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A Long Term Trading Model for Portfolio Management

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Abstract: ***We use the output of our wave smoothing algorithm to analyze intermediate trend turning points from which we formulate a long/short trading system geared to the long-term investor. This system, which is well suited as a mutual fund or etf, significantly outperformed the S&P 500 over a span of 15 years beginning January 2000. We empirically test our trades using simple money management and an exhaustive simulation.***

INTRODUCTION

In [2] we showed how our unique wave smoothing algorithm (WSA) outputs turning points, in the financial markets, at successive levels of granularity (corresponding roughly to daily, weekly, etc…). We focus on the development of trading systems that pivot on key turning points that act as support/resistance. When the price trades above/below strong resistance/support ([1], [3]), it often signals a reversal.

Our trading system, suitable for use as a mutual fund or etf, produces very profitable results, beating the S&P 500 over a 15 year period beginning January 1, 2000 and ending December 31, 2014.

The average profit/loss potential of our setups (buy/sell signals) is realized using simple money management. Our money management system assumes an initial bankroll of $100,000 and we use an exhaustive simulation to demonstrate the practicality and profitability of our trading system.

SETUP

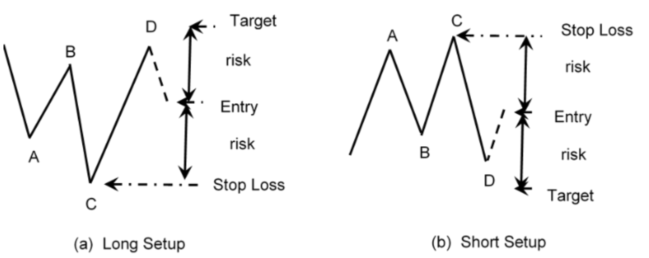

Figure 1: Long and Short setup

Our system uses Level 2 DataPoints generated by the WSA. A DataPoint is a collection of data that includes a daily low or high. The DataPoints are generated as follows: Level 0 is a set of ordered daily highs and lows. Level 1 is generated from Level 0 by extracting relative highs and lows from Level 0. A relative high is a high that is greater than or equal to both the previous and next high. A similar definition applies for a relative low. These points are ordered as consecutive lows and highs, satisfying certain rules (e.g., there cannot be two consecutive lows or highs, also there cannot be a high followed by a higher low and vice-versa, see Appendix B). Recursively, we generate Level 2 DataPoints from Level 1 etc. We showed in [2] that from level to level the number of DataPoints is reduced by a factor of approximately 5. Thus Level 1 DataPoints are approximately five days apart and Level 2 DataPoints are, on average, 25 days apart.

The long setup we employ consists of identifying four consecutive Level 2 DataPoints A, B, C, and D as in Fig 1.

For the end of a bull market, which we define as two consecutive Level 2 highs with the second high higher than the first, we look to go short when A is a relative high, B a relative low, C a relative high that is greater than A and D a relative low that is lower than B. We set the entry point for the trade at risk percent less than DataPoint C. DataPoint C becomes the stop loss. Not apparent in Figure 1, the entry point could be below D particularly when risk is high. The target will be set at an equal distance below the entry point so that the risk:reward ratio is 1:1.

For the end of a bear market, which we define as two consecutive Level 2 lows with the second low lower than the first, we look to go long when A is a relative low, B a relative high, C a relative low that is lower than A and D a relative high that is higher than B. We set the entry point for the trade at risk percent greater than DataPoint C. DataPoint C becomes the stop loss. Not apparent in Figure 1, the entry point could actually be above D particularly when risk is high. The target will be set at an equal distance above the entry point so that the risk:reward ratio is 1:1.

Note: not every setup results in a trade; the setup is cancelled if the target or stop is reached prior to the entry price.

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EMPIRICAL RESULTS

We backtested 76 markets over a 15 year period, from 01/01/2000 to 12/31/2014 (except for some ETFs and stocks that do not go back as far as 2000). We used 32 stocks, 22 ETFs tracking major indices, and 22 ETFs tracking commodities (for a list of all markets see appendix A). These markets were chosen based on trading volume and consistency with our previous papers.

Table 1 shows the total number of trades generated per market based on risk percent over this 15 year period. For example, for risk=25%, the setup generated a total of 1183 trades (623 in stocks, 299 in index ETFs and 261 in commodity ETFs). There were 671 long trades and 512 short trades. The best winning percent for long trades is for a risk of 20% (66.16%) and the worst is for a risk of 5% (55.96). For short trades, the best winning percentage is for a risk of 30% (47.50%) and the worst is 10% risk (40.46%).

Category/ %Risk	5	10	15	20	25	30
NTL	520	779	779	736	671	582
NTS	646	734	709	592	512	461
NWL	55.96	61.74	65.59	66.16	65.57	65.97
NWS	44.11	40.46	43.15	43.58	45.70	47.50
APPTL	0.69	2.19	4.57	6.24	7.37	9.19
APPTS	0.55	-1.72	-2.01	-2.25	-1.93	-1.90

Table I: Results over all markets by risk percent (NTL: Number Trades Long, NTS: Number Trades Short, NWL: Number Winners Long, NWS: Number Winners Short, APPTL: Average Percent Profit per Trade for Longs, APPTS: Average Percent Profit per Trade for Shorts).

Figure 2 shows the percentage of winning trades for all categories, short and long. For risk=25%, for example, there are 56.97% winning trades overall, 65.57% winning long trades and 45.70% winning short trades. One can speculate that the disparity between the long and short results is due to the predominantly bullish nature of the markets over this period of time.

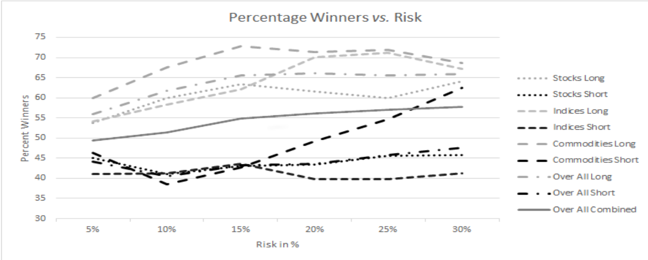

Figure 2: Percent winning trades versus risk percent

From Figure 3, we can see that the long trades perform much better than the shorts. All categories display a positive average percent profit per trade for the long side, while only commodities are positive on the short side, and only for 25% and 30% risk. Notice also that the average profit per trade increases as the risk percent increases over all long trades.

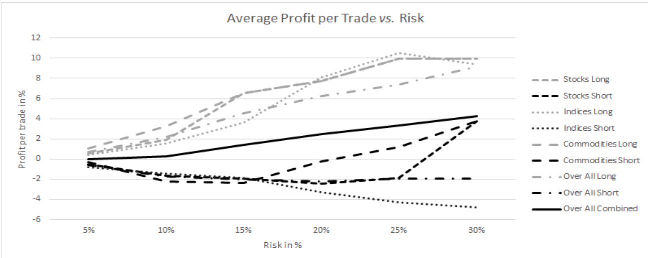

Figure 3: Average profit per trade for each category by risk

When comparing the statistics between the long trades and the short trades, one would conclude, that any trading system based solely on the long setups should perform better than the long and short trades combined. While we have found this to be true, when we run only the long trades we experience much greater volatility than when we include the short trades. Conservative investors would likely prefer including the short trades to limit exposure to huge losses as experienced by many investors from 2007 through March of 2009. Thus, we elect to present the results of simulations of our trading system for long/short combined.

HYPOTHESIS TESTING

Our null hypothesis is that a random approach could achieve similar results. Overall, the average percent profit per trade for our trade setups is 4.23%. We designed a random simulation with the same parameters as ours: total number of trades of 1043, risk of 30%, and 582 long and 461 short trades. These numbers were generated using a uniform probability. We ran 10,000 simulations and the average percent profit per trade was 0.9881 with a standard deviation of 0.9750. This corresponds to a z-score of 3.325 for our trade setups, which falls in the 99.92% confidence level. Thus, we reject the null hypothesis that our results can be achieved randomly.

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A REAL-TIME TRADING SIMULATION

MONEY MANAGEMENT

The data from the table above do not paint a complete picture of the potential profit/loss in real time trading as it does not take into account money management. Toward that end, we utilize a simple money management system tailored to the above setup. We assume a $100,000 initial bankroll, which is adjusted at the close of each trade. We simulate the system limiting the maximum number of active trades to: 5, 10, 15 and 20. We also vary the risk from 5% to 30% by 5% increments. Suppose we use 5 as the maximum number of active trades, with a risk of 20%. The maximum amount invested in each trade is one-fifth of the current bankroll. The available funds for trading, is that part of the bankroll that is not invested in an active trade. If the available funds are less than the maximum amount, we can still enter a new trade as long as the available funds is greater than or equal to 80% of the maximum amount.

As an example, suppose as above our initial bankroll is $100,000 and we enter the first five trades each with $20,000 invested. Our available funds for trading, is now zero. Further, suppose that the first trade to close yields a gain of $4000 (the only possibility is a gain/loss of $4000 with a 20% risk). Then, the current bankroll will be $104,000 and our available funds for trading $24,000. Thus, we will invest the maximum amount of $104,000/5 = $20,800 in the next possible trade. After the next trade is entered, the available funds for trading is only $3,200. If the next trade to close suffers a loss of $4000, then the current bankroll will be $100,000, and the maximum amount to invest is $100,000/5 = 20,000. However, the available funds for trading is $16,000+$3,200 = $19,200. In this case, since the available funds is larger than 80% of the maximum amount to invest, which is $16,640, the entire $19,200 will be invested in the next trade and the simulation continues in this manner.

AN EXHAUSTIVE SIMULATION

Several trades may trigger on the same day. The system may not be able to execute all of them: there may not be enough empty active trades and/or the available funds may be insufficient. Since we cannot precisely determine which of the trades triggered first, we must decide, in our simulation, which trade to consider. We may elect to enter the trades based on some predefined criteria such as choosing the trade with the earliest setup time or perhaps base the decision on an alphabetical ordering by symbol name; but this will not give an accurate statistical model. Therefore, we approximate the real time situation by using a Monte Carlo-like simulation that aims to cover all possibilities as per [4], and present the mean results for annual return and maximum drawdown. The drawdown is the largest percentage loss from any peak to trough of the bankroll over the 15 years. We performed 500 simulations for each combination of risk percent and maximum number of active trades. The next section reflects the mean results of these 24 simulations.

RESULTS

In total, we performed 500 simulations for each of 24 combinations: 4 maximum active trades (5, 10, 15 and 20) times 6 risk percents (5, 10, 15, 20, 25 and 30). Each simulation used random choices in case of two or more trades occurring on the same day that could not be executed as explained above. We compute the average annual return as well as the average maximum drawdown over the entire 15 year period. The drawdown is of great importance as it is a strong indicator of potential volatility/stability of the system. Below we give a summary by market, for our long/short system. We also show the annual return over each of the 15 years for select combinations. We plot these against the annual return of the S&P 500.

Stocks

From Figure 4, we see that the drawdown for stocks increases as the risk increases to peak at 15% risk and decreases from there. In general, the drawdown decreases as the number of active trades increases, which is to be expected due to having more baskets for your eggs. The drawdown remains consistently low for risk levels of 20, 25 and 30. The worst drawdown of 48.66% occurs for maximum active trades of 5 and risk of 15%. The minimum drawdown of 7.86% is realized when the maximum number of active trades is 20 and risk of 5%.

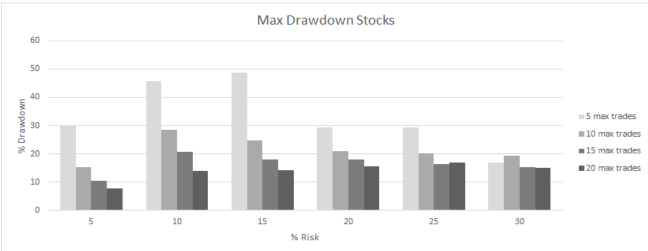

Figure 4: Maximum drawdown for stocks

The annual return, as can be seen from Figure 5, increases for risks of 5, 10 and 15 percent and dips for 20% before once again rising until 30%. The maximum annual return of 6% occurs at the highest risk of 30% and maximum active trades of 5. Although, there is a high risk percent, this combination produces a low drawdown of 16.94%. The second most attractive combination for stocks is maximum active trades of 10 and risk of 30% which gives an annual yield of 5.55% and maximum drawdown of 19.37%.

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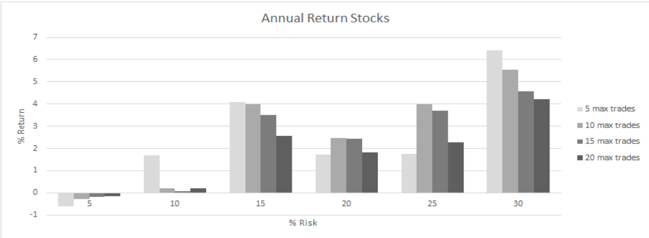

Figure 5: Average Annual Return for stocks

ETFs tracking indices

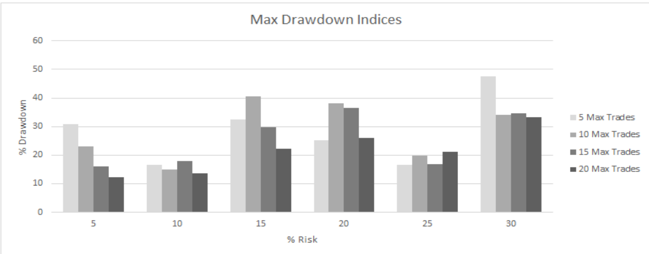

Figure 6: Maximum drawdown for Indices

From Figure 6, the drawdown for indices increases as the risk increases to peak at 20% risk, dips considerably for 25% risk, and increases again for 30% risk. The annual return increases as the risk increases to reach a maximum at 25% risk, then falls off again for 30% risk.

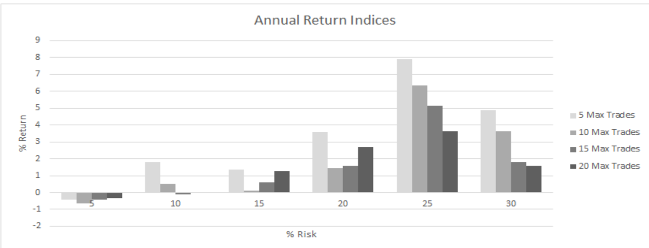

Figure 7: Average Annual Return for Indices

The maximum annual return of 7.92% (Figure 7) occurs at a risk level of 25% and maximum number of active trades of 5. It carries a relatively low drawdown of 16.49%. The second most attractive combination is maximum active trades of 10 for the same risk level of 25%, which gives an annual yield of 6.33% and a maximum drawdown of 19.66%.

ETFs tracking commodities

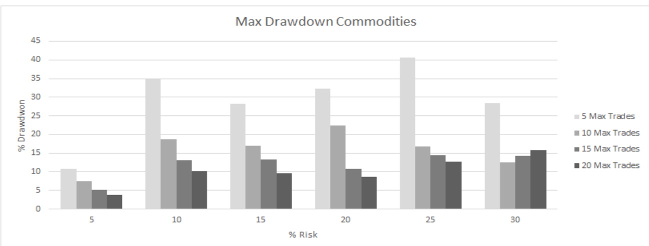

Figure 8: Maximum drawdown for commodities

Figure 8 shows the maximum drawdown and annual return for commodities. For a maximum number of active trades of 5, the drawdown is substantially higher than all other possibilities. The maximum annual return of 5.35% occurs at 25% risk for a maximum number of active trades of 10. The drawdown for this combination is a relatively low 16.78%. The maximum active trades of 15 and 25% risk is also good with a smaller maximum drawdown of 14.41% and annual return of 5.068% (see Figure 9).

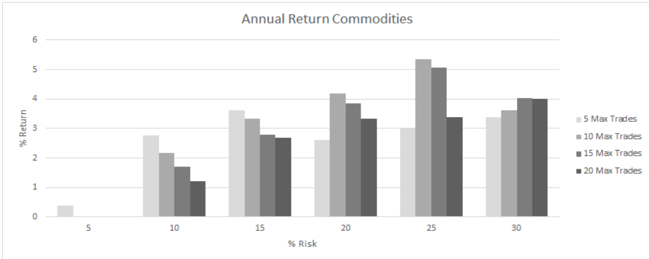

Figure 9: Average Annual Return for commodities

Simulation over all markets

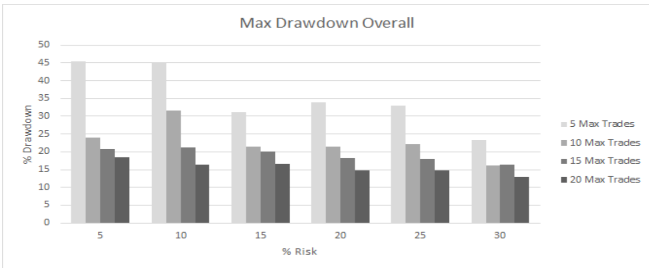

Figure 10: Maximum drawdown over all markets

Combining all trades together, we get a smoothing of the individual markets except for the maximum number of active trades of 5 (see Figure 10), which is choppy especially for annualized return. The drawdown remains stable over most risk levels (see Figure 10). The best annualized return of 5.57% is obtained for maximum active trades of 5 and risk of 30%. The drawdown for this combination is 23.39%. The combination of 20 active trades with 30% risk is better suited for a conservative investor; it yields an annualized return of 5.02% (see Figure 11) with a maximum drawdown of 12.92%. The average annual return for the S&P 500 over the same period is 4.07% with a drawdown of 57.7%. The selloff in the S&P 500 caused many long term investors to be "shook" out of their equity positions well before the trough was reached in March 2009, including those investors in 401K and other retirement accounts, some selling at or near the bottom. In contrast, with our long/short trading system, investors would barely have noticed the maximum drawdown of a little less than 13%.

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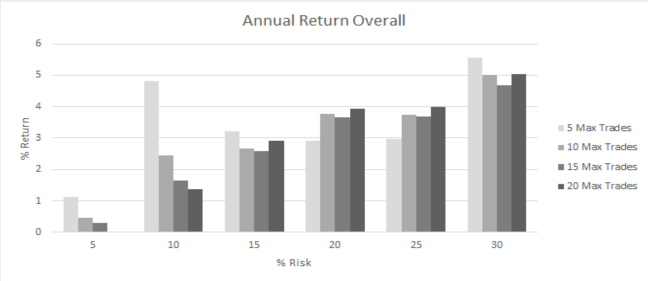

Figure 11: Annual return over all markets

We can see the dramatic outperformance of our trading system compared to the S&P 500. Furthermore, in year ending 2008, the S&P 500 experienced nearly a 50% annual loss, compared to our trading system which was essentially flat. Our hypothetical bankroll of $100,000 invested at the beginning of year 2000 was worth about $50,000 at the end of 2008 for those investing in spy, an etf that mirrored the S&P 500, while in our virtual investment fund our bankroll was around $150,000 or triple the S&P 500. The average balances at the end of 2014 are approximately $140,000, and $200,000 for the S&P 500 and our long/short system respectively.

Choosing the best combination

We decided to focus on what we consider to be the best combination, which is maximum trades of 20 and 30% risk. We ran an exhaustive simulation with 100,000 trials for this case. Figure 12 shows the balance at the end of each year for the worst, the mean and the best case contrasted to the S&P500. Even the worst simulation showed very small declines in years where the S&P500 experienced huge losses. The maximum loss, which occurred at the end of 2012 is 4.5% and the total gain over the 15 years is nearly the same as the S&P500 with a maximum drawdown of only 12.3%. The best simulation, which shows a maximum yearly loss of 5.64% in 2001, has an ending balance more than twice the S&P500 with a maximum drawdown of 10.3%. We computed the Sharpe ratio using our annual returns for the long/short case against 90-Day Treasury Bills yearly average yields and arrived at a result of 0.51. This gives a good risk reward profile.

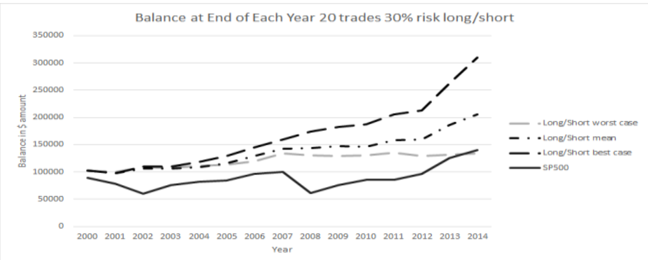

Figure 12: Worst, best and average simulation

Figure 13 depicts the outcomes of the 100,000 trial simulations, for the maximum number of trades of 20 and 30% risk. We can assert with 81.44% confidence that the end balance for long/short will be at least $190,000.

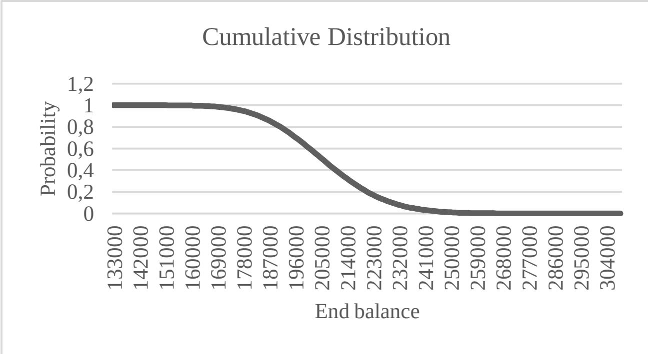

Figure 13: Distribution for end balance

CONCLUSION

In this paper, we devised a trading system that aims to predict intermediate to long term turning points in the financial markets. We used Level 2 turning points as described in [2]. We identified a simple pattern of 4 such points and conjectured that this pattern signaled a change in direction of trend. We varied levels of risk percent, as well as maximum active trades allowed. We projected annualized returns using a Monte Carlo-like simulation for each combination of risk percent and maximum active trades. These results were analyzed separately for stocks, commodities, indices and over all markets. We showed that our trading system performed much better than the S&P 500 in terms of both annualized return and maximum drawdown, for various risk percentages in combination with maximum active trades. The trading systems that we highlighted may be suitable as a mutual fund or an etf.

Our preference, as conservative investors, is to favor a long/short system with 20 maximum active trades and 30% risk per trade. Thus we ran an expansive simulation with 100,000 trials for this combination. This system minimizes the drawdown, limits the annual loss, while outperforming the S&P 500. We showed significance at the 99.2 confidence level and showed a .51 Sharpe ratio of our system versus 90 day treasuries. Also, we computed the Sharpe ratio of spy, the etf that mirrors the spx, to be .10 showing that our system has a much better risk reward than the S&P 500.

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APPENDIX A

Stocks

AAPL, AKS, AMZN, BAC, BBY, BCS, BIDU, BRCD, C, CAT, CSCO, DAL, DOW, EMC, EPI, F, GE, GLW, GOOG, IBM, INTC, JPM, LVLT, MSFT, NFLX, NOK, NVS, S, SFD, SIRI, SYMC, TSN.

ETFs tracking Commodities

DBA, DBC, GLD, GDX, IYM, SHY, SLV, SLX, TLT, UNG, USO, XHB, XLB, XLE, XLF, XLI, XLK, XLP, XLU, XLV, XLY, XME.

ETFs tracking Indices

DIA, EEM, EWA, EWC, EWG, EWH, EWJ, EWM, EWS, EWT, EWW, EWY, EWZ, FXI, IWD, IWF, IWM, QQQ, RSX, SPY, VWO, VXX.

APPENDIX B

The Wave Smoothing Algorithm

Let H(k) be the set of high DataPoints in version k, where k=0 represents the initial set of data and L(k) the set of low DataPoints in version k. D(k), which is the version k wave structure, is the set resulting from merging H(k) and L(k) in ascending order according to periodNumber satisfying the set of constraints described below. Let $h_{k,i}$ be the ith element in set H(k), similarly $l_{k,i}$ the ith element in set L(k), and $d_{k,i}$ the ith element in wave structure D(k). We generate successive sets of DataPoints recursively as follows:

Recall that H(0)={the ordered set of all DataPoints representing daily highs extracted from the initial data} with a similar definition for L(0). Thus, D(0) is the set resulting from merging L(0) and H(0) in ascending sequence by periodNumber with $h_{0,0}$ appearing before $l_{0,0}$ ($D(0) = \{h_{0,0}, l_{0,0}, h_{0,1}, l_{0,1}, \ldots, h_{0,N-1}, l_{0,N-1}\}$, where N is the length of the initial file). By construction, each periodNumber is repeated exactly twice in D(0) (e.g. $h_{0,0}$.periodNumber =$l_{0,0}$.periodNumber). Recursively, the set of highs in version k is $H(k) = \{h_{k-1,i} | h_{k-1,i} \geq h_{k-1,i+1}$ and $h_{k-1,i} \geq h_{k-1,i-1}\}$; the set of lows in version k is $L(k) = \{ l_{k-1,i} | l_{k-1,i} \leq l_{k-1,i+1}$ and $l_{k-1,i} \leq l_{k-1,i-1}\}$.

The version k wave structure D(k) is derived by first merging the two sets H(k) and L(k) according to the periodNumber, followed by weeding out anomalies from D(k) according to the following set of rules:

1. If $d_{k,i}$.direction = $d_{k,i+1}$.direction and $d_{k,i}$.direction = high, then we have two consecutive high DataPoints; in this case, delete the smaller of the two. Similarly, delete the larger of any two consecutive low DataPoints occurring in D(k).

2. If $d_{k,i}$.direction = high and $d_{k,i+1}$.direction = low and $d_{k,i} < d_{k,i+1}$; then we have a high followed by a low that is higher. In this case, delete $d_{k,i+1}$. Similarly, if $d_{k,i}$.direction = low and $d_{k,i+1}$.direction = high and $d_{k,i} > d_{k,i+1}$, then delete $d_{k,i+1}$.

3. Repeat 1 and 2 until no changes are made.

4. Update H(k) and L(k) as $H(k) = \{d_{k,i} | d_{k,i}$.direction = high$\}$ and $L(k) = \{d_{k,i} | d_{k,i}$.direction = low$\}$ maintaining the order according to periodNumber.