Gold Price Forecast based on ESMD Multi-Frequency Combination Model

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Abstract. The time series of gold price has the characteristics of nonlinearity, non-stationary and high noise, which cannot be fully described by using traditional single model. Based on the decomposition reconstruction theory, a combined prediction model based on the pole symmetry mode decomposition (ESMD) is proposed. Firstly, the gold price time series is decomposed into multiple eigenmode components by using the ESMD method, and these components are recombined into high, medium and low frequency parts. Secondly, the appropriate prediction methods are selected for the three parts of the different frequencies of recombination: The nonlinear autoregressive neural network predicts the high frequency part, and the IF and low frequency parts are predicted by the multi-task, and least squares support vector machine. Finally, the prediction results of the three parts are integrated to obtain the prediction result of the gold price. It shows that the model proposed in this paper has higher accuracy and is a more effective method for predicting gold price.

1. Introduction
Gold is a special commodity with commodity attributes, currency attributes and safe-haven attributes, which play an important role in national economic security and national defense security. Since 2016, along with the global economic recovery, commodities have ended a five-year bear market and returned to investors' configurable assets. Effective time series analysis and forecasting of gold prices is conducive to gold investors and producers to discover the inherent laws of economic operations, and understanding the characteristics of the gold market, providing them with great help in making decisions, which is conducive to improving market risk prevention capabilities. And reduce the loss of gold value.

At present, the research on gold price forecast is mainly based on traditional statistical methods and measurement models. For example, Pedrudee applies SVR and decision tree algorithm [1], Antonino applies BP neural network model [2], GA-BP neural network model [3], FAR model of wavelet transform [4], ARFIMA model [5], ARMA-GARCH model [6]. With the nonlinear and non-stationary characteristics, these models cannot effectively grasp the nonlinear mode in the gold price series, which have no use in realistic commercial behaviors. To overcome the shortcomings of the traditional models, the EMD-SVMS-SVM model is proposed. In this model, the gold price sequence is decomposed into several components of different scales and frequencies and a trend term, and then reconstruct them into three components by using reconstruction algorithm. By using three different SVM models, three components are predicted separately. Finally, the final prediction result is obtained. The results show that the model is better than a single SVM, GA-BP and other models.

However, there are still the following shortcomings: using just a single SVM model in the prediction, without considering the frequency anisotropy, nonlinearity, and stationarity of each
component, cannot fully get the effect, due to the variability, complexity, and prediction of the gold price, the predicted result has a big error. Therefore, this paper takes into account the characteristics of different modal components, and finds appropriate prediction models to predict different components. For low-frequency components and trend terms, the correlation between adjacent time points is ignored in time series prediction in traditional SVM, In this paper, advanced multi-task LS-SVM is applied to time series prediction, and multiple phases are constructed. The learning task of the neighboring point uses the data set of the multi-task combination to train the MTLS-SVM model to restrain each other and improve the prediction accuracy. 3. There are some shortcomings in the EMD decomposition method: modal aliasing, the number of screening times is difficult to determine, and the decomposition trend function is too rough. Pole-symmetric mode decomposition (ESMD) is a new method of data analysis. It discards the spectrum analysis relying on integral transformation, and proposes a direct interpolation method for data, which more intuitively reflects the time-varying amplitude and frequency of each mode, and makes use of it. The least squares optimize the residual modal components to form an adaptive global moving average, and the optimal number of screenings is determined. Therefore, ESMD is used to decompose the gold price sequence to overcome the inherent defects of EMD. For the problem of large prediction error of SVM for high frequency part, a more suitable nonlinear autoregressive (NAR) model is used for prediction to improve prediction accuracy.

In summary, to find a more appropriate gold price forecasting method, an ESMD combined forecasting model is proposed. Taking the Au9995 price series as the research object, the original gold price sequence is first decomposed into different eigenmode components and a trend component by ESMD. According to the fluctuation characteristics of different components, the classification is reconstructed into high frequency, low frequency and trend items. Different models are selected according to different frequency component characteristics for prediction. Finally, the prediction results are summed to obtain the final prediction result. The results show that the prediction accuracy of the ESMD combined model proposed in this paper is significantly improved, and the validity of the model is verified.

2. Combined Prediction Model based on ESMD

With the characteristics of nonlinearity, non-stationary and high noise, traditional prediction model can not fully describe the characteristics of gold price fluctuations, which brings many difficulties to its prediction problems. In this paper, original sequence is decomposed, and the characteristics of each component is analyzed, which is used to explore its essential features and internal laws, and find prediction methods suitable for different components to improve the prediction accuracy. Therefore, in view of the idea of decomposition and reconstruction, this paper proposes a combined prediction model based on ESMD. The model is based only on the time series data of gold price, and does not consider other influencing factors, avoiding the uncertainty of data input variables and the uncertainty of model parameters.

2.1. ESMD Model

The existing gold price sequence is decomposed by using the empirical modal decomposition (EMD). The decomposition is adaptive and can highlight the local features of the data, which can effectively reflect the characteristic information of the original data. However, there are some shortcomings in the EMD decomposition method: modal aliasing, the number of screenings is difficult to determine, and the decomposition trend function is too rough. The pole-symmetric mode decomposition (ESMD) discards the spectrum analysis by means of integral transformation, and proposes a direct interpolation method for data, which more intuitively reflects the time-varying amplitude and frequency of each mode, and optimizes the residual modal component by least squares. An adaptive global moving average is formed, and the optimal number of screenings is determined. Therefore, in order to overcome the inherent defects of EMD, this paper uses ESMD to decompose the gold price sequence to obtain m components M and 1 trend term R. The ESMD algorithm steps:

Step 1: Find all the extreme points of the gold price sequence data Y, and marked as \( E_i \);
Step 2: Connect the adjacent extreme points with line segments and marked as \( F_i \);
Step 3: Supplement the left and right boundary points \( F_0, F_n \);
Step 4: Construct \( P \)-interpolation lines using the obtained \( n+1 \) midpoints and calculate their median curve \( L^* \).
Step 5: Repeat the above steps for \( Y - L^* \) until \( |L^*| < \varepsilon \) or the number of screenings reaches the preset maximum value \( K \). At this time, the first mode \( M_1 \) is decomposed;
Step 6: Repeat the above steps for \( Y - M_1 \) to get \( M_2, M_3, \ldots, M_m \) until the final margin \( R \) has only a certain number of poles left.
Step 7: Let the maximum number of screenings \( K \) change within an integer interval, repeat the above steps, calculate the variance ratio \( \frac{\delta}{\delta_0} \), and plot their variation with \( K \), relative standard deviation of \( \delta: Y - R, \delta_0: \) raw data Y Standard deviation.
Step 8: Find the maximum number of screenings for the minimum variance ratio and repeat the first six steps until all results are output.

2.2. Gold Price Sequence Prediction

By using the fine-to-course reconstruction method, the \( m \) modal \( M_{i,j} \) decomposed by ESMD is divided into high frequency and low frequency data, and high frequency, low frequency and trend terms are obtained. After BDS test, the modal data is nonlinear. Therefore, the selection of nonlinear model prediction is more reasonable. Through the empirical analysis of this paper, it is found that the fluctuation of high-frequency data has nonlinearity, chaos and abruptness, and nonlinear autoregressive (NAR) model is used to describe more reasonable low-frequency data. The fluctuations of the trend terms are relatively flat, nonlinear, and closely related between adjacent time points. The multi-task LS-SVM prediction is more accurate.

2.2.1. High-frequency data prediction model

nonlinear autoregressive (NAR) model can be defined as:

\[
y_1(t) = G[y_1(t-k), \ldots, y_1(t-1)] + K\varepsilon_t \tag{1}
\]

\( y_1(t-k), \ldots, y_1(t-1) \) is the high-frequency component value of gold price at \( t-k, \ldots, t-1 \), and \( y_1(t) \) is the high-frequency component value of gold price at time \( t \). \( G \) is a nonlinear function, \( K \) is a constant, and \( \varepsilon_t \) is a Gaussian random variable.

2.2.2. Prediction model for low frequency data and trend items

For low-frequency components and trend terms, the traditional SVM applied to time series prediction ignores the close correlation between adjacent time points. In this paper, advanced multi-task LS-SVM is applied to time series prediction by constructing multiple adjacent points. The learning task is to use the multi-task combination data set to train the MTLS-SVM model [8], so that they are mutually restrained and improve the prediction accuracy.

Multitasking least squares support vector machine (MTLS-SVM) model

Suppose there are \( m \) tasks, each task has \( l_i \) training samples, \( \{x_{i,j}, y_{i,j}\}_{j=1}^{l_i} \), a total of \( l = \sum_{i=1}^{m} l_i \) training samples, let \( \omega_i = \omega_0 + \mu_i \), where \( \omega_0 \) contains the common information, and \( \mu_i \) contains the specific information of each task. By minimizing the following objective function, find \( \omega_0, \{\mu_i\}_{i=1}^{m} \) and \( \beta = (\beta_1, \beta_2, \ldots, \beta_m)^T \):

\[
\begin{align*}
\min & \quad f(\omega_0, \{\mu_i\}_{i=1}^{m}, \{\theta_i\}_{i=1}^{m}) = \frac{1}{2} \omega_0^T \omega_0 + \frac{1}{2} \sum_{i=1}^{m} \mu_i^T \mu_i + \rho \frac{1}{2} \sum_{i=1}^{m} \theta_i^T \theta_i \\
\text{s.t.} & \quad y_i = \theta_i^T (\omega_0 + \mu_i) + \beta_i 1_n + \theta_i, \quad \theta_i = (\theta_{i,1}, \theta_{i,2}, \ldots, \theta_{i,n})^T
\end{align*} \tag{2}
\]

where \( \theta_i \) is the mapping from the original space to the high-dimensional space, and \( \gamma, \rho \) is Two regularization parameters. Lagrangian function:

\[
L(\omega_0, \{\mu_i\}_{i=1}^{m}, \{\theta_i\}_{i=1}^{m}, \{\alpha_i\}_{i=1}^{m}) = f(\omega_0, \{\mu_i\}_{i=1}^{m}, \{\theta_i\}_{i=1}^{m}) - \sum_{i=1}^{m} \alpha_i^T (\theta_i^T (\omega_0 + \mu_i) + \beta_i 1_n + \theta_i - y_i) \tag{3}
\]
\( \alpha_i \) is the Lagrangian multiplier, KKT condition:

\[
\begin{align*}
\frac{\partial L}{\partial \omega_0} = 0 &\Rightarrow \omega_0 = \emptyset \alpha \\
\frac{\partial L}{\partial \mu_i} = 0 &\Rightarrow \mu_i = \frac{m}{\gamma} \emptyset_i \alpha_i, \forall i \in N_m \\
\frac{\partial L}{\partial \beta_i} = 0 &\Rightarrow \alpha_i^T 1_{n_i} = 0, \forall i \in N_m \\
\frac{\partial L}{\partial \theta_i} = 0 &\Rightarrow \alpha_i = \rho \theta_i, \forall i \in N_m \\
\frac{\partial L}{\partial \alpha_i} = 0 &\Rightarrow \omega_0 = Z \alpha, \forall i \in N_m
\end{align*}
\tag{4}
\]

Get the decision function

\[
y_i(x) = \sum_i^m \sum_j \delta_{i,j} k(x_{i,j}, x) + \frac{m}{\gamma} \sum_j \delta_{i,j} k(x_{i,j}, x) + \beta_i
\tag{5}
\]

Where \( \delta_{i,j} \) is the Lagrangian multiplier of the j-th sample of the i-th task, and \( k(x_{i,j}, x) \) is the kernel function. Due to the existence between adjacent time points Close correlation, multi-task learning can use \( t+1, t+2, \ldots, t+m \) at the same time as predictive output, and multiple tasks play a role in mutual restraint, improving prediction accuracy.

2.3. Combined Gold Price Forecasting Model

The gold price prediction model proposed in this paper is the ESMD multi-frequency combination model. The steps of the model are as follows:

Step 1: decompose the gold price sequence with ESMD to obtain \( m \) components \( M \) and 1 trend term \( R \).

Step 2: using the fine-to-course reconstruction method, the \( m \) modal \( M_i \) decomposed by ESMD is divided into high frequency and low frequency data to obtain high frequency, low frequency and trend term \( R \).

Step 3: high-frequency data were predicted by nonlinear autoregressive (NAR) model, and low-frequency data and trend terms were predicted by multi-task LS-SVM.

Step 4: the sum is the final predicted value. Evaluate the forecast results.

The flow chart of the ESMD multi-frequency combination model is as follows:
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Figure 1. flow chart of the ESMD multi-frequency combination model

3. Empirical Analysis

This paper selects the daily closing price of Shanghai Gold Exchange Au9995 from November 26, 2002 to July 27, 2017, a total of 3,400 data. In the past, 2,720 data were training sets and the last 680 data bits were tested. This paper uses MATLAB and R software for data processing, and selects the mobile window to obtain advanced prediction values. Finally, the evaluation criteria are applied.

3.1. Analysis of Gold Price Characteristics

(1) Randomness. Using the BOX randomness test, the P value is < 2.2e-16, so it is not a random sequence with analytical value.

(2) Stationarity. The KPSS method was used to test the stationarity. The T statistic (8.6774) was larger than the test threshold (0.347, 0.463, 0.574, 0.739) at the significance level of 1%, 5%, and 10%, which was non-stationary.

(3) Linearity test. Using the BDS method, for different standard deviations, the P value is 0 less than the significance level of 0.05, indicating nonlinearity.

3.2. Decomposition Prediction

The gold price sequence is obtained by ESMD decomposition to obtain 8 components M and a trend term R. The result is shown in Figure 2.
Figure 2. Decomposition prediction results

The component M is reconstructed according to the fine-to-coarse reconstruction, and the T-test of the mean of the superposition and the sequence is calculated. The test results are shown in Table 1.

|     | $S_1$  | $S_2$  | $S_3$  | $S_4$  | $S_5$  | $S_6$  | $S_7$  | $S_8$  |
|-----|--------|--------|--------|--------|--------|--------|--------|--------|
| Average | 0.00790 | 0.01153 | 0.01900 | -0.04860 | 0.020668 | 0.02527 | 0.026347 | -0.37529 |
| 2213 | 716    | 327    | 306    | 35      | 983    | 35      | 69      |
| t test value | 0.34235 | 0.32578 | 0.38645 | -0.69977 | 0.19289 | 0.18895 | 0.13412 | -1.6627 |

The mean value of the test value at $S_8$ is significantly non-zero. Therefore, $M_1 - M_7$ is superimposed as a high frequency component, and $M_8$ is a low frequency component. The reconstructed component is shown in Figure 3.

Figure 3. Result of reconstructed component
Using the NAR and MT-LSSVM with different kernel functions and parameters, the low-frequency components, high-frequency components and trend items of the gold closing price sample sequence are trained to predict the external values of the samples, and the final predicted values are obtained. The prediction effect is shown in Table 2.

| Evaluation index | ESMD model | EMD-SVM |
|------------------|------------|---------|
| MSE              | 1.9106     | 2.8990  |
| MAPE             | 0.0068     | 0.0989  |
| RMSE             | 2.5777     | 5.9988  |

4. Analysis Conclusion
Gold has commodity attributes, currency attributes and safe-haven attributes, and plays an important role in national economic security and national defense security. Along with the global economic recovery in 2016, commodities have ended a five-year bear market and returned to investors' configurable assets. This paper proposes a gold price forecasting method based on ESMD multi-frequency combination model, which improves the prediction accuracy, helps gold investors and producers to discover the inherent laws of economic operation, understand the characteristics of the gold market, and provide decision-making for them. A lot of help is helpful to improve market risk prevention ability and reduce the loss of gold value.

5. References
[1] Pedrudee Ongsritrakul, Nuanwan Soonthornphisaj. Apply Decision Tree and Support Vector Regression to Predict the Gold Price[C]. Proceedings of the International Joint Conference on Neural Networks, Portland, OR, United States, 2003:2488-2492.
[2] Antonino Parisi, Franco Parisi, David Diaz. Forecasting gold price changes: Rolling and recursive neural network models[J]. Journal of Multinational financial management, 2008, 18(5):477-487.
[3] Chunmei Liu. Price forecast for gold futures based on GA-BP neural network[C]. Proceedings International Conference on Management and Service Science, September 20-22, 2009, Wuhan, China.
[4] Vinay B. Gavirangaswamy, Gagan Gupta, Ajay Gupta, and Rajeev Agrawal. 2013. Assessment of ARIMA-based prediction techniques for road-traffic volume. In Proceedings of the Fifth International Conference on Management of Emergent Digital EcoSystems (MEDES '13). ACM, New York, NY, USA, 246-251.
[5] Dmitri Model and Moshe Eizenman. 2012. A general framework for extension of a tracking range of user-calibration-free remote eye-gaze tracking systems. In Proceedings of the Symposium on Eye Tracking Research and Applications (ETRA '12), Stephen N. Spencer (Ed.). ACM, New York, NY, USA, 253-256.
[6] Mohammad Moshirpour, Nariman Mani, Armin Eberlein, and Behrouz Far. 2013. Model based approach to detect emergent behavior in multi-agent systems. In Proceedings of the 2013 international conference on Autonomous agents and multi-agent systems (AAMAS '13). International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 1285-1286.
[7] Shuo Xu, Xin An, Xiaodong Qiao, Lijun Zhu, and Lin Li, 2013. Multi-Output Least-Squares Support Vector Regression Machines. Pattern Recognition Letters, Vol. 34, No. 9, pp. 1078-1084. DOI: 10.1016/j.patrec.2013.01.015.
[8] Shuo Xu, Xin An, Xiaodong Qiao, and Lijun Zhu, 2013. Multi-Task Least-Squares Support Vector Machines. Multimedia Tools and Applications. DOI: 10.1007/s11042-013-1526-5.