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Noise Canceling in Volatility Forecasting Using an Adaptive Neural Network Filter

Soheil Almasi Monfared[a] and David Enke[b,*]

[a]Laboratory for Investment and Financial Engineering, Missouri University of Science and Technology, 223 Eng. Mgt., Rolla, MO, 65409-0370
[b]Laboratory for Investment and Financial Engineeirng, Missouri University of Science and Technology, 221 Eng. Mgt., Rolla, MO, 65409-0370

Abstract

Volatility forecasting models are becoming more accurate, but noise looks to be an inseparable part of these forecasts. Nonetheless, using adaptive filters to cancel the noise should help improve the performance of the forecasting models. Adaptive filters have the advantage of changing based on the environment. This feature is vital when they are used along with a model for volatility forecasting and error cancellation in the financial markets. Nonlinear Autoregressive (NAR) neural networks have simple structures, but they are efficient tools in error cancelation systems when working with non-stationary and random walk noise processes. For this research, an adaptive threshold filter is designed to respond to changes in its environment when a GARCH(1,1) model makes errors in its volatility forecast. It is shown that this filter can forecast the noise (errors) in the GARCH(1,1) outputs when there is a non-stationary time series of errors. The model reduces the mean squared errors by 42.9%. A sample portfolio of five stocks from the S&P 500 index from 4/2007 to 12/2010 is studied to illustrate the performance of the model.

Keywords: Volatility Forecasting; GARCH; Noise Cancelling; Adaptive Filters; Neural Networks

1. Introduction

Volatility forecasting methods are becoming more accurate, with most methods being able to forecast the general trend, at least in the short term [20]. Nonetheless, noise (error) is an inseparable part of the forecast. Some of the more commonly used techniques in volatility forecasting include: 1.) Econometric models, for instance, the

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* Corresponding author. Tel: +1-573-341-4749
E-mail address: enke@mst.edu

Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model introduced by Bollerslev [1] in 1986 [11,12]; 2.) Artificial intelligence models, for instance, using neural networks to forecast the S&P 100 implied volatility by Malliaris and Salchenberger [2,13,14]; and 3.) Hybrid models that utilize both econometric and artificial intelligence to increase the accuracy, for instance, volatility forecasting using a hybrid GJR-GARCH neural network model by Almasi and Enke [3,15,16]. Unfortunately, even with a successful forecast, the remaining noise is not easy to model due to non-stationary or random walk processes. Moreover, due to latent nature of volatility, as well as using a proxy such as squared return, the noise in the proxy has the previously mentioned undesired effects [4,5]. Other sources of noise, including microstructure noise that comes from measurement errors and impacts the accuracy of the forecast and R^2, should be corrected accordingly [6, 7, 8, 9, 10].

A proposed solution for this noise problem is to use an adaptive filter as suggested by Widrow [17,18]. For this approach, instead of changing the original forecasting model (any model from the three main categories), an adaptive neural network model is matched with the forecasting model to predict the noise in its output. By subtracting the forecasted noise, the final forecast should be more accurate. Thus, the main focus of this paper is to use a neural network adaptive filter to reduce GARCH(1,1) forecasting noise (error). The main difference of this new hybrid model approach is the application of a neural network as a noise forecaster.

2. Model and Dataset

The data used in this paper is downloaded from the Yahoo finance database (finance.yahoo.com). A portfolio of size five was randomly selected from the S&P 500 index, and includes The Allstate Corporation, The Walt Disney Company, W.W. Grainger, Inc., Hewlett-Packard Company, and Brown-Forman Corporation. The adjusted daily closing price from 4/2/2007 to 12/31/2010 is utilized. The log return is computed using formula 1 below.

$$r_t = \ln(\frac{p_t}{p_{t-1}}) \tag{1}$$

where p_t is the stock price at time t and r_t is the log return. The portfolio is optimized every 90 days to keep the optimal position of each stock. The minimum position for each stock is 5%. This portfolio optimization is done utilizing a Sharpe ratio [19] maximization, as defined in formula 2.

$$S = \frac{r_p}{\sigma_p} \tag{2}$$

where r_p and σ_p are the return and risk of the portfolio, respectively. A GARCH(1,1) model provides the volatility forecast, while a NAR neural network model with a lag of 3 (NAR(3)) and a threshold combiner provide adaptive filtering. Figure 1 shows the model structure and data processing.
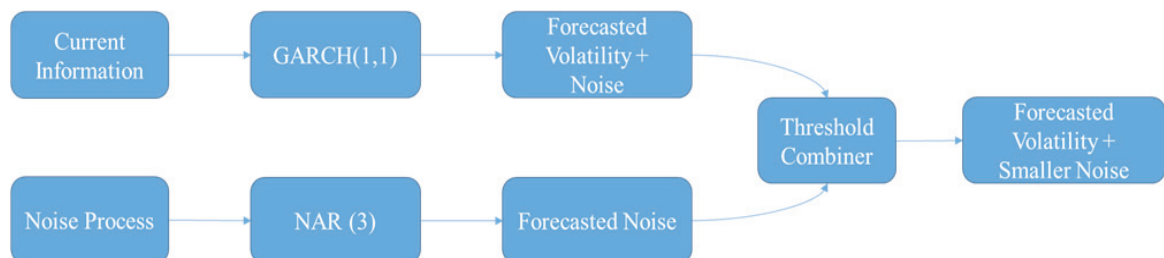

Fig. 1. Volatility forecasting model including both forecasting and filtering

The filtering includes a NAR(3) model that forecasts the noise process from a GARCH(1,1) forecast, as well as a threshold combiner that subtracts the forecasted noise from the GARCH(1,1) output (that includes some noise) whenever the absolute value of the forecasted noise is larger than the last day's noise (error). In other words, the

filter comes in action only if the magnitude of the forecasted noise is larger than the last observed noise value. This design is on purpose. In this context, the noise is non-periodic and very small in size (e.g. 10^{-4}). According to the Augmented Dickey-Fuller test, the noise process is not stationary. According to the Variance Ratio test, the process is a random walk. Thus, the complexity of the noise leads to using a flexible and non-linear forecasting tool, such as a neural network [3]. The threshold combiner gives more stability to the model due to its controlling role in the filter that uses noise forecasts only when they are larger than expected noises. In a random walk process the expected value for the next step is the current value of the process, thus, it defines the threshold value in the threshold combiner component of the model's adaptive filter. The role of the filter is to reduce the larger than expected noises.

NAR(3) uses six sigmoid neurons in its hidden layer, along with one linear output neuron. The GARCH(1,1) model is updated every day based on the last 30 days of log return data to forecast the one step ahead volatility. The proxy of the volatility is the squared return of the portfolio, calculated based on the portfolio return for the last 30 days. Formulas 3 and 4 below show the GARCH(1,1) and non-linear optimization process for daily updating of the model.

$$\sigma_{t+1}^2 = \omega + \alpha r_t^2 + \beta \sigma_t^2 \tag{3}$$

$$\underset{\omega,\alpha,\beta}{Max}\left[\sum_i -\ln(\sigma_i^2) - (\frac{r_i^2}{\sigma_i^2}) \right] \tag{4}$$

$s.t.$

$\omega > 0$

$\alpha, \beta \geq 0$

$\omega + \alpha + \beta = 1$

The NAR(3) is updated every day based on the last 500 days of noise to forecast the one step ahead forecasts. Figure 2 shows the structure of NAR(3) neural network. All the processes are coded and implemented in MATLAB utilizing the Neural Network and Optimization toolboxes.
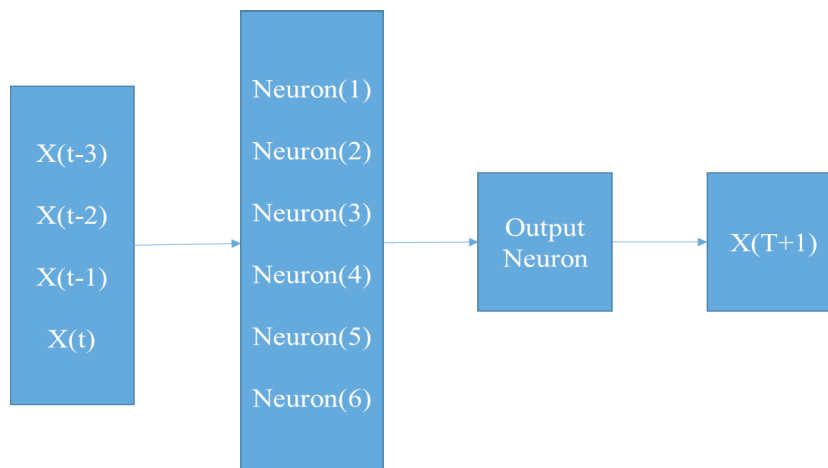

Fig. 2. Nonlinear autoregressive neural network with lag 3 and six neurons in the hidden layer

3. Results

Table 1 compares the hybrid model results in terms of the mean squared error (MSE) of the volatility forecasts.

Table 1. Comparison of volatility forecasting model performance

Volatility Forecasting Model	MSE
GARCH(1,1)	8.42E-09
GARCH(1,1) with Adaptive Noise Cancelling Filter	4.81E-09

According to Table 1, using an adaptive noise cancelling filter reduces the noise by 42.9%, giving evidence of the effectiveness of this filter for the complex noise process. Figure 3 shows the actual volatility, GARCH(1,1) forecast, and the GARCH(1,1) forecast using an adaptive noise-cancelling filter.
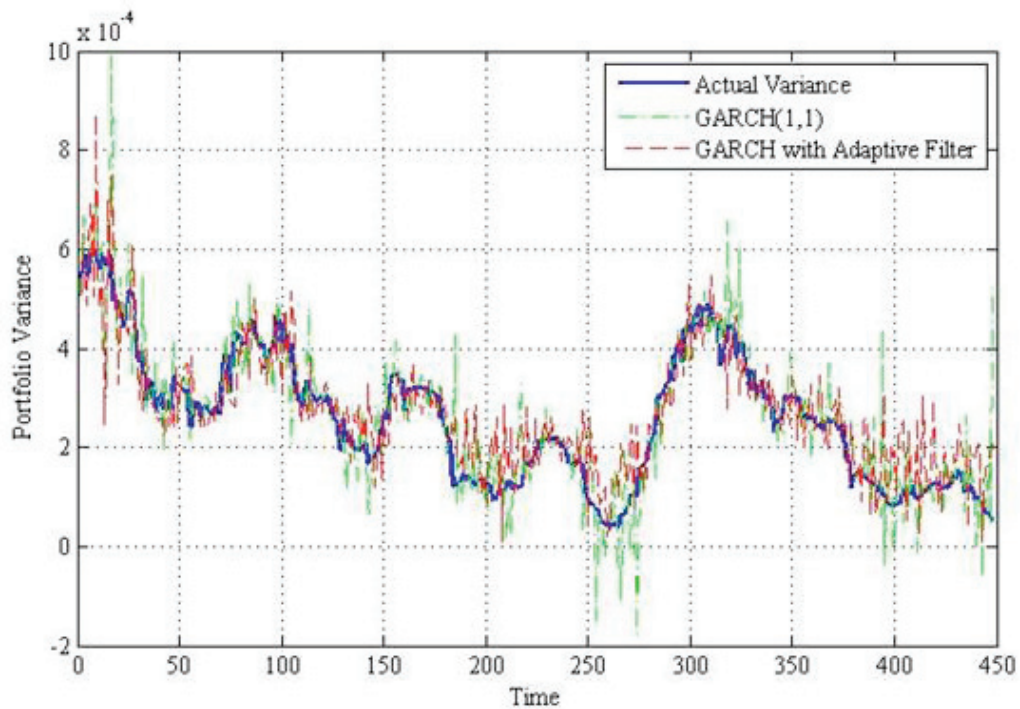

Fig. 3. Actual volatility versus GARCH(1,1) and GARCH(1,1) with an adaptive filter

As seen in Figure 3, the filter improves the performance of the GARCH(1,1) model. The performance of this model when the NAR(3) filter is used, both with or without threshold combiner, is the same since the size of the forecasted errors are larger than the last GARCH(1,1) noise level for all data points. As such, this filter is always used during the study period. This makes sense given that the GARCH(1,1) forecasts is different from the actual values and does not follow the trend, as illustrated in Figure 3.

4. Conclusion

It is widely accepted that neural networks are useful for forecasting in high volatility conditions [3]. This research has shown that they are also beneficial in extracting information from non-stationary and random walk processes. This information can be used to improve the performance of a parallel forecaster model (GARCH(1,1) in this case). The noise (error) analysis is a prerequisite for designing this type of adaptive filter.

Future research can test the performance of threshold noise cancelling filters in different economic situations, parallel to other forecasting models, such as neural networks or hybrid models. The stabilizing ability of the threshold combiner is still a question that needs further investigation.

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