Predictive Indicators

SLIDE 1

MESA Software

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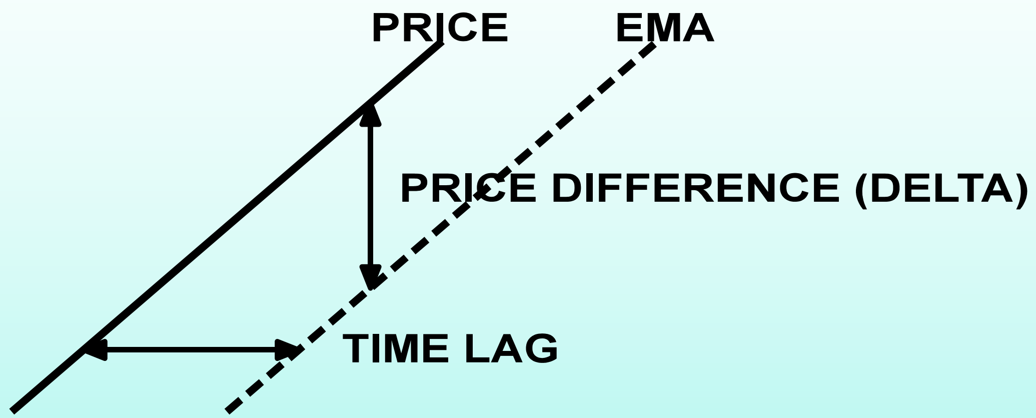
AGENDA

- Exponential Moving Averages
  - Why lag is important
  - How to compute the EMA constant to produce a given lag
- Higher order filters
  - Let your computer do a superior job of smoothing
- Essence of Predictive Filters
- Linear Kalman Filters
- Nonlinear Kalman Filters
- Theoretically Optimum Predictive Filters
- Zero Lag smoothing

Fundamental Concept of Predictive Filters

- In the trend mode price difference is directly related to time lag



- Procedure to generate a predictive line:
  - Take an EMA of price (better, a 3 Pole filter)
  - Take the difference (delta) between the price and its EMA
  - Form the predictor by adding delta to the price
    - equivalent to adding 2*delta to EMA

A Simple Predictive Trading System

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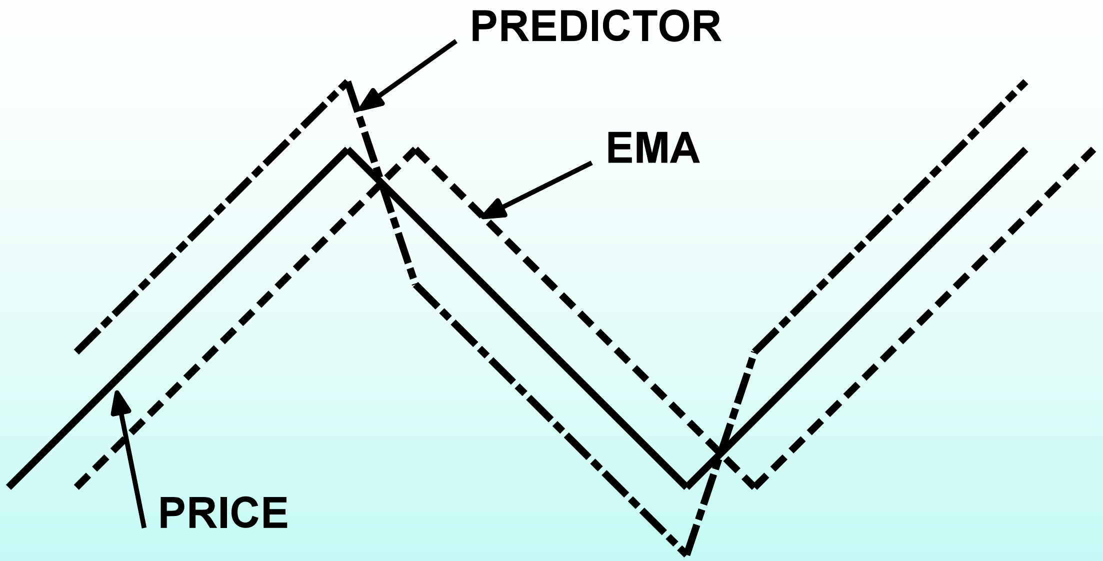

- **Rules:**
  - **Buy when Predictor crosses EMA from bottom to top**
  - **Sell when Predictor crosses EMA from top to bottom**
- **Usually produces too many whipsaws to be practical**

Secrets of Predictive Filters

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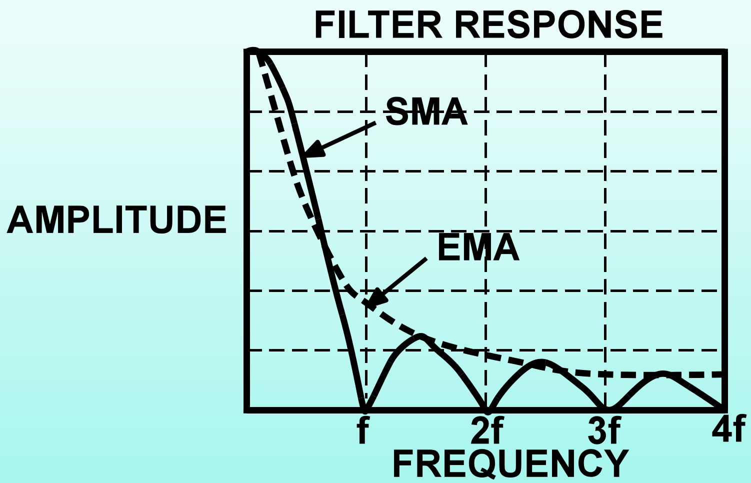
- All averages lag (and smooth)
- All differences lead (and are more noisy)
- The objective of filters is to eliminate the unwanted frequency components
- The range of trading frequencies makes a single filter approach impractical
- A better approach divides the market into two modes
  - Cycle Mode
  - Trend Mode
    - A Trend can be a piece of a longer cycle

Simple and Exponential Moving Averages

- **EMA constant is usually related to the length of an SMA**
  - "Filter Price Data", J.K. Hutson, TASAC Vol. 2, page 102
  - The equation is $\alpha = 2 / (\text{Length} + 1)$



- **Only delay and amplitude smoothing are important**
  - Delay is the most important criteria for traders
  - An EMA has superior rejection for a given delay

Relating Lag to the EMA Constant

- **An EMA is calculated as:**

$$g(z) = \alpha * f(z) + (1 - \alpha) * g(z - 1)$$

where g() is the output
f() is the input
z is the incrementing variable

- **Assume the following for a trend mode**
  - f() increments by 1 for each step of z
    - has a value of "i" on the "i th" day
  - k is the output lag

$$i - k = \alpha * i + (1 - \alpha) * (i - k - 1)$$

$$= \alpha * i + (i - k) - 1 - \alpha * i + \alpha * (k + 1)$$

$$0 = \alpha * (k + 1) - 1$$

Then $k = 1/\alpha - 1$ OR $\alpha = 1/(k + 1)$

Relationship of Lag and EMA Constant

α	k (Lag)
.5	1
.4	1.5
.3	2.33
.25	3
.2	4
.1	9
.05	19

- **Small α cannot be used for short term analysis due to excessive lag**

EMA is a Low Pass Filter

$g(z) = \alpha * f(z) + (1 - \alpha) * g(z - 1)$

Use Z Transform notation (unit lag = 1/z)

$g = \alpha * f + (1 - \alpha) * g/z$

Solving the algebra: $g = \alpha * f * z / (z - (1 - \alpha))$

- Output is related to input by a first order polynomial
- Called 1 Pole filter because response goes to infinity when $z = 1 - \alpha$
- Higher order polynomials produce better filtering
  - Second order: $g = kf / (z^2 + az + b)$
  - Third order: $g = kf / (z^3 + az^2 + bz + c)$

Higher Order Filters Give Better Filtering

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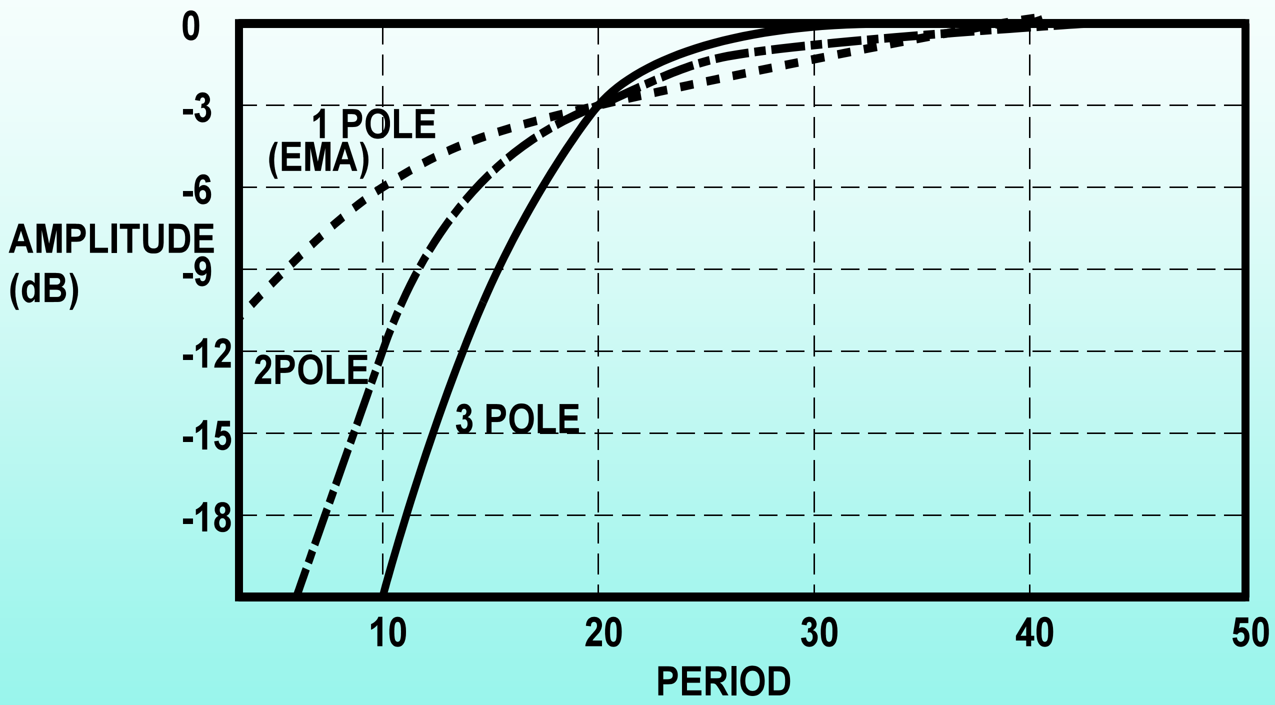
Smoothing increases with filter order
High Frequencies (short cycles) are more sharply rejected



Higher Order Filter Design Equations

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- Delay = N * P / π^2 (N is order, P is cutoff period)
- Second Order Butterworth equations:

  a = exp(-1.414*π/P)

  b = 2*a*Cos(1.414*π/P)

  g = b*g[1] - a*a*g[2] + ((1 - b + a*a)/4)*(f + 2*f[1] + f[2])

- Third Order Butterworth equations:

  a = exp(-π/P)

  b = 2*a*Cos(1.732*π/P)

  c = exp(-2*π/P)

  g = (b + c)*g[1] - (c + b*c)*g[2] + c*c*g[3]
  + ((1 - b + c)*(1 - c) / 8)*(f + 3*f[1] + 3*f[2] + f[3])

where g is output, f is input

14 Bar Cutoff
1, 2, & 3 Pole LowPass Filters

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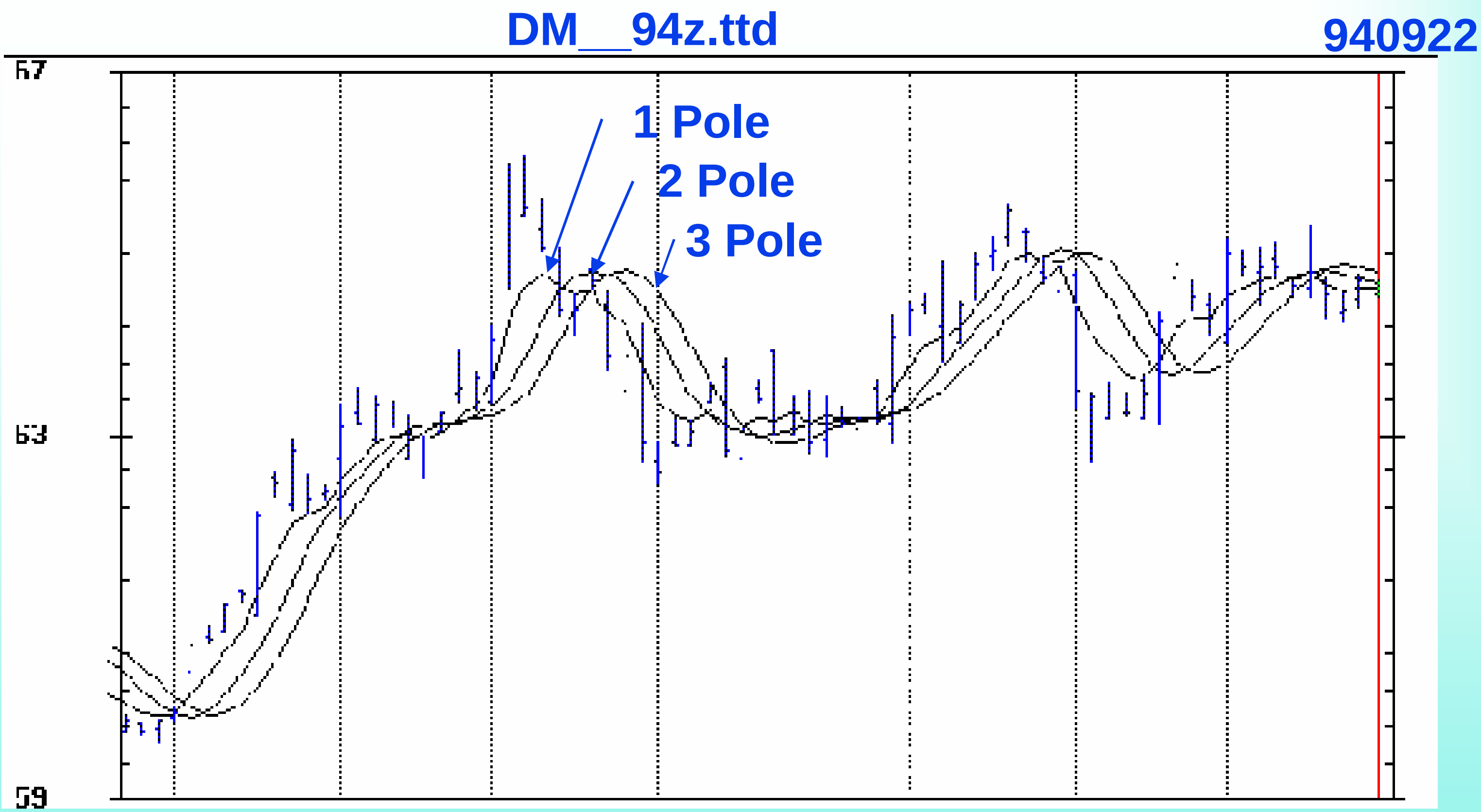

- Increased Lag is the penalty for increased smoothing

1 & 3 Pole LowPass Filters Equalized for 2 Bar Lag

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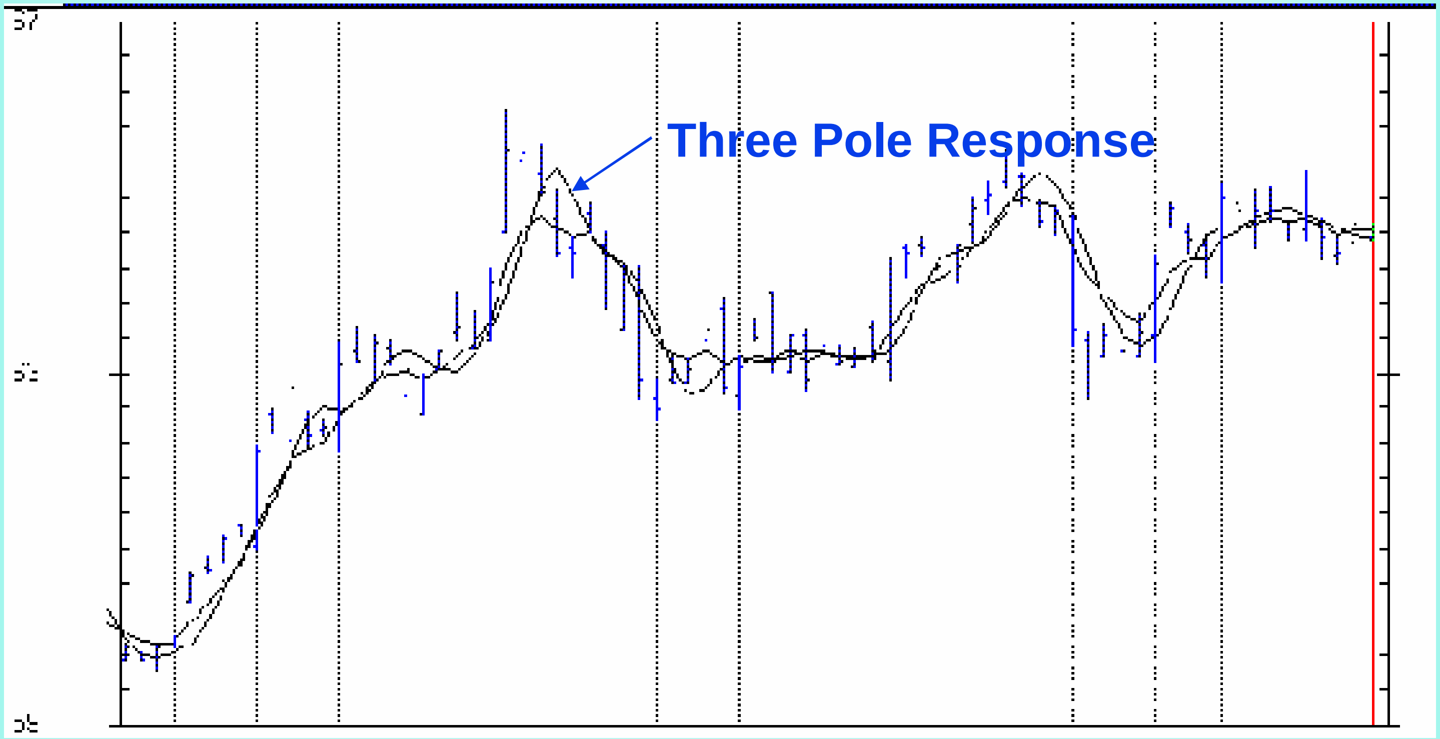

- Higher Order filters give better fidelity for an equal amount of lag

Linear Kalman Filters

- Originally used to predict ballistic trajectories
- Basic ideal is to correct the previous estimate using the current error to modify the estimate
- Procedure for a Linear Kalman Filter:
  - Previous estimate is the EMA
  - Estimate Lag error based on price change
  - Multiply the price rate of change by the lag-related constant

$$g(z) = \alpha * f(z) + (1 - \alpha) * g(z - 1) + \gamma * (f(z) - f(z - 1))$$

Computing Kalman Coefficients

- As before, increment f() by 1 for each step of z

$$i - k = \alpha * i + (1 - \alpha)*(i - k - 1) + \gamma*(i - (i - 1))$$

$$= \alpha * i + (i - k) - 1 - \alpha * i + \alpha *(k + 1) + \gamma$$

$$0 = \alpha *(k + 1) - 1 + \gamma$$

$$\gamma = 1 - \alpha *(k + 1)$$

K	γ
1 (Lag)	$1 - 2*\alpha$
0	$1 - \alpha$
-1 (Lead)	1
-2	$1 + \alpha$

- Now lag is under control for any EMA constant
- Leading functions are too noisy to be useful

Linear Kalman Filter
1 Day Lag

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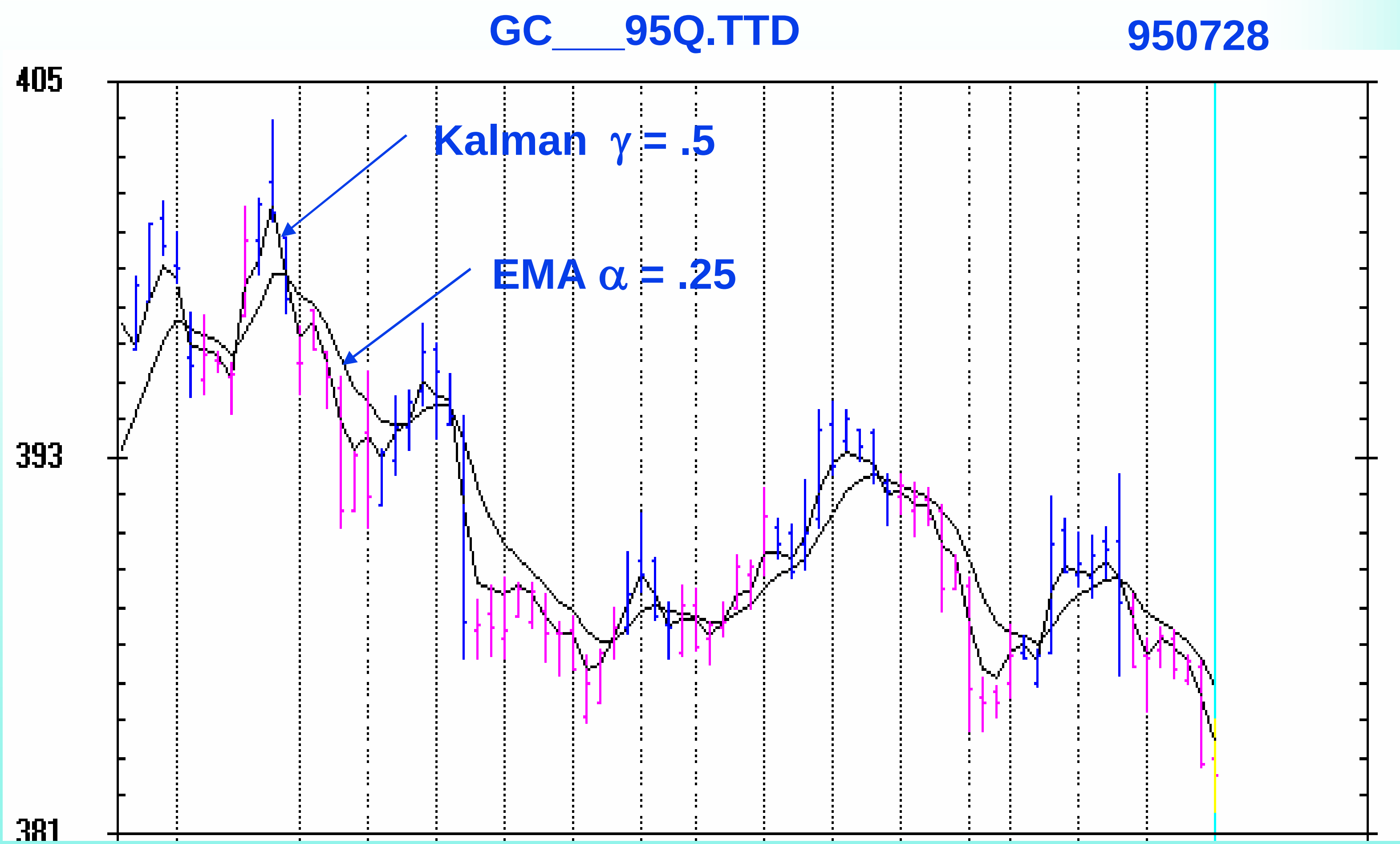

Nonlinear Kalman Filter

- Take EMA of price (better, a 3 Pole filter)
- Take the difference (delta) between Price and its EMA
- Take an EMA of delta (or a 3 Pole filter)
  - Smoothing will help reduce whipsaws
  - Ideally, smoothing introduces no major trend mode lag because delta is detrended
- Add the smoothed delta to EMA for a zero lag curve.
- Add 2*(smoothed delta) to EMA for a smoother predictive line

Zero Lag
Nonlinear Kalman Filter Example

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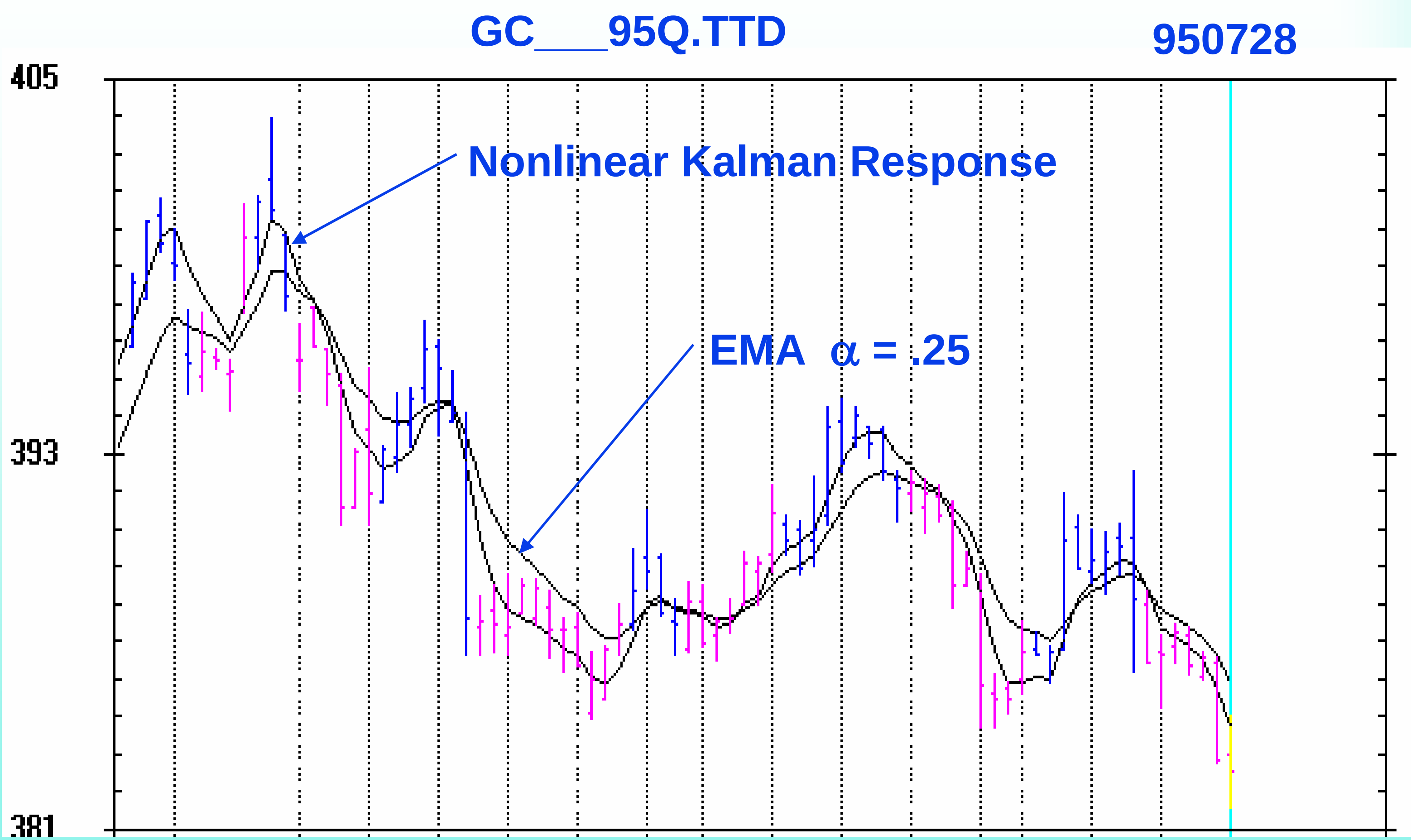

Theoretically Optimum Predictive Filters

- Optimum predictive filters are solutions to the generalized Wiener-Hopf integral equation
  - "Statistical Theory of Communication", Y.W. Lee, John Wiley and Sons, 1960
- Optimum Predictive filters pertain only to the market cycle mode (Must use detrended waveforms)
- Two solutions are of interest to traders
  - Pure predictor (noise free case)
    - See "The BandPass Indicator", John Ehlers, TASAC, September 1994, page 51
  - Predicting in the presence of noise
    - See "Optimum Predictive Filters", John Ehlers, TASAC, June 1995, Page 38

Pure Predictor

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- Calculations start by taking two 3 Pole Low Pass filters for smoothing
  - Period1 = .707 * Dominant Cycle
  - Period2 = 1.414 * Dominant Cycle
- Ratio of the two periods is 2:1
  - The second filter has twice the lag of the first
- Take the difference of the two filter outputs
  - The difference detrends the information
  - The resultant is in phase with the cycle component of the price
- A very smooth (noise-free) replica of the cycle component of the price is established. This is the BandPass Filter output.

Sinewave “momentum” phase leads by 90 degrees

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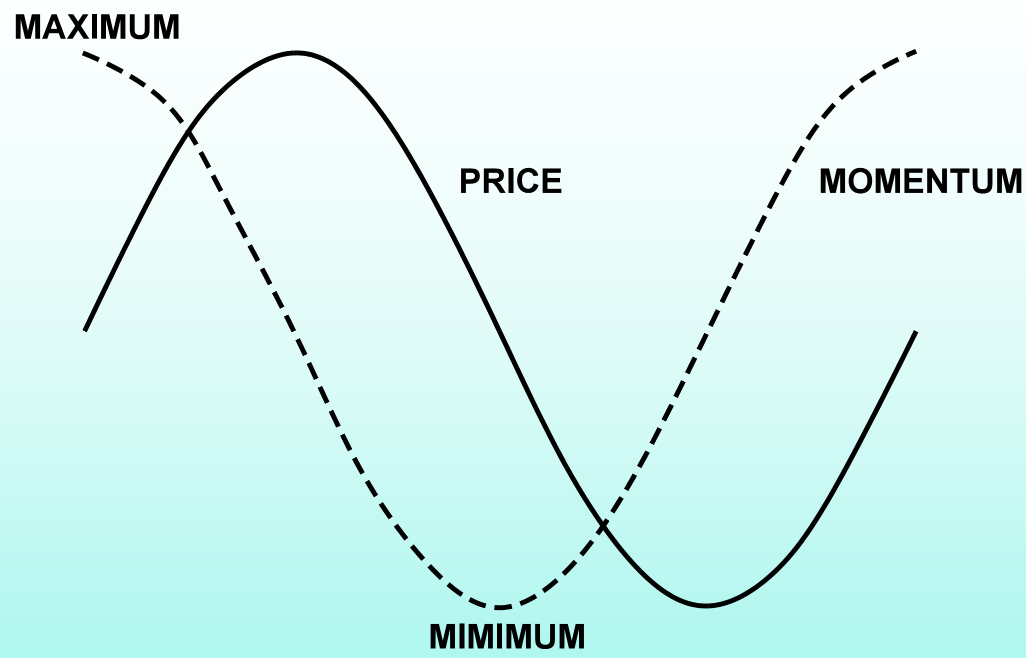

“Momentum” is similar to a calculus derivative.

$d(\sin(\omega * t)) / dt = \omega * \cos(\omega * t)$

$1/\omega = P/(2*\pi)$ must be used as an amplitude normalizer.

Computing the Noise-Free Predictor

- Take the “momentum” of the BandPass Filter output (simple one day difference).
- Normalize amplitude by multiplying the “momentum” by $P_o / (2*\pi)$
- Produce 30 degree leading function
  - Multiply normalized “momentum” by .577 (tan(30) = .577)
  - Add product to BandPass Filter output
- Reduce leading function amplitude
  - Multiply by .87 to normalize vector amplitude
  - Multiply again by .75 to reduce amplitude below BandPass amplitude.
    - Crossover entry signal always leads by 1/8th of a cycle

Noise-Free Predictor Vector Construction

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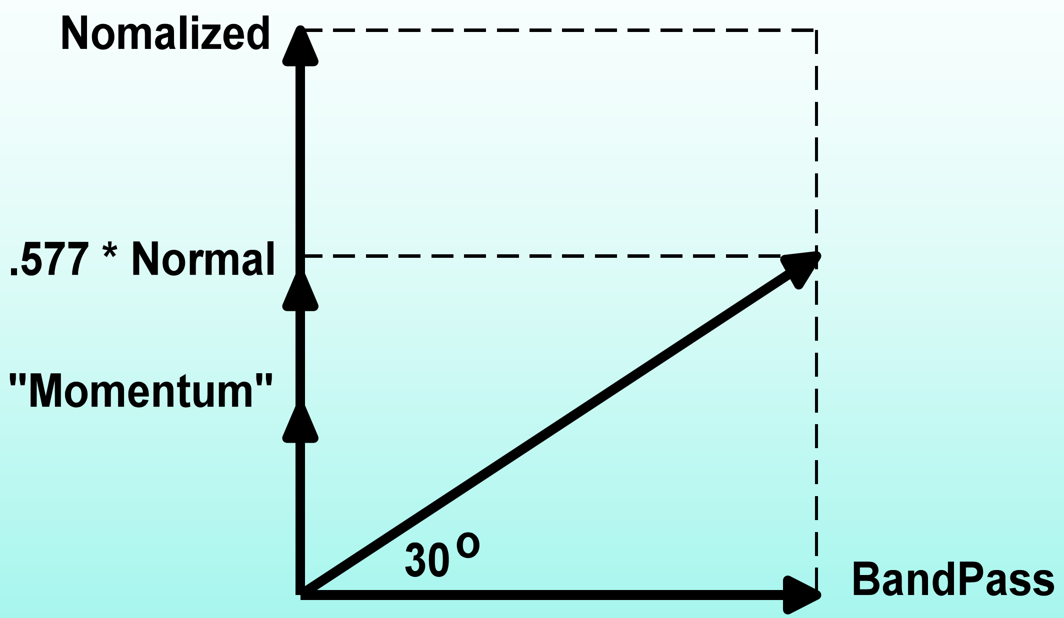

The Complete BandPass Indicator

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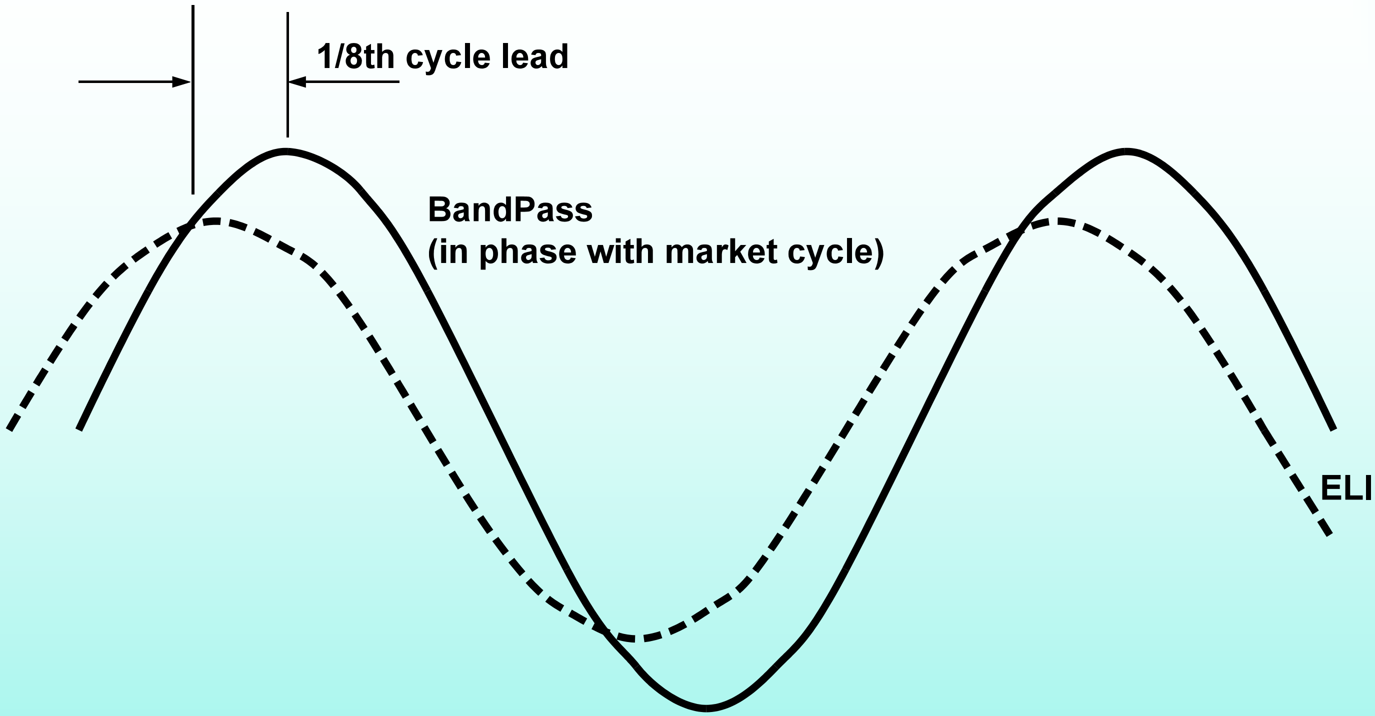

The BandPass Indicator is automatically tuned in:

- MESA for Windows
- 3D for Windows

BandPass Indicator Crossings Give Buy/Sell Signals

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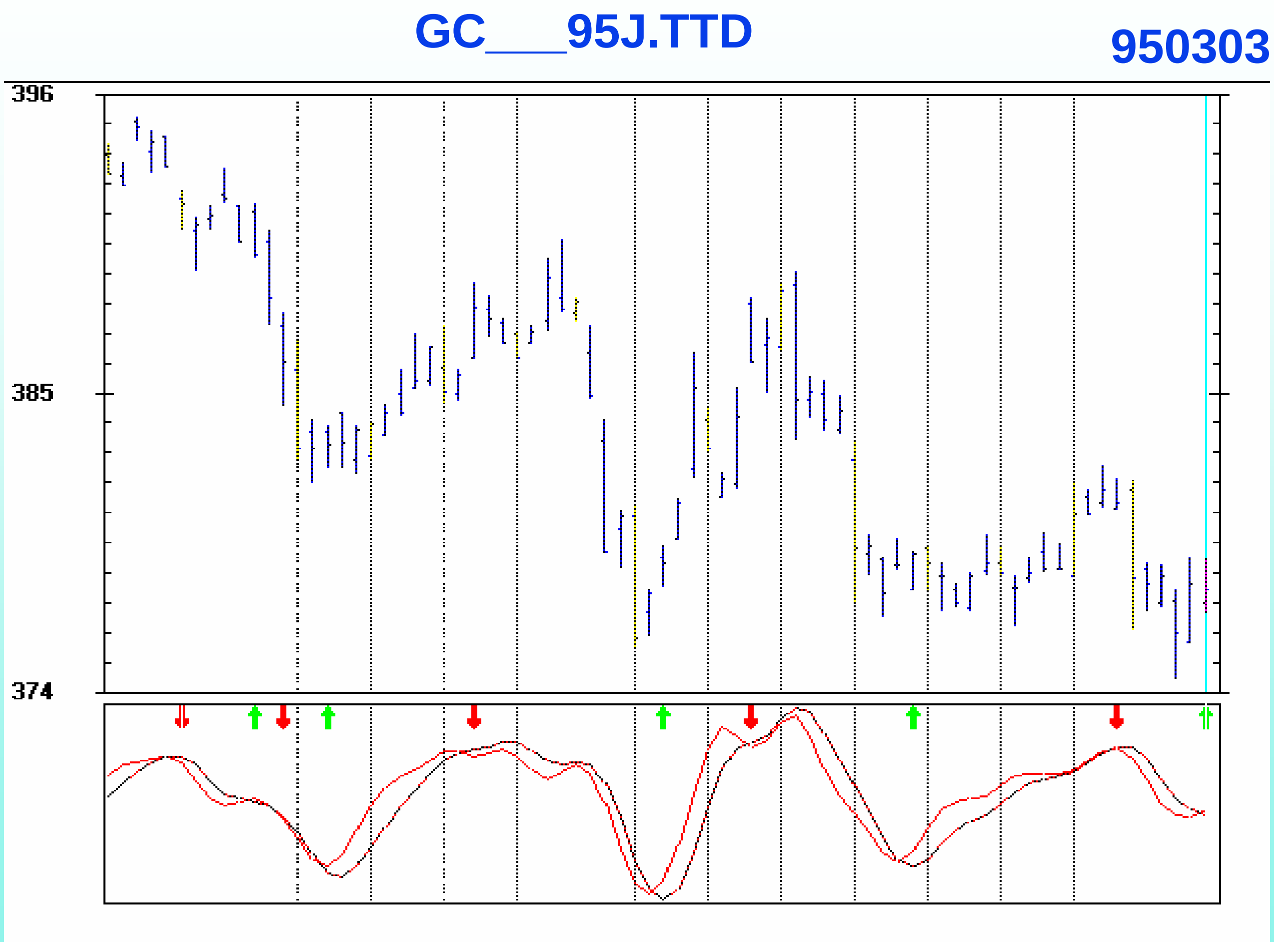

Optimum Predictive Filter in the Presence of Noise

- Start with RSI or Stochastic Indicator
  - Provides detrended waveform
  - Adjust length until the waveform resembles a sinewave
- Technique is useful only when the waveform has a Poisson probability distribution
  - The midpoint crossings must be relatively regular
- Take an EMA of the RSI
  - α = .25 is nominally correct (gives a 3 day lag)
- Subtract the EMA from the RSI to produce the predictor
  - Remember the fundamental premise in constructing predictive filters?

RSI and Optimum Predictive Filter

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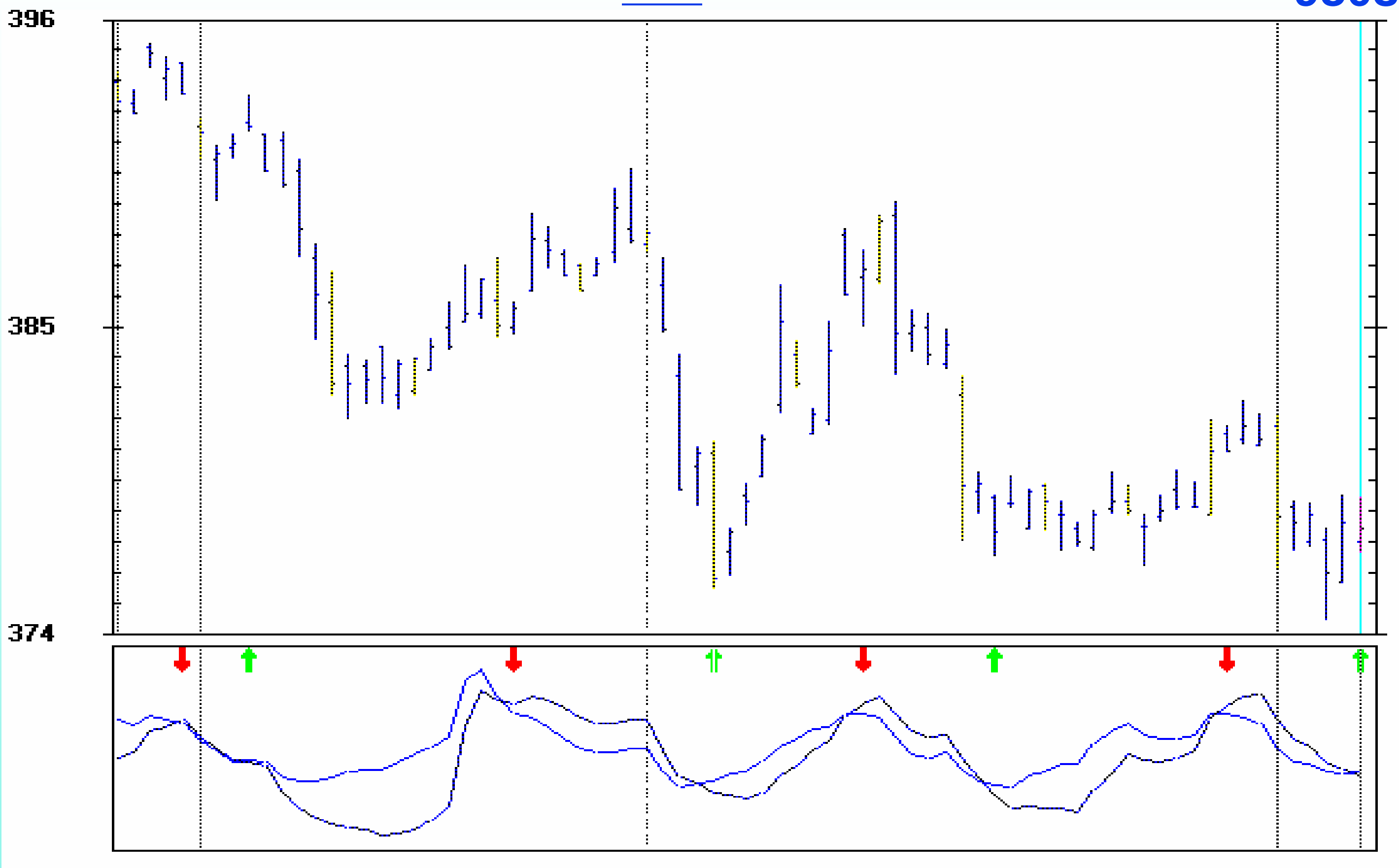

Zero Lag Filters

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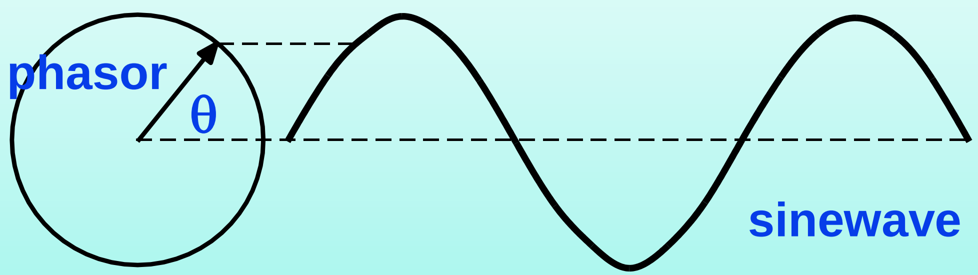
- Zero Lag filters are constructed using cycle theory
- A phasor accurately depicts cyclic amplitude and phase characteristics



- Phasors ignore the cyclic rotation and examine only relative lead and lag relationships

Zero Lag Filter Construction

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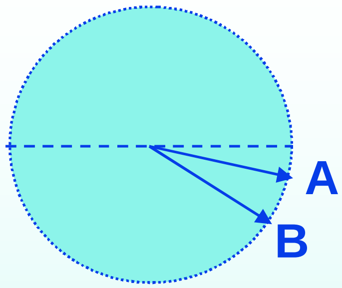
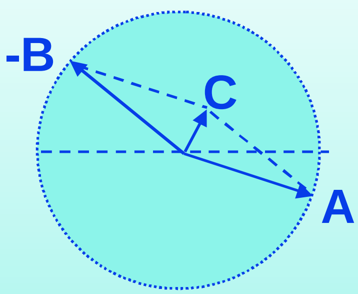
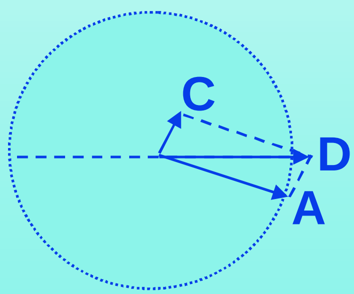


- Phasor A has a lag of DominantCycle/16
- Phasor B has twice the lag of Phasor A



- Subtract B from A by reversing B and adding
- Resultant is detrended leading angle Phasor C



- Vector add C to A
- Resultant is zero lag, non-detrended Phasor D

Zero Lag Filter Example

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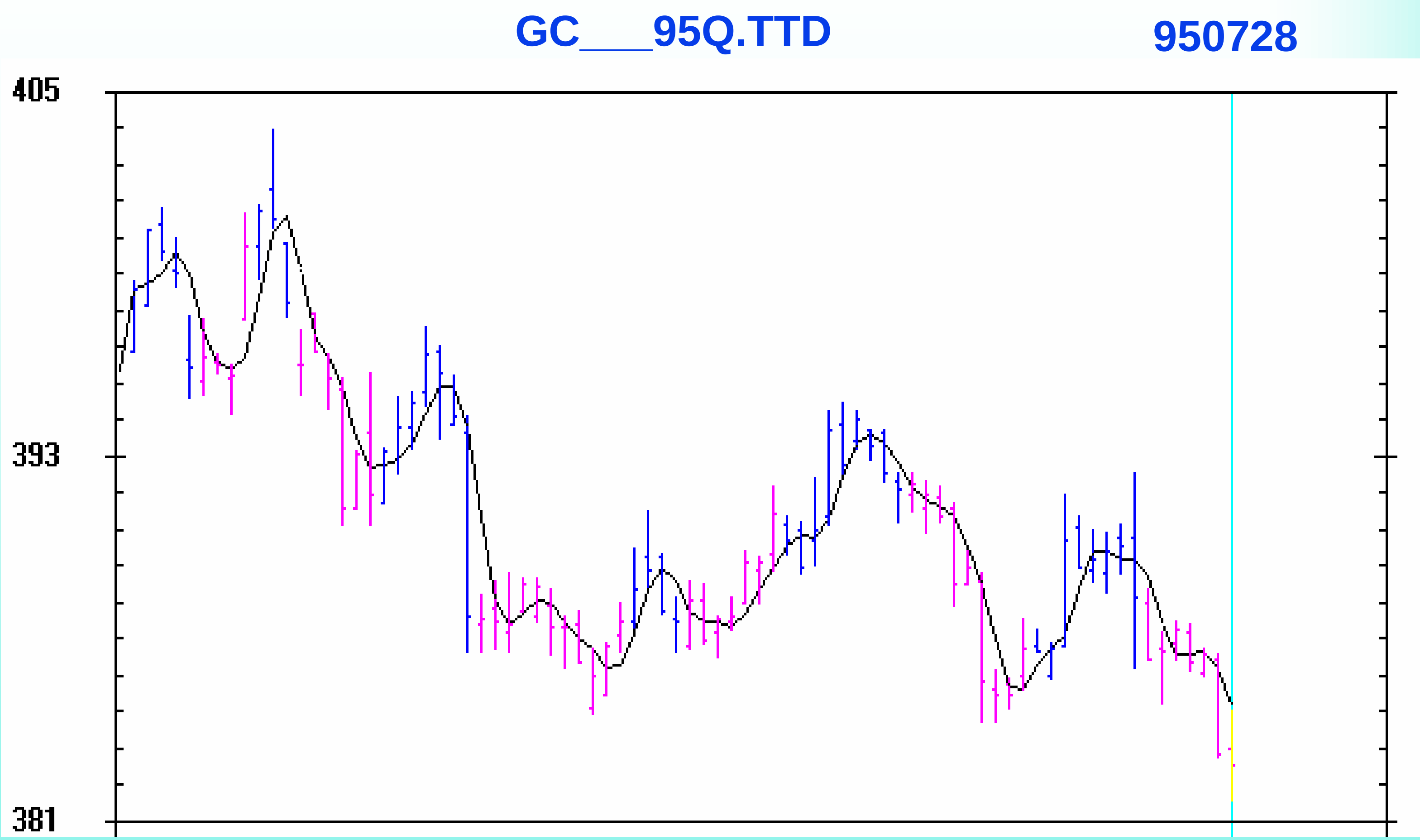

A Zero Lag Filter Application

- Take a 3 Pole zero lag filter of price highs
- Take a 3 Pole zero lag filter of price lows
- Calculate statistics of the high and low variations
  - Add 2 Standard Deviations to the Highs Zero Lag Filter
  - Subtract 2 Standard Deviations to the Lows Zero Lag Filter
- Resultant channels can be used as stop values for a stop-and-reverse system
- Remove the +/- Std Deviations near cycle turns
- SUMMIT for Windows uses this procedure

SUMMARY

- What you have learned:
  - How to relate filter lag to EMA constant
  - How to compute Higher Order Butterworth Filters
  - How to control lag using a Linear Kalman Filter
  - How to compute a Nonlinear Kalman Filter
    - Possible start for a crossover system
  - How to compute Optimum Predictive Filters for the cycle mode
    - Pure Predictor (Noise-Free, using higher order filters)
    - With RSI or Stochastics
  - How to compute a zero lag filter