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Signal Processing
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Signal Processing Using Empirical Mode Decomposition

Signal processing is the process of using a computer for numerical calculations. Multiple algorithms have been created that improve the process of identifying signals. Though computer capability have increased, humans are necessary to manipulate algorithms so they can be efficiently implemented. We implement these techniques to find patterns in the future movements of financial securities. Below we will describe the use of EMD in pattern recognition.

Empirical mode decomposition (EMD) is a nonlinear signal- transformation method developed by Huang et al. (1998, 1999). It is used to decompose a nonlinear and non-stationary time series into a sum of intrinsic mode function (IMF) components with individual intrinsic time scale properties.

$$x(t) = \sum_{i=1}^{n} \mathrm{imf}_i(t) + r(t).$$

IMF must satisfy the following two conditions:

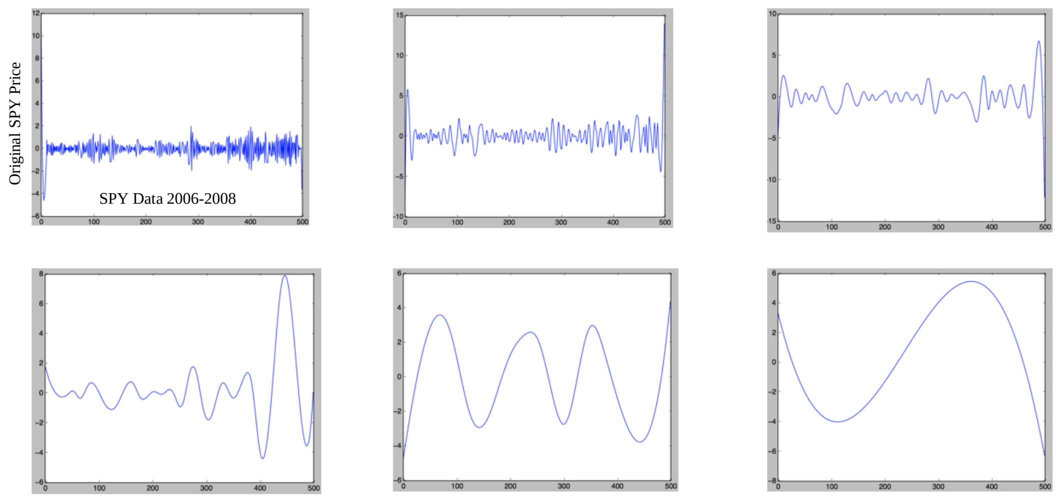
- The number of extreme values and zero-crossings either are equal or differ at the most by one.
- The mean value of the envelope constructed by the local maxima and minima is zero at any point .

Procedure

1. Identify all the local maxima and minima of x(t).
2. Obtain the upper envelope x_u(t) and the lower envelope x_l (t) of the x(t) through interpolation.
3. Use the upper envelope x_u (t) and the lower envelope x_l (t) to compute the first mean time series m_1 (t), that is, m_1(t)= [x_u(t) + x_l (t)]/2.
4. Evaluate the difference between the original time series x(t) and the mean time series and get the first IMF h_1 (t), that is, h_1(t)= x(t) − m_1 (t). Moreover, we see whether h_1 (t) satisfies the two conditions of an IMF property. If they are not satisfied, we repeat steps 1–3 of the decomposition procedure to eventually find the first IMF.

5. After we obtain the first IMF, a repeat of the above steps is necessary to find the second IMF, until we reach the final time series r(t) as a residue component that becomes a monotonic function, which is suggested for stopping the decomposition procedure. Figure 1 shows each IMF represented at different frequency for the S&P 500 stock price index exchange traded fund (SPY).

Figure 1. Intrinsic Mode Function Decomposition



Note: If all frequencies are added to the trend line in Figure 2, the sum is original S&P price series.

Figure 2. Monotonic Trend Function

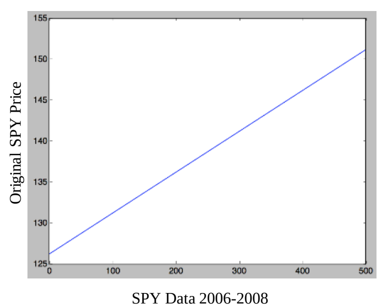


Figure 2 gives us the trend after S&P price has finished decomposing. The six functions in Figure 1 represent IMFs at different frequencies. When you subtract them from the original stock price, you arrive at Figure 2, the trend.

Signal Processing Applied to Trading

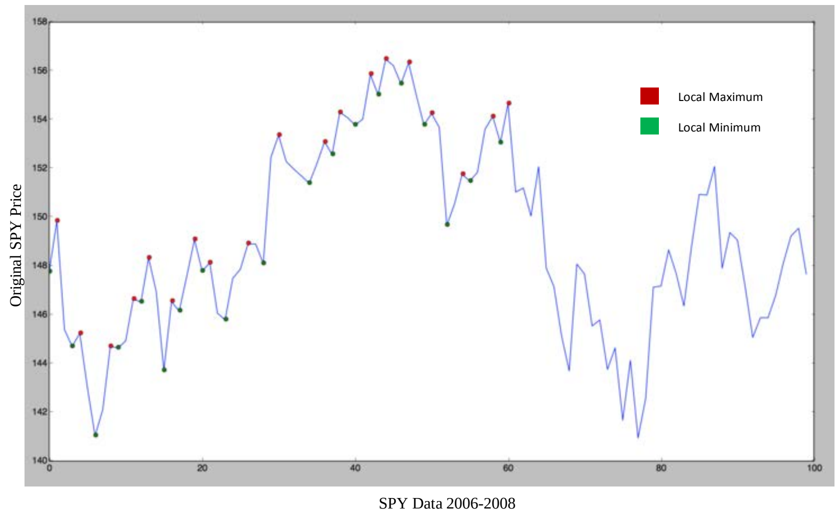
We adapt techniques from EMD decomposition to create our signal processing strategy. First, we apply pattern recognition to identify support and resistance using Empirical Mode Decomposition.

First we identify local maximum and minimum of original time series following same process as EMD. Figure 3 shows local maximum and minimum points for the S&P Index.

$$\text{Local Maximum: } E_0 < E_1 > E_2$$

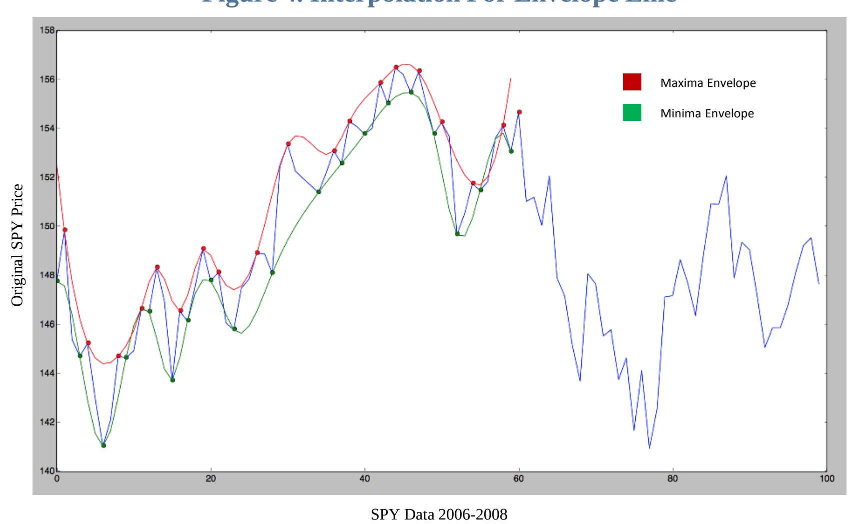
$$\text{Local Maximum: } E_0 > E_1 < E_2$$

Figure 3. Extrema Points



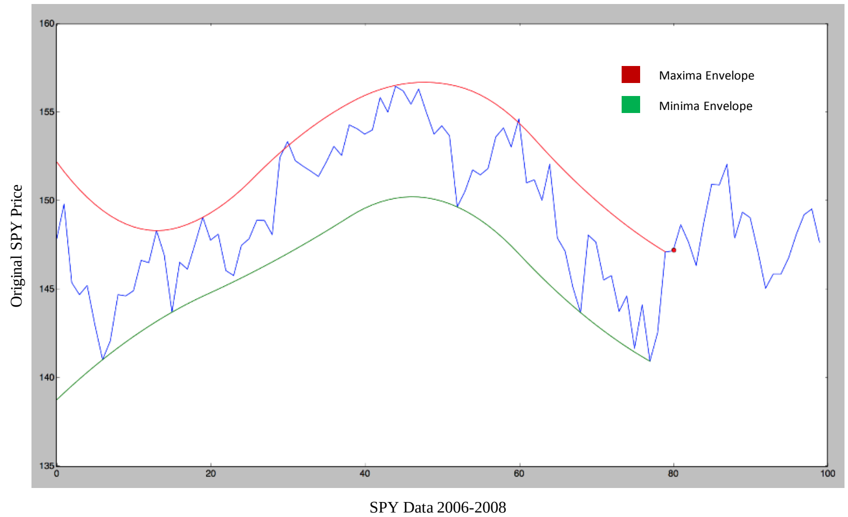
We link all local maxima and local minima using interpolation to form an envelope line of the original time series. Interpolation is a method of constructing new data points given a set of known variables. Figure 4 below shows interpolation applied to S&P

Figure 4. Interpolation For Envelope Line



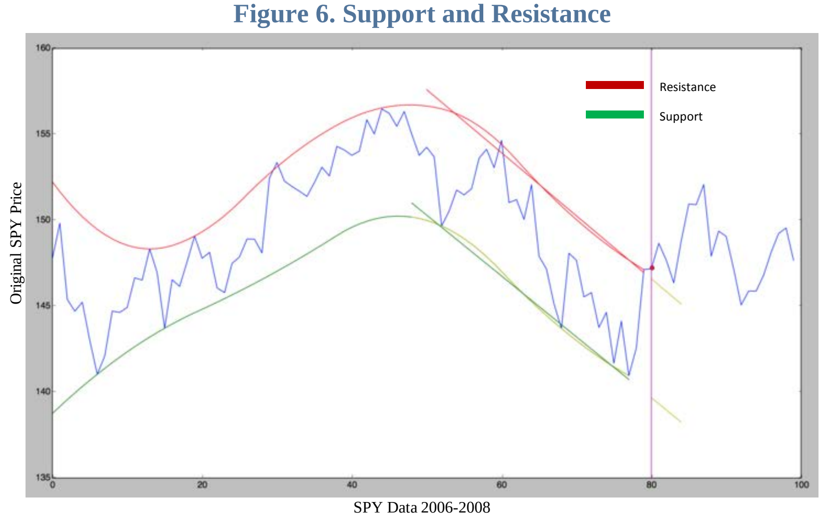
To smoothen our envelope line, we apply interpolation on our existing envelope. Figure 5 shows our new lines. This creates less variability between the two curves.

Figure 5. Interpolation On Original Envelope Line



We apply first order polynomial regression to our new envelope. The regression creates a straight line representative of a trend. It uses historical data to set a threshold for its parameters. The threshold is based on recognizing patterns in sum of squared errors over a time period. We finally arrive at our support and resistance lines, as seen in Figure 6.

Figure 6. Support and Resistance



Trading Strategy

We have our support and resistance lines, now we use this information to predict the future movement of the S&P Index. We apply three different strategies on this signal: breakout, slope, and mean-reversion. Below we describe the process for our breakout strategy.

Determine when to enter and exit positions using breakout from support and resistance lines. If stock price goes more than x percent outside support or resistance line, enter a position. Close using a stop loss. We recalculate the support and resistance lines every five periods, giving us predictions from $time_t$ to t_5 at each calculation.

Parameter 1:

$$\text{Break out percentage} = \text{Constant}_1 * \text{Volatility[past 60 days]}$$

Parameter 2:

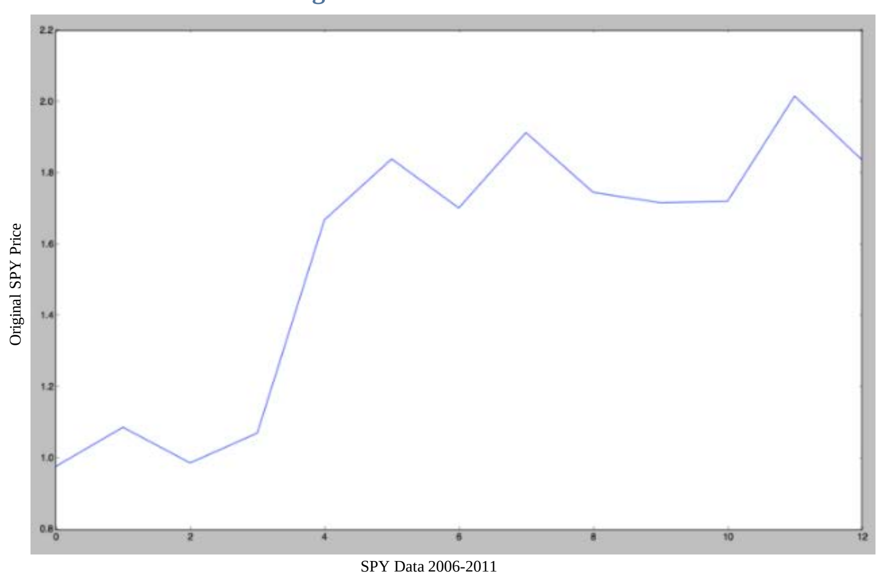
$$\text{Stop-loss percentage} = \text{Constant}_2 * \text{Volatility[past 60 days]}$$

To find the constant we apply grid search to all combinations of stop loss and position enter thresholds. Determine the best combination of the two parameters. A separate constant is used for each.

Volatility is incorporated into the entry and exit positions because high volatility cycles that would result in us entering a position could easily trigger stop losses. We define volatility as the standard deviation of returns over a given period.

To test our strategy, we use data on S&P 500 Index exchange traded fund SPY from 2006-2017. January 1, 2006-July 31, 2011 are in sample data (Figure 7), and August 1, 2011-February 1, 2017 are out of sample.

Figure 7. Profit and Loss



Note: Does not include transaction fees, gross of taxes.
Disclaimer: Past performance is not indicative of future results.

The period used for in sample testing shows strong backtested results from 2006-2011 on the S&P 500 Index ETF. This strategy executed 13 trades during the period, but had worse performance from 2011-2017. We will next apply empirical mode decomposition to higher frequency data. The signal will track the trend of a security and enter a position if over a threshold. Stay tuned for future research.

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