Wavelet Analysis of Crude Oil Futures

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Ian Akash Morrison

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Ian Akash Morrison

Authors:
Ian Akash Morrison
Aniruddha Sen

Online:
< http://cnx.org/content/col11397/1.1/ >

C O N N E X I O N S

Rice University, Houston, Texas

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Chapter 1

Wavelet Analysis of Crude Oil Futures: Project Overview[1]

Overview

The oscillation of stocks, futures, or commodity prices over time in financial markets seems highly random. But taken as a time series, the data looks similar to signals we might study in the field of electrical engineering. This begs the question, **can we analyze these signals using common principles of signal processing? Might we uncover a cycle or periodicity in the signal? Can we predict prices and make millions of dollars?** We found through analysis of crude oil futures data from 1986 to the present that though common Fourier methods used in ELEC 301 could not uncover reliable periodicity, the related method of wavelet analysis produces both short-term periodicity in the CWT and a significantly de-noised signal in the DWT.

This is also an investigation into a field referred to "financial engineering" from the perspective of two electrical engineers. On a personal level, we are studying both electrical engineering and economics at Rice University and are interested in learning what components of signal processing are applicable to the analysis of financial markets.

The data set that was chosen was historical oil futures daily closing prices from 1986 until 2011 due to its expected periodicity with the seasonal cycle of demand for oil and gas.

Placeholder for Picture

[1] This content is available online at <http://cnx.org/content/m41906/1.1/>.

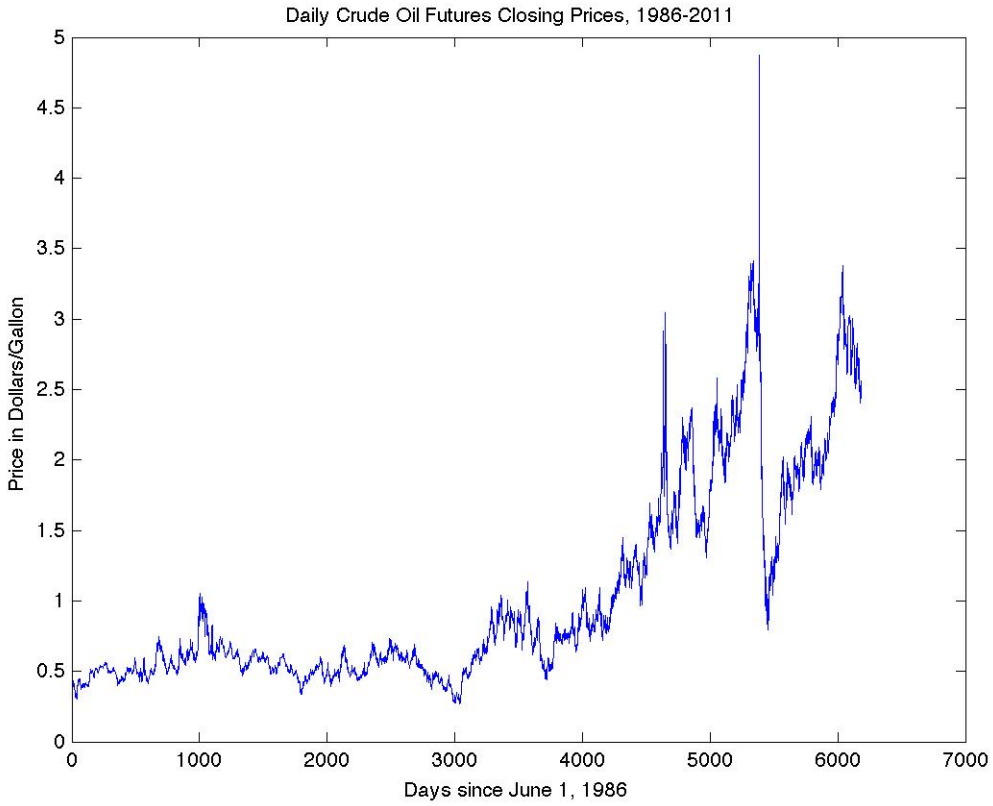


Figure 1.1: Historical Prices of Crude Oil Futures

Objectives

1. Investigate financial engineering.
2. Utilize signal processing techniques to analyze commodity futures prices.
3. Predict future prices.
4. Make million$!

Chapter 2

Trading and Time Series Analysis[1]

Relevance to Traders

The crude oil futures market is important to traders, investors, and business leaders. Short-term or "high-frequency" traders trade quickly on positive margin to make money. Medium-term traders tend to follow the business cycle by buying when the market is at a low and selling or shorting when it's at a high. Long-term investors are looking for long-term , reliable growth. Business leaders in the oil industry, on the other hand, are looking at futures and deciding when it's time to increase or decrease production. Management teams in fuel-dependent industries, such a aviation and shipping, are looking to see when its time to buy oil futures to guarantee purchase at some fixed (and predictable) future price.

All these market participators are looking for the same thing in their technical analysis of the market: patterns. The main patterns that time series analysis goes after are trend and seasonality.

- **Trend** is an overall trend of the time series. This can often be found by "filtering" the time series

[1]This content is available online at <http://cnx.org/content/m41899/1.1/>.

using a moving-window average.

- **Seasonality** is the periodic recurrence of a similar pattern in the data. This can be seen in consumer demand for fuel over the course of many years.

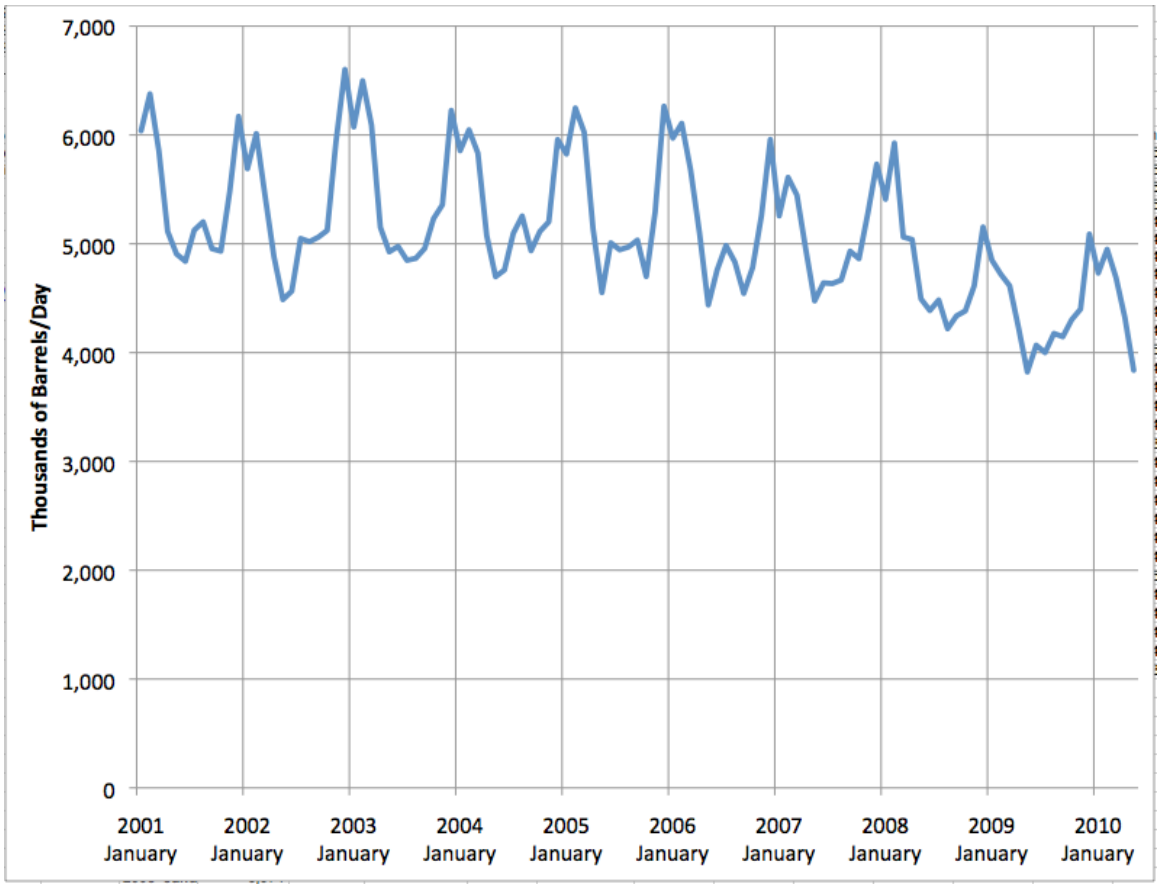


Figure 2.1: Gasoline consumer demand since 2001. Notice the periodicity present in this time series.

Chapter 3

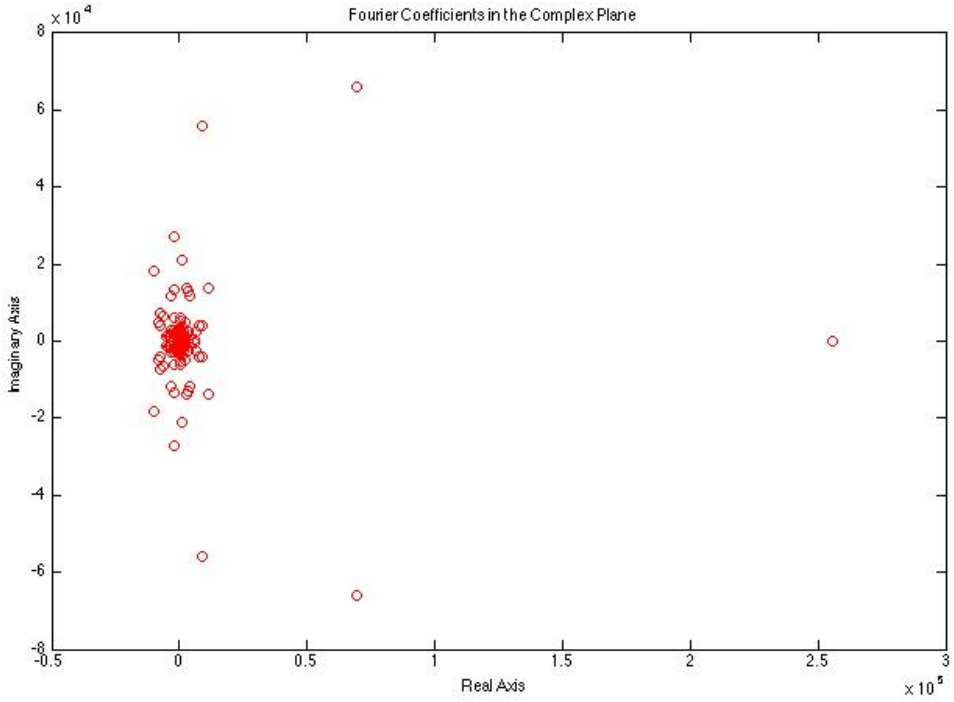
Fourier Analysis to Uncover Seasonality[1]

Fourier Analysis Applied to Crude Oil Futures

In order to find seasonality, we first applied Fourier analysis (FFT) to the time series, expecting to simply uncover a degree of periodicity in the price of the futures. However, no semblance of periodicity was found. A plot of the Fourier coefficients in the complex plane gives a simple view of the results, which are highly inconclusive as the "frequencies" are centered around zero and are highly non-specific.

On further research, it became evident that in non-linear time series, linear analysis (i.e. traditional Fourier analysis) is not a valid approach. This is because simple Fourier analysis does not account for trends, drift, abrupt changes, and beginnings and ends of events, all of which are incredibly important parts of signals.

Placeholder for Picture



[1] This content is available online at <http://cnx.org/content/m41902/1.1/>.

Chapter 4

Wavelet Analysis: A New Approach[1]

The Path to a Solution

To try to solve some of the problems caused by taking an inconclusive transform of a whole time series, Dennis Gabor developed Short-Time Fourier Analysis on windowed signals in 1946. However, this approach offered no variability to determine time or frequency more accurately in any particular window. Wavelet analysis was developed as a windowing technique which allowed for *differently-sized windows* to be compared to a wavelet signal, therefore allowing determination of time AND frequency. The basic premise is derived from Fourier transforms, but instead of composing a signal of different frequency and amplitude sinusoids, wavelets of the same waveform but different *lengths* are compared and correlated to a signal.

Wavelet analysis has many benefits which make it a more applicable tool for analyzing the financial markets. This:

- uses **long**-time wavelet-analysis intervals for finding precise **low**-frequency information.
- uses **short**-time wavelet-analysis intervals for finding precise **high**-frequency information.
- performs local analysis, which allows us see frequency events at a specific times in a signal.
- works much better with non-linear signals.

[1] This content is available online at <http://cnx.org/content/m41905/1.1/>.

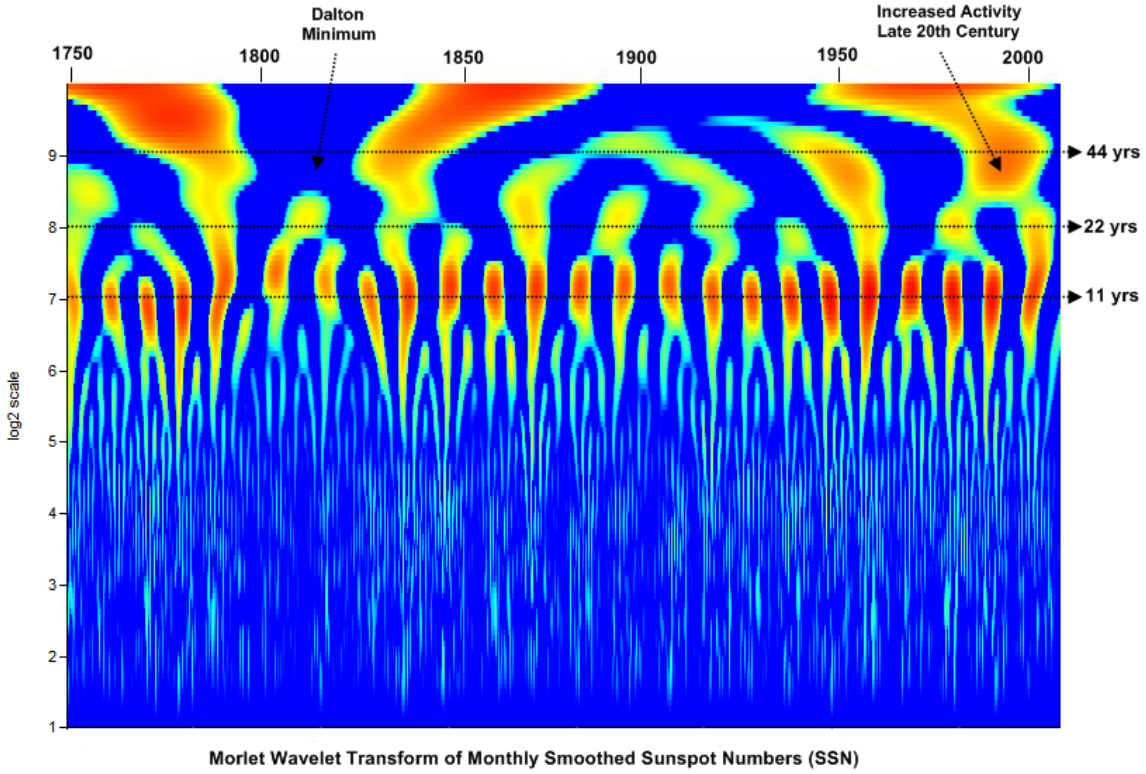


Figure 4.1: This is an example of wavelet analysis applied to sunspot size. The pattern indicates a few patterns, the most prevalent of which is a cycle of roughly 11 years.

Chapter 5

The Continuous Wavelet Transform[1]

The Continuous Wavelet Transform allows us to see the correlation of all the different lengths wavelets to the signal itself in the time domain. Use the cwt command in Matlab to obtain the transform. What is interesting about this transform, unlike the Fourier transform, is that it allows one to see breaks within the original signal and the exact position of those breaks as seen in the following figure.

[1] This content is available online at <http://cnx.org/content/m41838/1.1/>.

Sine Wave with Break

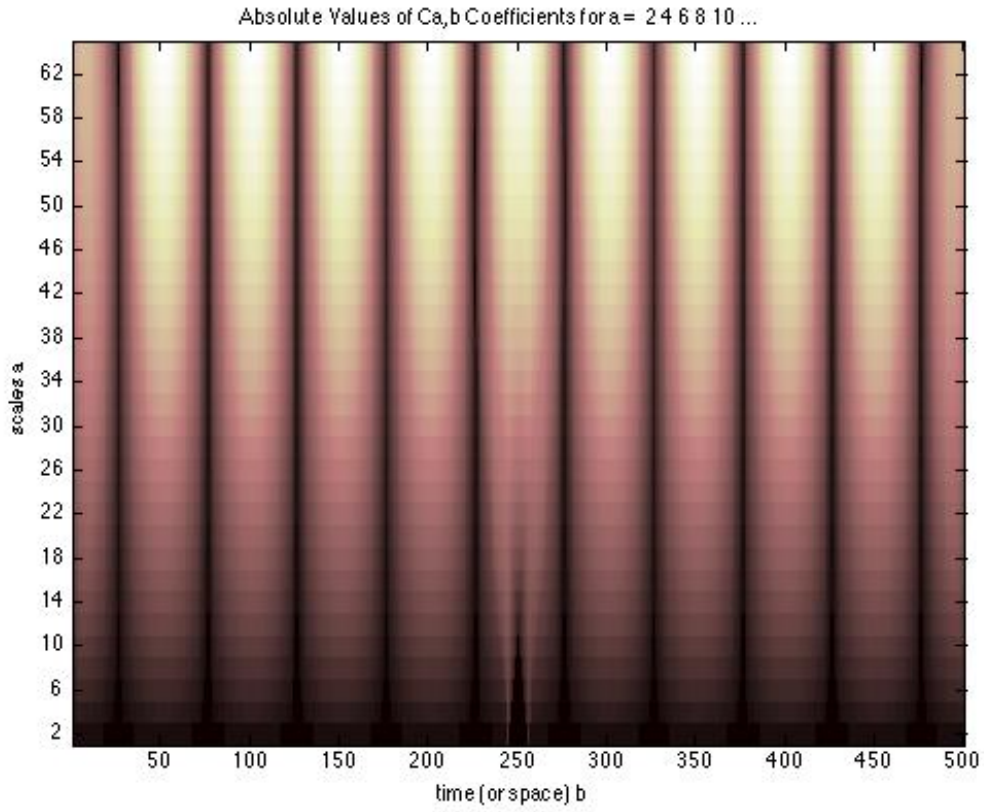


Figure 5.1: Notice the definite break in the middle of the sine wave.

We can now use this wavelet transform on other non-periodic signals to get a more detailed response from the Fourier Transform.

Chapter 6

The Discrete Wavelet Transform[1]

The Discrete Wavelet Transform allows us to see Approximations and Differences of s signal. Using the dwt function in Matlab allows us to see the approximation of a signal which is the signal after some of the noise is taken out. The noise is represented by the difference. The discrete wavelet transform allows us to take out the noise of a signal while still retaining the integrity of the signal. The following figure shows us the level three approximation of a signal with the noises taken out.

Approximations and Differences

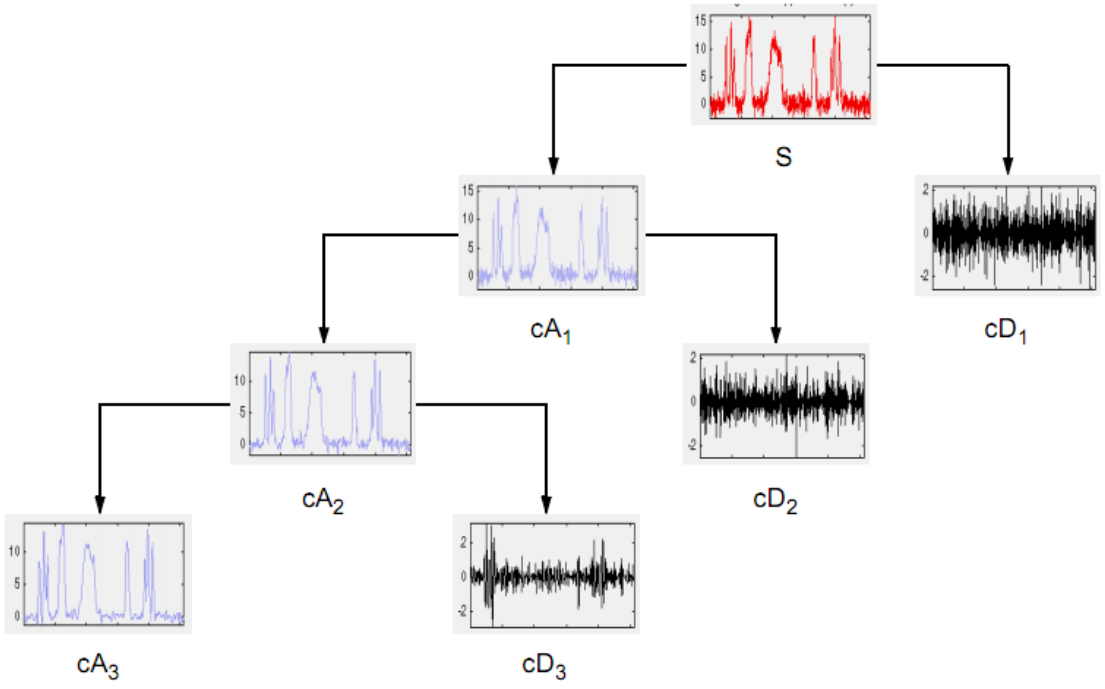


Figure 6.1: The level 3 Approximation and corresponding Differences.

[1] This content is available online at <http://cnx.org/content/m41839/1.1/>.

Chapter 7

Application to Crude Oil Futures[1]

The Continuous Wavelet Transform and Discrete Wavelet Transform were both used in the non-linear and aperiodic Crude Oil Futures signal. It allowed us to see possible periodicity and trends within the signal. The next two figures shows us both the Continuous and Discrete wavelet transforms.

Crude Oil Futures Continuous Wavelet Transform

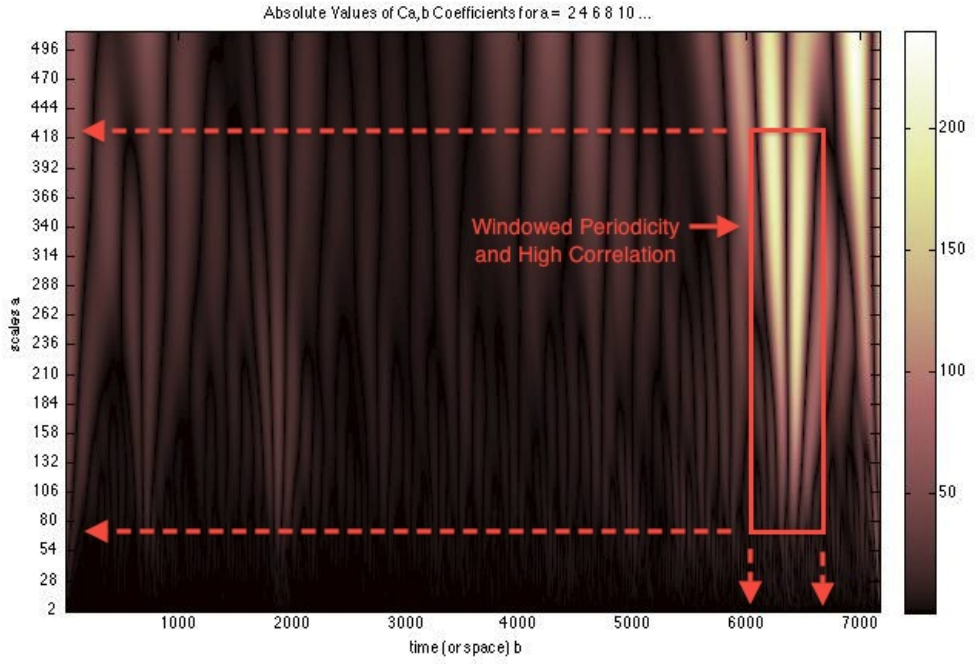


Figure 7.1: Continuous Wavelet Transform of Crude Oil Futures.

[1] This content is available online at <http://cnx.org/content/m41850/1.1/>.

Level 3 Approximation of Crude Oil Futures

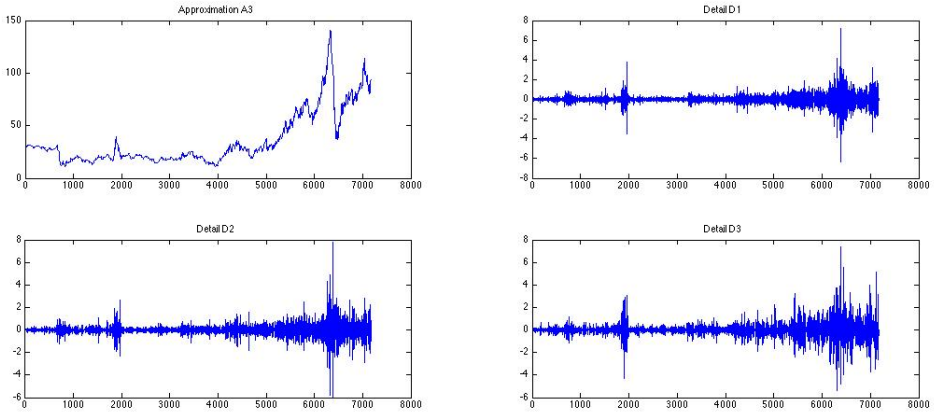


Figure 7.2: The Level 3 Approximation of Crude Oil Futures.

Chapter 8

Conclusion[1]

Using the db4 wavelet gave us more of a detailed response than the db1 wavelet. Performing the CWT on the signal revealed periodicity within the specific windows with high correlation coefficients within those windows. However, these periodic windows cannot conclusively imply periodicity in any other windowed time-frame. This is due to the random nature of the signal itself. Performing the DWT allowed us to filter a substantial amount of high-frequency noise with out losing too much of the signals integrity. Recomposing the signal using the 3rd order approximation allowed us to see trends in the signal without the noise. In terms of high frequency trading of Crude Oil Futures, seeing these trends without the noise would give traders a clearer picture of when to make the correct trade.

[1] This content is available online at <http://cnx.org/content/m41887/1.1/>.

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Wavelet Analysis of Crude Oil Futures
An exploratory project investigating "financial engineering" from the perspective of electrical engineers. This approach focuses on signal-processing methods applied to time series analysis of crude oil futures (daily closing prices from 1986 to 2011).