMF_j(t) + r_N(t) \tag{1}$$

where N is the number of IMF which are nearly orthogonal to each other and all have nearly zero means; and $r_n(t)$ is the final residue which is the low frequency trend of the signal $s(t)$. Usually, the standard deviation (SD) computed from two consecutive sifting results is used as criterion to stop the sifting process by limiting the SD size (Huang et al., 1998; Chen et al., 2009) as:

$$SD(k) = \frac{\sum_{t=0}^{T} |d_{k-1}(t) - d_k(t)|^2}{\sum_{t=0}^{T} d_{k-1}^2(t)} < \varepsilon \tag{2}$$

where k is the index of the kth difference between the signal $s(t)$ and the envelope mean $e(t)$. The term ε is a pre-determined stopping value. For instance, its value is set to 0.001.

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