AN AUTOMATIC ANALYSIS OF VOLATILE FINANCIAL TIME SERIES

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Introduction

What is a Time Series?

A time series is a sequence of measurements through time. Mathematically, a time series may be represented as

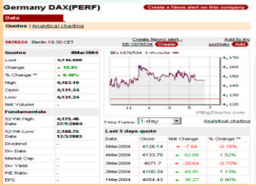
$$X = \{x_t,\ t = 1, \dots, N\}$$

where ***t*** is the time index and ***N*** is the total number of observations. A financial time series is a sequence of numbers related to the value of a financial instrument, e.g. currency, shares and so on; a meteorological time series is a sequence of numbers related to weather parameters, e.g. temperature, pressure, humidity etc.

Any time series comprises a whole range of information which may or may not be perceived by inspection alone: the sequence of numbers may consist of cycles of repeated duration, sudden changes, long-term and short-term decline or rise, and / or correlation amongst the numbers in the sequence.

Analysing and Reporting Financial Markets:

How Experts Summarize a Time Series?



Germany DAX(PERF)

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Data

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Quotes	8Mar2004
Last	4,146.990
Change	▲ 19.85
% Change **	▲ 0.48%
High	4,163.19
Open	4,131.34
Low	4,131.34
Net Volume	-
Fundamentals	
52 Wk High Date	4,175.48 27/1/2004
52 Wk Low Date	2,188.75 12/3/2003
Dividend	-
Div Date	
Market Cap	-
Div Yield	-
P/E Ratio	-
EPS	-

Time Frame: 1-day

Last 5 days quote

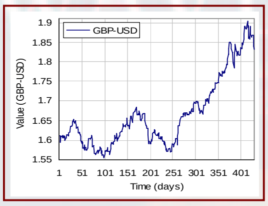
Date	Close	Net Change	% Change **
5Mar2004	4126.14	▼ -7.64	-0.18%
4Mar2004	4133.78	▲ 62.08	1.52%
3Mar2004	4071.7	▼ -28.64	-0.70%
2Mar2004	4100.34	▲ 45.91	1.13%
1Mar2004	4054.43	▲ 36.27	0.90%

The figure to the left shows an excerpt from FINANCIAL TIMES (FT.COM). The time series shown is the composite German index, the DAX, while surrounding it are the various numeric data associated with the index.

Experts study the behaviour of such time series by analysing the various numeric data associated with it. For example, the time series shown here may have some **chief features like, cycles, turning points, trends and volatility patterns** which could have bearing on its future behaviour and value. A description of such "chief features" is usually provided by experts in words – that is **experts summarize a time series**.

Financial Time Series: Nonstationarity and Volatility

A financial time series exhibits two central properties: nonstationarity and time varying volatility. In a broad sense, **nonstationarity means that a variable has no clear tendency to return to a constant value or linear trend**.



The figure above shows a daily series: the value of the British Pound expressed in US Dollars. This exchange rate series does not seem to be stationary, i.e., return to a fixed value or fluctuate around a linear trend (in which case the deviations from the trend would be stationary). It is therefore proper to assume that this series and others like it are generated by ***nonstationary processes*** and ***follow stochastic trends***.

The second central property of a financial time series is that its volatility varies over time. **Volatility is defined as the first difference of a series**. The value of financial instruments depends on the expected volatility (covariance structure) of returns. Volatility is analogous to risk: financial institutions undertake volatility assessments as part of their risk analysis exercise. Mathematically, *Volatility* can be expressed as:

$$r_t = |\log(x_t) - \log(x_t\text{-}1)|$$

An important objective of research in time series analysis is to test hypotheses and estimate relationship amongst such variables. However, **inferences drawn from a stationary analysis would not be valid if the series being examined are indeed realizations of nonstationary processes**. Similarly, **an efficient analysis of a volatile time series cannot be accomplished without addressing the issue of time varying volatility**.

Research Objective

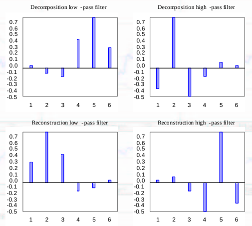
We believe that nonstationarity and time-varying volatility are the two most important inherent characteristics of a financial time series. Therefore, any attempt to analyse and summarise such time serial data needs to take into account these two central properties. Traditional time series analysis methods involve decomposing a series into trend, seasonal variations, cyclical changes and the remaining "irregular" fluctuations. However, for such a decomposition to be unique and effective, the underlying phenomena of the process (nonstationarity and time-varying volatility) need to be understood and addressed well.

Our research objective is **to automatically summarize nonstationary and volatile financial time series data with respect to "chief features" like cycles, trends, turning points and variance change**.

The Approach

Separating Slow and Rapidly Moving Time Series: Wavelet Filtering

Recently it has been claimed that wavelet filtering provides insight into the dynamics of financial time series beyond that of current classical statistical methodology. The figure below shows the **Daubechies** six-coefficient wavelet filters.



Ingrid Daubechies

A number of concepts, for example, nonstationarity, multiresolution, and approximate decorrelation have emerged from wavelet filters [2]. **Wavelet analysis decomposes a time series into several sub-series (approximation and details), which may be associated with particular time scales**. The interpretation of features in complex financial time series is made easy by first applying the wavelet transform and subsequently interpreting each individual sub-series.

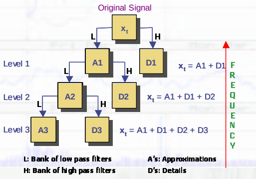
Daubechies, I., "Ten Lectures on Wavelets", SIAM, Philadelphia, 1992.

Discrete Wavelet Transform (DWT)

The discrete wavelet transform (DWT) can be seen as a repeated convolution process. The discrete convolution process can be expressed by the following formula:

$$w * x_t = \sum_{i=-\infty}^{\infty} w_i x_{t-i}$$

Here x_t is the original signal while *w* is the low or high-pass filter corresponding to the prototype wavelet (for example, **Daubechies** six-coefficient wavelet filters). The DWT is implemented using **Mallat's** pyramidal algorithm. This approach is shown below:



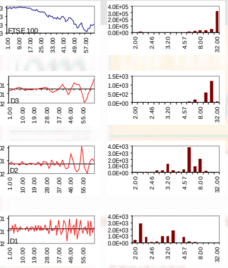
Stéphane Mallat

The input data **x_t, is filtered using a high-pass and a low-pass filter**, the output from the high-pass filter is kept and the above filtering **process is repeated on the output from the low-pass filter**.

Mallat, S., "A Theory for Multiresolution Signal Decomposition: The Wavelet Representation", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 11, p. 674-693, July 1989.

DWT and the Fourier Power Spectrum

The figure below shows a *level-3* 'db3' DWT multiresolution analysis (MRA) of the daily value of the FTSE 100 index for a period of 63 days. The price series is plotted in the top row (blue) while below it – from top to bottom – are the wavelet details D_3, D_2 and D_1 (red). In the right panel are the corresponding Fourier Power Spectra of the series in the left panel.



According to **Fourier analysis**, any finite time series x_t, can be represented as **a combination of several sinusoids having different amplitudes and frequencies**.

Joseph Fourier

The equation given below is known as Parseval's relation where the squared magnitude of the Fourier transform $|X_k|^2$ is known as the **Fourier power spectrum** of the original signal x_t:

$$\sum_{t=0}^{N-1} |x_t|^2 = \frac{1}{N} \sum_{k=0}^{N-1} |X_k|^2$$

Hence **a Fourier power spectrum is the distribution of a signal with respect to its frequency** and its peak value would indicate the most dominant cycle of the analyzed signal.

Consider again the figure to the left. In wavelet details D_3, there is a noticeable fluctuation from the 40th day onwards and its corresponding Fourier power spectrum indicates a peak at 16. This implies that a 16-day cycle has started on the 40th day in the FTSE 100 series and this might persist.

Statistic NCSS

In the the so-called **long memory processes**, the **correlations between variables do not decay at a sufficiently fast rate**. The normalised cumulative sum of squares (**NCSS**) index can be used to test for homogeneity of variance, on a scale-by-scale basis, for such long memory processes [4]. This provides a statically sound technique of testing for nonstationary features without knowing the exact nature of the correlation structure in a given time series. It is defined as

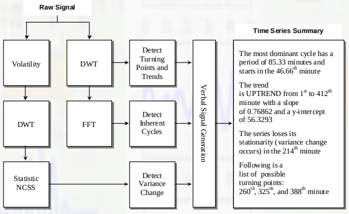
$$\tilde{P}_k \equiv \frac{\sum_{t=L_j-1}^{k} \tilde{W}_{j,t}^2}{\sum_{t=L_j-1}^{N-1} \tilde{W}_{j,t}^2},\ k = L_j - 1, \dots, N-2$$

where *N* is the total number of samples, *L* is the length of the filter used for the DWT analysis and W_j is the *level-j* DWT of the volatility series v_t.

The Outcome:

A Prototype for Summarizing Volatile Financial Time Series

Using the mathematical theories discussed, we have developed **a prototype system** that takes into account nonstationarity, volatility and long-range dependencies, to **automatically extract chief features from a time series and generates a verbal description of each of the extracted features [1]**. System architecture is shown in figure below.



The most dominant cycle has a period of 85.33 minutes and starts in the 46.66th minute

The trend is UPTREND from 1st to 412th minute with a slope of 0.76862 and a y-intercept of 56.3293

The series loses its stationarity (variance change occurs) in the 214th minute

Following is a list of possible turning points: 260th, 325th, and 388th minute

Our system uses a combination of the discrete wavelet transform (DWT) and the fast Fourier transform (FFT) to extract all the features from a time series. The functionality of the system can be summed up in the following steps:

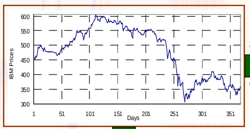
1. The FFT power spectra of the DWT sub-series help us to detect and locate cycles in the original signal.
2. The extrema of the DWT sub-series detect major edges in the signal and hence correspond to most of the turning points [3].
3. The recursive DWT filtering process removes long and short-term fluctuations from the signal in each recursion to give a linear trend in the end.
4. The variance change location is detected using the DWT on the volatility time series and making use of the so-called normalised cumulative sum of squares (NCSS) index.
5. Once numerical information (outlining the trend, cycles, turning points and variance change) is extracted from raw data, it is jelled with predefined strings to generate a meaningful summary of the input time series x_t.

Initial experiments with our prototype have been encouraging and we plan to carry this research forward to improve the efficacy of our methods and algorithms.

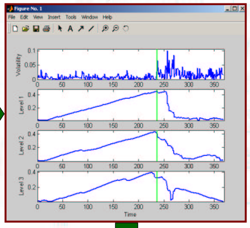
IBM Prices:

System Output for Cycles, Trend, Turning Points and Variance Change

We present results of a study performed on the daily IBM prices from May 17, 1961 to November 2, 1962. This is the classic data studied in Box and Jenkins [2]. Top left corner of the figure below shows the original series. The other three portions of the figure show the various outputs from our system.



Variance Change



Trend and Turning Points

Verbal Signals

Feature	IBM Series (May 17, 1961-November 2, 1962)
Trend	Downtrend $S_L'(t) = -(0.27)\,t + 500.05$
Dominant Cycle	85.3 days Starts on the 46th day
Key Turning Points	113th, 270th, and 321st day
Variance Change Occurs on the	237th day

The outputs shown here visualize the trend, turning points and variance change**. The turning points are marked red on the time series (bottom left portion)**. The **trend is a downtrend** and is **shown with a falling green line (bottom left portion)**.

For variance change, the volatility of the original series is shown followed by three levels of the NCSS index (top right portion). The **peak value of the NCSS index detects where exactly a variance change occurs** or where the series loses its stationarity. All these features are summarized by our system by generating **verbal signals** for each feature (bottom right portion). We have not shown the visualization of **cycles** for this series, however, the verbal signal generated **describes it as 85.3 days, starting on the 46th day**.

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Acknowledgments

This work has been funded by the EU co-funded project Generic Information-based Decision Assistant (GIDA IST-2000-31123). Project Partners:

UniS
JRC CONSULTANCY
finsoft
Ibermática