Noise Filtering of Foreign Exchange Data

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Abstract: To maximise profits when currency trading, it is important to separate the trend and noise components of the data. To correctly identify the turning points, it is ideal to keep the delay as short as possible. It is shown that a low delay filter can be developed, although the attenuation is limited to 6 dB in the stop band. Improved attenuation can be achieved at the expense of increased delay.

Keywords: Low delay filters, Phase response, Low pass filters, Trend identification

1 INTRODUCTION

The foreign exchange market is the world's largest and most liquid financial trading market with a volume of over $2 trillion each day [1]. Because currencies are traded around the world, there is no centralized market. This means that the market is open 24 hours a day, only closing over the weekends. The availability of Internet trading platforms enables virtually anybody to trade at a relatively low cost.

Foreign currency trading consists of simultaneously selling one currency and buying another currency. The two currencies traded are referred to as a currency pair, and the relative exchange rate between the two currencies in the pair determines the relative value. When trading for investment, or speculation, it is not necessary to physically have funds in either of the pair traded. Selling of a currency is called going "*short*" in that currency, which effectively means borrowing that currency in order to execute the trade. The currency that is bought is called the "*long*" side of the trade because a positive balance is being held in that currency. At the time of the trade, when the position on the currency pair traded is "*opened*", the long and short sides of the trade are of equal value. However, with time, the exchange rate will almost certainly move. This means that the relative value of the long and short sides will change with time. The goal is to use this fluctuation in exchange rate to obtain a profit. After some time, the open position is then "*closed*". This involves selling back the long currency and buying the short currency, and repaying the loan. However, with the movement in the exchange rate, there may be an excess or a shortage of the original short currency. This difference is therefore the profit or loss from the trade.

As in any open market, the balance between supply and demand governs the exchange rate at any time. This is largely governed by perceived value (there is no way of calculating the true value). The exchange rate can be influenced by interest rates, balance of trade, economic growth, unemployment, inflation, consumer and business confidence, retail sales, housing starts, political stability, and so on [1]. Within the economics community, a range of sophisticated models have been developed that relate the exchange rate to the various fundamental factors. While many of these models are quite powerful, they tend to be most useful after the fact in explaining historical movements and the factors that led to these movements. Such models are more useful to analysts, and perhaps longer term traders, but provide less useful information for shorter term trading.

In an efficient market, the current price has factored in all relevant information about a currency of the available at that time. However, because information does not travel instantaneously, and because its effects on a currency cannot be determined instantly, an exchange rate is constantly moving. Immediately after scheduled government announcements there is often considerably volatility as the market digests the news. It is not even the news itself that affects the price, but whether or not the news meets the expectations that have already been factored into a market.

While volatility is essential to make profits from currency speculation, it is this same volatility that also makes speculation risky. It is necessary to anticipate movements in the exchange rate, which, in an efficient market, is equivalent to anticipating the driving factors – world events. Note that every other currency trader is also doing likewise, so it is necessary to be smarter or one step ahead of the game. That said, exchange rates often move in trends (in the statistical sense) so one common trading strategy is to identify a trend and trade with the trend.

While an exchange rate is in a constant state of flux, a trend is a bias or tendency to move in one direction over time. Technical analysis aims to identify and capture such trends and use them for forecasting. Traditional technical analysis focuses on identifying patterns in the movement of the exchange rate and uses these to predict the turning points or ends of trends [2]. While much of technical analysis tends to be subjective, with the trader identifying and interpreting the patterns, there are also many systems built using objective indicators, and even neural networks (see for example [3]).

To maximize profits with trend trading is important to correctly identify the start and end of the trend. While it is relatively easy to identify the beginning and end of trends in the middle of a graph (i.e. in hindsight), it is much more difficult to do so on the right hand side of the graph. For example consider Figure 1. Is the movement on the right hand side (from 4 a.m. to 6 a.m.) noise, or does it mark the end of the trend? In fact, it is noise, as is revealed in Figure 2, which shows that there is a significant price movement from this point continuing upwards in the direction of the previous trend. The same question could also be asked of the right hand side of Figure 2, which does in fact mark the end of this short-term trend.

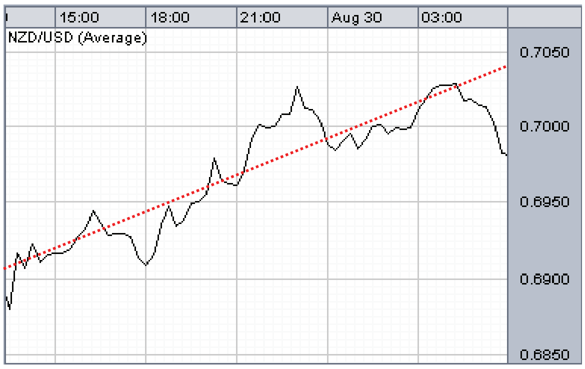

Figure 1: A short term trend. Is the movement from 4 a.m. – 6 a.m. the end of a trend or noise?

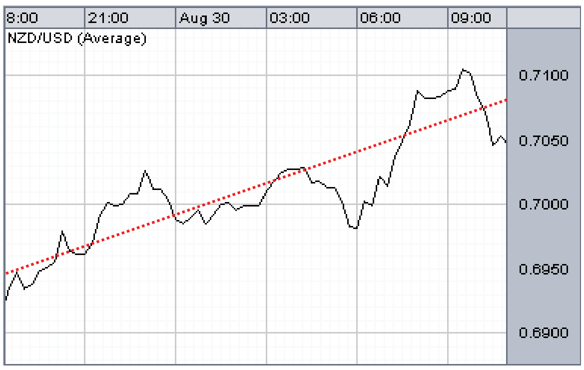

Figure 2: The trend continues over at least the next 5 hours. Is the latest move the end of the trend?

The distinction between trends and noise depends significantly on the time scale of interest. In fact random price fluctuations appear over a wide range of scales, with trends on a short time scale appearing as noise on a long time scale. This is most obvious when considering Figure 9 at the end of the paper. The character of the fluctuations and trends appears similar on time scales as short as 30 seconds per sample through to 1 day per sample. This represents a range of time scales of over 5 orders of magnitude. This uniformity of variation over such a wide range of time scales implies that the noise is white.

The time frame of interest is generally chosen by selecting an appropriate sample rate. Interestingly, no anti-alias filters are used with currency data; the samples are invariably the exchange rate at the sample times. The aim of reducing the sampling rate is not to give a perfect reconstruction, but to reduce the volume of data that needs to be interpreted, and to hide the finer detail that is not of interest to the trader. If necessary, the trader can obtain a feel for the price movements during the interval from the minimum and maximum values of the exchange rate between the samples, as shown in Figure 3. These enable the trader to more effectively gauge the level of noise at the shorter time intervals, and effectively provide something similar to anti-alias filtering by constraining the range of movement between the samples.

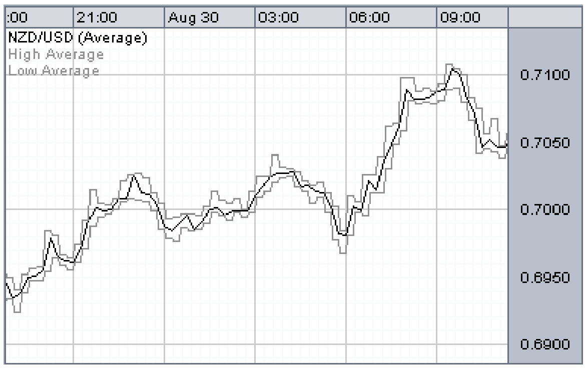

Figure 3. Figure 2 with high and low prices during each 15 minute interval marked.

One reason for not using anti-aliasing filters is that any such filters would introduce a delay into the signal, potentially distorting critical timing information.

This paper takes a signal processing approach and attempts to design a filter for reducing the noise with foreign exchange data in a way that is potentially useful for identifying the ends of trends in real-time rather than in hindsight. Section 2 considers the noise smoothing filters that are commonly available in currency trading platforms, and identifies the problems associated with them. Section 3 designs a causal, low delay, noise smoothing filter. The trade-off between delay and noise smoothing becomes apparent, leading to the design of a family of filters that explicitly balances the delay and smoothing properties of the filters.

2 NOISE FILTERING

A number of indicators or filters have been developed to smooth the noise and help identify the trends. Of particular interest are the turning points in the trends, which mark the most profitable points to enter and exit the market. Any relatively short deviations from the trend are noise so low pass filters based on moving averages are typically used. Since the timeframe of interest is usually chosen by selecting the sample rate, the window size, *w*, for such filters typically varies from 10 to 50. Fluctuations significantly shorter in duration than the length of the filter are therefore removed.

2.1 Standard Filters

The simplest filter is a simple moving average (*SMA*), with equal weights given to the last *w* samples:

$$SMA[n] = \sum_{i=0}^{w-1} \tfrac{1}{w} x[n-i] \,. \tag{1}$$

For a given window size, this provides the best noise smoothing, with larger window sizes giving a smoother curve. However, since the output signal is delayed by $w/2$ samples, more smoothing will also give significantly more delay. Another limitation of the *SMA* is that fluctuations leaving the window (*w* samples ago) have as much influence on the output as what is currently happening, in spite of the fact that such movements are less relevant than the current price.

Another filter that can be used to partially overcome these limitations is the linear weighted moving average (*WMA*). This provides more weight on recent, more relevant, data, tapering to no weight as the sample falls out the end of the window:

$$WMA[n] = \sum_{i=0}^{w-1} \tfrac{2(w-i)}{(w+1)w} x[n-i] \,. \tag{2}$$

For a given filter length, both the smoothing and the delay for the *WMA* are less than those for the *SMA*.

Similar to the WMA is the exponential moving average (EMA) where the weights are exponentially weighted. This is implemented as a first order recursive filter, where the nominal window width, *w*, is used to give the recursive weight:

$$EMA[n] = \tfrac{w-1}{w+1} EMA[n-1] + \tfrac{2}{w+1} x[n] \,. \tag{3}$$

2.2 Problem

The phase shift from the filters inevitably results in the smoothed output being delayed from the original signal. The delay means that the trend may have ended and significant retracement (change in trend direction) has taken place before it is apparent in the filtered output. While the presence of noise means that some delay is inevitable before the end of a trend is recognized, any additional delay costs money as the price falls from the high at the end of the trend.

Figure 4 shows the magnitude of the frequency response and phase delay of the previously described filters with a window of length 15. It is interesting that all three filters have similar low-pass frequency response characteristics; there is negligible difference in the stop-band attenuation. The width of the pass-band differs slightly, with the WMA being the widest, and the EMA being the narrowest. This would imply that the WMA gives slightly poorer smoothing than the SMA, which agrees with observations.

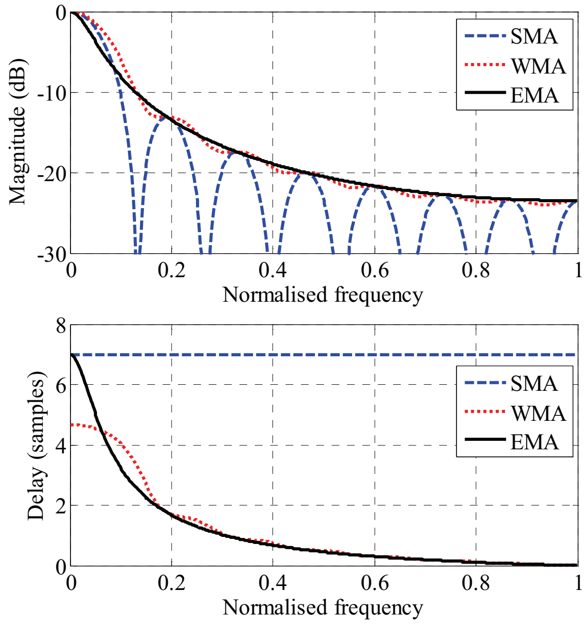

Figure 4: Frequency response and delay for the standard noise smoothing filters; $w = 15$.

The delay characteristics however are quite different. The SMA has a constant delay having symmetric filter weights. With the other two filters, the delay decreases with increasing frequency, although this is of limited value as the high frequencies represent the noise that is attenuated by the filters. In the passband, the WMA has an almost constant delay of about 2/3 of that of the SMA. The average delay of the EMA is somewhere between the other two filters.

A delay-free (zero-phase) non-recursive filter requires symmetric weights balanced about the current sample [4]. This is possible when studying historic data (in the centre of the graph), but not when processing real-time data. Ideally what is required is a causal filter (one that only uses past values) that has little or no phase delay in the pass band.

3 FILTER DESIGN

The approach taken to design a causal filter was to first define a non-causal, zero-phase filter, and then approximate this by a causal filter of the same length.

3.1 Non-causal Reference Filter

An estimate of the noise free signal can be obtained by filtering the noisy signal with a symmetric, non-causal filter. This is possible on historic data for odd window lengths:

$$y_{ref}[n] = \sum_{i=-\frac{w-1}{2}}^{\frac{w-1}{2}} h_{ref}[i]x[n-i] \quad (4)$$

where the reference filter coefficients, $h_{ref}[i]$, are chosen to give good attenuation of the noise. This is equivalent to designing a causal linear-phase filter, and advancing the output in time to give no delay. Arbitrarily, an equi-ripple filter with 40 dB attenuation of the high frequencies was chosen. This reference filter has a slightly wider pass-band than the standard filters. However because of the higher attenuation in the stop-band, the output is actually smoother than any of the standard filters.

3.2 Causal Low Delay Filter

The next step is to choose the filter coefficients of a causal filter (of the same length) in such a way as to best approximate the response of the reference filter. To achieve this, the filter coefficients were optimised to minimise the sum of the squared difference between the outputs of the causal filter and the reference filter:

$$h[i] = \underset{h[i]}{\arg\min} \sum_n \left(y_{ref}[n] - \sum_{i=0}^{w-1} h[i]x[n-i] \right)^2 . \quad (5)$$

In practice, because $x[n]$ and $y_{ref}[n]$ are so similar the resulting system of equations is ill-conditioned. This may be improved by explicitly enforcing the constraint

$$\sum_{i=0}^{w-1} h[i] = 1 . \quad (6)$$

Rearranging (6) gives

$$h[0] = 1 - \sum_{i=1}^{w-1} h[i] \quad (7)$$

which, when substituted into (5) gives

$$\sum_n \left(\left(y_{ref}[n] - x[n] \right) - \sum_{i=1}^{w-1} h[i]\left(x[n-i] - x[n] \right) \right)^2 . \quad (8)$$

The subtraction of $x[n]$ from each sample in the sum removes the relatively large offset, effectively renormalizing the least squares equations.

The resultant filter weights are illustrated in Figure 5. Note that over half the weight is given to the current sample ($h[0]$), and half of the samples ($h[8]$ to $h[14]$) are given negligible weighting. The characteristics of this filter are shown in Figure 6. The goal of a low delay has been achieved, although this has come at the cost of a severely reduced attenuation of the noise. It was found that regardless of the filter length, the attenuation within the stop-band was approximately 6 dB, and increasing the filter length had only a minor effect on smoothing the noise.

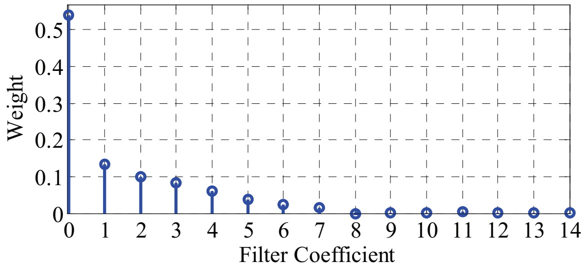

Figure 5: The filter weights (impulse response) of the derived low delay filter for $w = 15$.

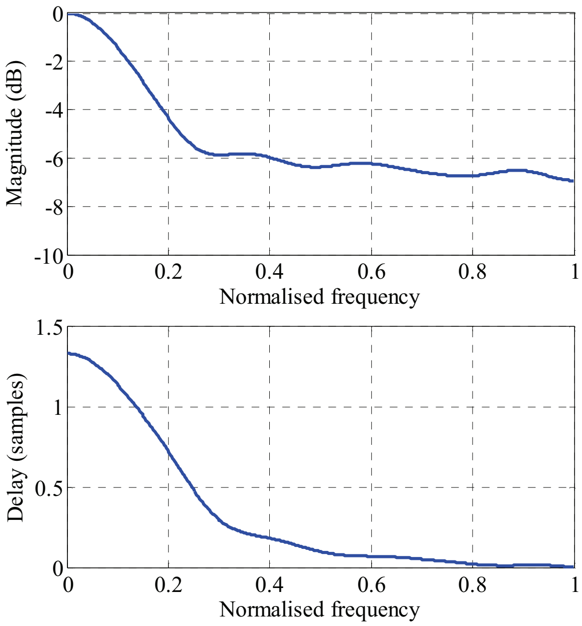

Figure 6: Frequency response and delay for the causal low-delay filter; $w = 15$.

The large weight given to the current sample is what enables the low delay to be achieved. However giving 50% of the weight to a single sample also accounts for the limit of 6 dB attenuation.

While the delay represents a significant improvement over the standard filters, insufficient noise has been removed from the output for such a filter to be useful for trading.

3.3 Delay – Attenuation Trade-off

To improve the stop-band attenuation, it is necessary to reduce the weight of $h[0]$. The other filter coefficients will consequently increase from equation (6). The increased weight given to the delayed samples will increase the delay in the output. This leads to a trade-off between the filter delay and the attenuation that may be achieved in the stop-band.

One mechanism of achieving this trade-off would be to delay the reference filter by k samples when solving for the coefficients of the causal filter:

$$h[i] = \underset{h[i]}{\arg\min} \sum_n \left(y_{ref}[n-k] - \sum_{i=0}^{w-1} h[i]x[n-i] \right)^2 . \quad (9)$$

This gives a family of filters with characteristics shown in Figure 7. As the delay is increased, the response approaches that of the reference filter.

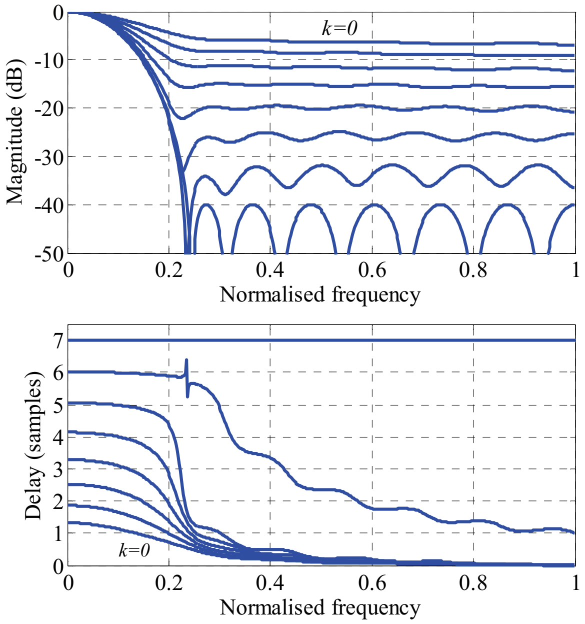

Figure 7: Frequency response and delay for $w = 15$ as the reference filter delay, *k*, varies from 0 to 7.

It is instructive to consider the filters in terms of the relationship between delay and stop-band attenuation. Figure 8 compares the standard filters with those derived from the 40 dB attenuation reference filter for a window size of 15 samples. The new filter performs better than the currently used standard filter, giving lower delay for a given level of attenuation, or better attenuation for a given delay.

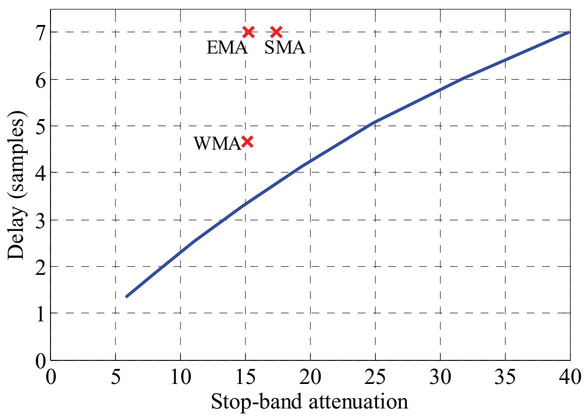

Figure 8: Trade-off between delay and attenuation

For higher order filters (using a larger window length), similar results and characteristics are obtained. With the higher order filters, the pass-band is narrower, filtering more noise and giving a smoother output. The cost of the longer filters, though is a longer delay.

4 CONCLUSIONS

A causal low-pass filter without delay cannot be constructed. However, a low delay filter can be designed, although this will be limited in its stop-band attenuation. In terms of currency trading, this makes intuitive sense: to be more certain that a movement is a change in trend rather than noise, it is necessary to wait longer, and to ensure the price does not revert to the trend. However, the consequence of this delay is that less profit is made on the trade. On the other hand, by closing a trade as soon as it appears that the price is moving the wrong direction will give a better profit if indeed the trend is reversing. However, closing early gives a greater probability that the trade will be closed as a result of noise rather than an actual trend change.

A family of FIR filters has been developed that allows a currency trader to balance between delay and noise attenuation. This means that a trader can effectively choose the appropriate filter for their trading style.

5 REFERENCES

[1] M.D. Archer and J.L. Bickford, *Getting Started in Currency Trading*. Hoboken, New Jersey: John Wiley & Sons (2005).

[2] M.N. Kahn, *Technical Analysis Plain and Simple: Charting the Markets in Your Language*. 2 ed: FT Press (2006).

[3] J. Yao and C.L. Tan, "A case study on using neural networks to perform technical forecasting of Forex", *Neurocomputing*, **34:** 79-98 (2000).

[4] S.K. Mitra, *Digital signal processing: a computer-based approach*. Singapore: McGraw-Hill (1998).

Figure 9: Price fluctuations over a wide range of time scales. Top graph – daily data; 2nd graph – hourly data; 3rd graph – 5 minute data; bottom graph – 30 second data.