FOUNDATION FOR THE STUDY OF CYCLES

The World Center for Cycles Research

THE CYCLE SCANNER ALGORITHM

Whitepaper

Introduction on how to apply cyclic analysis to detect dominant cycles

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Content

Cycle Scanner Framework

This FSC whitepaper provides background on the algorithms and code used for the Cycle Scanner framework which can be used at the fsc.cycle.tools website for FSC members.

Step 1: Detrending

The algorithm has a dynamic filter for detrending that is required for data preprocessing. Detrending ensures that the data under consideration is not affected by trends or one-time events. The extraction of linear trends in time series data is a required precondition for successful cycle research. In the business cycle literature, the Hodrick and Prescott (1980) filter (HP filter) has become the standard method for removing long-run movements, like trends, from the data. Hodrick and Prescott proposed the HP filter to decompose macroeconomic time series data into cycle and trend components. The HP filter assumes that movements in time series include a smooth and slowly changing trend component. By removing this trend component from the data series, the filter delivers the pure underlying cyclic behavior.

Visually, this detrending technique is like drawing a smooth linear freehand trend line through the plotted chart data and extracting this "freehand" trend line from the full data set. The resulting component is only based on the cyclic behavior without the underlying trend. Now, we can proceed and start to apply additional cycle analysis in the next step to detect the cycles that are dominant and genuine within this filtered data set.

However, we must carefully treat the output obtained from this pure mechanical detrending algorithm because it is well-known that this technique may generate spurious cycle variants; that is, the HP filter can generate cycle dynamics even if none are present in the original data. Hence, the presence of cycles in HP-filtered data does not imply that real cycles exist in the original data. Therefore, we need to apply additional mechanisms to validate genuine identified cycles afterward and to remove possible "invalid" cycles. Later, at step 3 of our Cycle Scanner framework, we will show how to circumvent this problem by including goodness-of-fit statistics for our genuine dominant cycle filtering. [1, 2]

To optimize the HP filter and to keep these shortcomings of spurious cycles as small as possible, first the proper adjustment of parameter "λ" in the decomposition of the HP filter is important.[3] Second, additional testing on how the estimated cyclical components behave based on cross-correlation

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[1] Cogley, T., Nason, J. (1992): "Effects of the Hodrick-Prescott filter on trend and difference stationary time series: Implications for business cycle research," Journal of Economic Dynamics and Control.
[2] "Hodrick-Prescott Filter in Practice," Source: http://www.depeco.econo.unlp.edu.ar/jemi/1999/trabajo01.pdf
[3] Ravn, M., Uhlig, H. (1997): "On adjusting the HP-Filter for the Frequency of Observations."

evaluations are needed to differentiate "genuine" cycles from "spurious" ones. Both adjustments have been incorporated into our Cycle Scanner framework to compensate for the drawbacks of the HP filter.

A review of the critical discussions on the HP filter method, however, indicates that the HP filter is likely to remain the standard method for detrending for still a long time to come. Ravn and Uhlig concluded in 1997 as follows:

> *"None of the shortcomings and undesirable properties are particularly compelling: the HP filter has withstood the test of the time and the fire of discussion remarkably well."*

To further optimize the detrending preprocessing, additional recent findings based on the work of Jim Hamilton (2016) might be considered. [4]

However, the HP filter has broad support in the scientific area, and is widely used. We have been able to successfully use the approach for years in cycle forecasting: Never change a running system too fast. Therefore, we strongly recommend that anyone who wants to rebuild a similar or more optimized detrending framework should conduct further research in this area.

Step 2: Cycle Detection

As we now have the cyclical data set prepared, the next step is to discover the individual cycles that are active. Subsequently, the engine needs to perform a spectral analysis and then isolate those cycles that are repetitive and have the largest amplitudes. For that, we need to decide on a cycle detection algorithm that suits our goal. Most cycle researchers are familiar with the fast Fourier transform (FFT) and many "FFT-based engines" are available to detect one or more cycles in data sets. What many do not know, however, is that there is a special subset: the Goertzel algorithm.

Originally, the algorithm was used to detect "dominant" tone frequencies used in landline phones for DTMF signaling, which was originally developed in 1958, long before the period of smartphones. Have you ever thought about how the telephone exchange knows what button has been pressed? The answer is the Goertzel algorithm. Today, the Goertzel algorithm is used extensively in communications for tone detection and is built into hardware as integrated circuits to detect tones of a button pushed in near-real-time.

Additionally, and even more important, the Goertzel algorithm was originally designed to detect cycles in data sets that have similar characteristics to contemporary financial series data. The problem a long time

[4] James D. Hamilton (2016): "Why You Should Never Use the Hodrick-Prescott Filter," Department of Economics, UC San Diego. Source http://econweb.ucsd.edu/~jhamilto/hp.pdf

ago was that a special tone needed to be detected in a very short amount of available data and with considerable noise. This is similar to the problem of determining dominant cycles in financial data sets observed today.

Therefore, instead of using standard Fourier or wavelet transforms, why not use a well-established variant of the discrete Fourier transform (DFT): the Goertzel algorithm? As our requirements for cycle detection in financial markets are similar to the ones Goertzel was addressing in the case of old phone lines?

Our research shows that the Goertzel algorithm delivers reliable results in decoding dominant cycles out of detrended financial data sets, outperforming other methods such as wavelets or MESA.

For sure, you need to apply the Goertzel DFT (GDFT) in a special way, as you need to apply a GDFT test on all possible wavelengths and use different methods to obtain the current phase and amplitude. That is, for covering a full cycle length spectrum, the Goertzel algorithm has a higher complexity than FFT algorithms. Nevertheless, using the Goertzel algorithm to obtain the dominant cycle length out of short and noisy data, along with standard versions to obtain the related current phase and amplitude for the detected cycle length, helps generate all dynamic cycle data for the active cycle at the last point of our data set under consideration. As we are not interested in the "averaged" cycle length for longer data sets, we want the cycle length and phase that are active on the last bar of the chart. Therefore, this combination of the Goertzel algorithm as the core, with additional analysis to obtain the current phase of the cycle at the end of the data set, is used.

Finally, this approach is supported by a study conducted by Dennis Meyers (2003) on the Goertzel method:[5]

> *"With very noisy data where the noise strength is greater than the signal strength, [...], only the Goertzel Algorithm can successfully identify the frequencies present."*

In addition, we can see an increasing amount of noise coming into play for financial markets. Some examples of this are high-frequency trading, pure algo-based trading engines, or alternative news. So, in our real-life environments, we will not see a "clean" financial data set as it is diluted by noise that hides the real underlying cycles. The Meyers study shows that the GDFT even outperforms the proposed method "MESA" used by John F. Ehlers in most of his cycle research.

Therefore, our cycle scanner framework applies the GDFT to the detrended data set to cover all possible cycle lengths. Once the most active cycle is detected based on the full spectrum GDFT analysis, we use an

[5] Source: http://meyersanalytics.com/publications2/MesaVsGDFT.pdf

additional run to check for the least current phase status on the last bar of our data set with a shorter subset of the original full data set, as we are interested in the status of the detected cycle length at the point of the analysis, or the last bar available.

Step 3: Cycle Validation

After finishing step 2, we will get a list of detected active cycles. Step 2 gave us a list of cycles with length, amplitude, and current phase status at the end of the data set. Now, we need to validate and rank these cycles as our approach is looking for the most dominant cycles out of this list.

Before we start to do some ranking, let us get back to what we introduced already in step 1: Based on the pitfalls of the HP-filter, we need to cross-check the detected cycles by using a second algorithm to validate if a cycle is genuine or perhaps spurious. So, this step is important to avoid getting "virtual" cycles that are not in the original data set and have just been returned by the detrending algorithm itself. Therefore, we apply a special form of statistical correlation analysis for each detected cycle length.

In this step, the statistical reliability of each cycle is evaluated. The goal of the algorithm is to exclude cycles that have been influenced by one-time random events (news, for example) and cycles that are not genuine.

One of the algorithms used for this purpose is a more sophisticated Bartels Test. The test builds on detailed mathematics (statistics) and measures the stability of the amplitude and phase of each cycle.

Bartels' statistical test for periodicity, published at the Carnegie Institution of Washington in 1932, was embraced by the Foundation for the Study of Cycles decades ago as the single best test for a given cycle's projected reliability, robustness, and consequently, usefulness.

It was originally published in 1935 by Julius Bartels in Volume 40 No. 1 of the scientific magazine "Terrestrial Magnetism and Atmospheric Electricity" with the title "Random fluctuations, Persistence, and quasi-persistence in geophysical and cosmical periodicities." Later, Charles E. Armstrong gave a brief example and case study on how to apply the Bartels test in financial time series data in 1973, titled "Applying the Bartels Test of Significance to a Time Series Cycle Analysis." [6]

The Bartels test returns a value that gives the measure of the likelihood of genuineness of a cycle: values range from 0 up to 1, and the lower the value, the less likely is that this cycle is due to chance, or random. The test considers both the consistency and the persistence of a given cycle within the data set it is applied to.

To make it more human readable as we are looking for an easily readable indication if the cycle is genuine, we just convert the raw Bartels value into a percentage that indicates how likely the cycle is

[6] Source: http://cyclesresearchinstitute.org/pdf/cycles-general/bartel.pdf

genuine by using the conversion formula: Cycle Genuine % = (1 - Bartels Score) * 100. It gives us a value between 0% (random) and 100% (genuine).

This test helps us now to filter out possible cycles that might have been detected in the cycle detection step (Step 2), but had only been in the data series for a short or random period and should therefore not be considered as dominant cycles in the underlying original data series.

As we have a final percentage score, we just need to define an individual threshold below which the cycles should be skipped. We recommend using a threshold of >49% and hence cycles with a Bartels genuine percentage value below 49% should be skipped by any cycle forecasting or analysis techniques that follow.

Step 4: Ranking

An important final step in making sense of the cyclic information is to establish a measurement for the strength of a cycle. Once the last step is completed, we have cycles that are dominant (based on their amplitude) and genuine (considering their driving force in the financial market). For trading purposes, this does not suffice. The price influence of a cycle per bar on the trading chart is the most crucial information.

Let me give you some examples by comparing two cycles. One cycle has a wavelength of 110 bars and an amplitude of 300. The other cycle has a wavelength of 60 bars and an amplitude of only 200.

So, if we apply the "standard" method for determining the dominant cycle, namely selecting the cycle with the highest amplitude, we would select the cycle with the wavelength of 110 and the amplitude of 300.

But let us look at the following information - the force of the cycle per bar:

Length 110 / Amplitude 300 → Strength per bar: 300 / 110 = 2.7

Length 60 / Amplitude 200 → Strength per bar: 200 / 60 = 3.3

For trading, it is more important to know which cycle has the biggest influence to drive the price per bar, and not only which cycle has the highest amplitude!

That is the reason I am introducing the measurement value "Cycle Strength." Our Cycle Scanner automatically calculates this value.

That said, to build a ranking based on the cycles left, we recommend sorting these cycles based on their "influence" per price bar. As we are looking for the most dominant cycles, these are the cycles that influence the price movement the most per single bar.

Sort the outcome according to the calculated cycle strength score. Now we have a top-to-bottom list of cycles having the highest influence on price movements per bar. And that is precisely what we need!

Summary: The dominant cycle

After the cycle scanner engine has completed all four steps, the cycle at the top of the list (with the highest cycle strength score) will provide us the information on the dominant cycle. In fact, the wavelength of this cycle is the dominant market vibration, which is very useful for trading.

However, not only is the result limited to the cycle length (based on our adjustments in Step 2, we not only have the dominant cycle length) but we also know—and this is very important—the current phase status of this cycle (Important: not the averaged phase over the full data set). This allows us to provide more valid cycle projections on the "right" side of the chart for trading instead of using the normally used "averaged" phase status over the full data set for this cycle.

Online Cycle Scanner Tool for FSC members

The cycle scanner toolset is available to FSC members with an easy to use interface to "drag'n drop" your dataset and see the results live on the screen. It should act as a starting point to detect cycles in different kinds of datasets.

https://app.cycles.foundation