METHODOLOGY FOR ELLIOTT WAVES PATTERN RECOGNITION

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KEYWORDS

Elliott waves, Fibonacci analysis, neural networks, pattern recognition, prediction.

ABSTRACT

The article is focused on an analysis and pattern recognition in time series, which are fractal in nature. The proposal methodology is based on an interdisciplinary approach that combines artificial neural networks, analytic programming, Elliott wave theory and knowledge modelling. The heart of the methodology are a methods, which is able to recognize Elliott waves structures including their deformation in the charts and helps to more efficient prediction of its trend. The functionality of the proposed methodology was validated in experimental simulations, for whose implementation was designed and created an application environment. Experimental simulations have shown that the method is usable to a wider class of problems than the theory itself allows only Elliott waves.This paper introduces a methodology that allows analysis of Elliot wave's patterns in time series for the purpose of a trend prediction.

INTRODUCTION - ELLIOTT WAVE PERSONALITY AND CHARACTERISTICS

Elliott wave analysts hold that each individual wave has its own signature or characteristic, which typically reflects the psychology of the moment (Poser2003). Understanding those personalities is a key to the application of the Wave Principle; they are defined as follows (Frost and Prechter 2001):

Five wave pattern - dominant trend (see Fig. 1)

- **Wave 1:** Wave one is rarely obvious at its inception. When the first wave of a new bull market begins, the fundamental news is almost universally negative. The previous trend is considered still strongly in force. Fundamental analyses continue to revise their earnings estimates lower; the economy probably does not look strong. Sentiment surveys are decidedly bearish, put options are in vogue, and implied volatility in the options market is high. Volume might increase a bit as prices rise, but not by enough to alert many technical analysts.

- **Wave 2:** Wave two corrects wave one, but can never extend beyond the starting point of wave one. Typically, the news is still bad. As prices retest the prior low, bearish sentiment quickly builds, and "the crowd" haughtily reminds all that the bear market is still deeply ensconced. Still, some positive signs appear for those who are looking: volume should be lower during wave two than during wave one, prices usually do not retrace more than 61.8% (see Fibonacci relationship) of the wave one gains, and prices should fall in a three wave pattern.

- **Wave 3:** Wave three is usually the largest and most powerful wave in a trend (although some research suggests that in commodity markets, wave five is the largest). The news is now positive and fundamental analysts start to raise earnings estimates. Prices rise quickly, corrections are short-lived and shallow. Anyone looking to "get in on a pullback" will likely miss the boat. As wave three starts, the news is probably still bearish, and most market players remain negative; but by wave three's midpoint, "the crowd" will often join the new bullish trend. Wave three often extends wave one by a ratio of 1.618:1.

- **Wave 4:** Wave four is typically clearly corrective. Prices may meander sideways for an extended period, and wave four typically retraces less than 38.2% of wave three (see Fibonacci relationships). Volume is well below than that of wave three. This is a good place to buy a pull back if you

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understand the potential ahead for wave 5. Still, fourth waves are often frustrating because of their lack of progress in the larger trend.

- **Wave 5:** Wave five is the final leg in the direction of the dominant trend. The news is almost universally positive and everyone is bullish. Unfortunately, this is when many average investors finally buy in, right before the top. Volume is often lower in wave five than in wave three, and many momentum indicators start to show divergences (prices reach a new high but the indicators do not reach a new peak). At the end of a major bull market, bears may very well be ridiculed (recall how forecasts for a top in the stock market during 2000 were received).

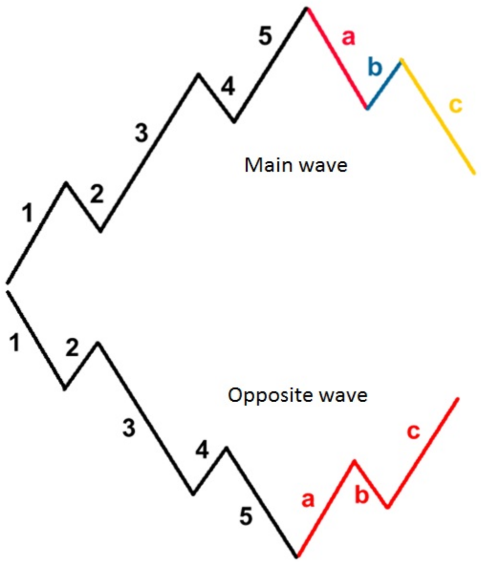

Figure 1: The basic pattern of Elliott wave

Three wave pattern - corrective trend (see Fig. 1)

- **Wave A:** Corrections are typically harder to identify than impulse moves. In wave A of a bear market, the fundamental news is usually still positive. Most analysts see the drop as a correction in a still-active bull market. Some technical indicators that accompany wave A include increased volume, rising implied volatility in the options markets and possibly a turn higher in open interest in related futures markets.

- **Wave B:** Prices reverse higher, which many see as a resumption of the now long-gone bull market. Those familiar with classical technical analysis may see the peak as the right shoulder of a head and shoulders reversal pattern. The volume during wave B should be lower than in wave A. By this point, fundamentals are probably no longer improving, but they most likely have not yet turned negative.

- **Wave C:** Prices move impulsively lower in five waves. Volume picks up, and by the third leg of wave C, almost everyone realizes that a bear market is firmly entrenched. Wave C is typically at least as large as wave A and often extends to 1.618 times wave A or beyond (Frost and Prechter 2001).

FIBONACCI ANALYSIS AND ELLIOTT WAVE THEORY

Fibonacci numbers provide the mathematical foundation for the Elliott Wave Theory. While the Fibonacci ratios have been adapted to various technical indicators, their utmost use in technical analysis remains the measurement of correction waves (Frost and Prechter 2001).
The Fibonacci number sequence 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89,...is made by simply starting at 1 and adding the previous number to arrive at the new number:

0+1=1, 1+1=2, 2+1=3, 3+2=5, 5+3=8, 8+5=13, 13+8=21, 21+13=34, 34+21=55, 55+34=89,…

This series has very numerous interesting properties:

- The ratio of any number to the next number in the series approaches 0.618 or 61.8% (the golden ratio) after the first 4 numbers. For example: 34/55 = 0.618

- The ratio of any number to the number that is found two places to the right approaches 0.382 or 38.2%. For example: 34/89 = 0.382

- The ratio of any number to the number that is found three places to the right approaches 0.236 or 23.6%. For example: 21/89 = 0.236

These relationships between every number in the series are the foundation of the common ratios used to determine price retracements and price extensions during a trend (see Fig. 2).

Figure 2: Fibonacci price retracements and price extensions (adapted fromhttp://www.markets.com/education/technical-analysis/fibonacci-elliot-wave.html)

A retracement is a move in price that "retraces" a portion of the previous move. Usually a stock will retrace at one of 3 common Fibonacci levels- 38.2%, 50%, and 61.8%. Fibonacci price retracements are determined from a prior low-to high swing to identify possible support levels as the market pulls back from a high.Retracements are also run from a prior high-to-low swing using the same ratios, looking for possible resistance levels as the market bounces from a low (Frost and Prechter 2001).
Fibonacci price extensions are used by traders to determine areas where they will wish to take profits in the next leg of an up-or downtrend. Percentage extension levels are plotted as horizontal lines above/below the previous trend move. The most popular extension levels are 61.8%, 100.0%, 138.2% and 161.8%.
In reality it is not always so easy to spot the correct Elliott wave pattern, nor do prices always behave exactly according to this pattern. Therefore it is advisable for a trader not to rely solely on Fibonacci ratios, but rather to use them in conjunction with other technical tools.

ELLIOT WAVES DETECTION

Elliott waves are characterized by wide and numerous descriptions of their distinctive phases, thus they are difficult to detect in time series.

Detection according to the rules

The first eventuality is the classification which gradually runs from smallest to largest parts of Elliott waves. This method is described in (Dostál and Sojka 2008). The process starts with finding a scale and separate mono-waves marking. There are completed patterns according to particular ratios. These patterns are a base for other patterns. This approach is often used for manual evaluation with their subsequent processing. The method uses seven rules, which classify waves into groups depending on a ratio of heights of neighbouring waves. The rules use Fibonacci ratios with a deviation of 5%. The only possibility of searching is to check each mono-wave through the conditions and some experience of a researcher is expected as well. Here, the aim is not to deal with the evaluated segment, but to respect single figures as complex units. This method is accurate, but it is computationally very time consuming and it is limited to the detection of mono-waves according to the predetermined number of specific rules.

Detection units and their progressive separation

The second eventuality is classification of big parts of Elliott waves and their subsequent decomposition into smaller parts. Patterns of impulsive character can be detected clearly thanks to more accurate conditions than patterns of correction phase. Therefore it is possible to detect patterns proposed in input data. Here, the aim is to find a figure and then to classify its smaller units. A disadvantage is that impulse phases are only detected directly, while correction phases must be derived. Another disadvantage during detection of large parts is that their internal structure is unknown as long as other pulses are not found in these parts.

Detection according to characteristic figures

The third eventuality is to restrict detection to some significant figures, which are significant with respect to parts of patterns according to the Elliott theory. Therefore, the method does not restrict to detecting mono-waves. Found figures can be processed further, while found figures generate additional parameters for further processing. A disadvantage is that we are able to find a lot of characteristic patters in input data, which is time consuming. Here, we have to choose patterns correctly for detection and to have sufficient amount of test data to disposal. However, this approach is very effective and, therefore, it was chosen as a detection method in the article.

DETECTION SYSTEM FOR ELLIOT WAVES PATTERN RECOGNITION BASED ON NEURAL NETWORKS

The core of detection system is the multi-classifier, which consists of the for the pattern recognition of structures with fractal dynamics. The multi-classifier (Fig. 3) is based on neural networks which are adapted by backpropagation (Volna, Kotyrba and Jarusek 2013).

- The first neural network is designed to recognize selected Elliott wave's patterns. Emphasis is placed on the ability of a network to evaluate the found patterns with a degree of consensus of similarity with the defined pattern from training set. It is also necessary to network guarantee information about a quality of the found pattern.

- The second neural network evaluated prediction of trend component on the basis of the recognized pattern. The whole prediction is based on the IF-THEN rules from which the training set is composed for the second neural network. In essence, the neural network represents a rule-based of knowledge system that is able to decide whether a time series respects corrective or impulse direction.

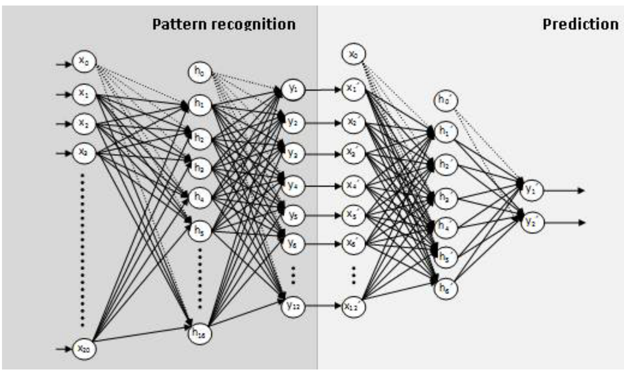

Figure 3: The multi-classifier proposal for the purpose of pattern recognition with consecutive prediction

Preparation of the training set of the first neural network using Fibonacci sequence

All patterns of training set were defined in order to represent the characteristics of Elliott wave to be identified in dependently of the time scale or the nature of the monitored data. When creating patterns, we used the properties of the Fibonacci sequence, which we used as a time filter so we could estimate when the impulse or correction would terminate. Time incorrections:

A wave = X units of time
B wave = 1.681 × X or B=< 0.618 × X
C wave = 0.618 × A (B) or
C=> 1.618 × A (B) or C= A+B

In the impulsive waves were taken into consideration waves where the first, third and fifth wave extended. These are patterns P6, P8, P10 in Fig. 4.

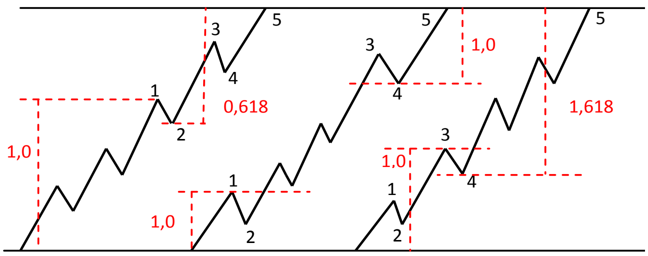

Figure 4: Extended phase of the impulse character

For example, when wave 3 is extended, waves 1 and 5 tend towards equality or a 0.618 relationship, as illustrated in Fig. 4. Actually, all three impulsive waves tend to be related by Fibonacci mathematics, whether by equality, 1.618 or 2.618 (whose inverses are 0.618 and 0.382). These impulse wave relationships usually occur in percentage terms. Wave 5's length is sometimes related by the Fibonacci ratio to the length of wave 1 through wave 3, as illustrated in Fig. 4. In those rare cases when wave 1 is extended, it is wave 2 that often subdivides the entire impulse wave into the wave, as shown in Fig. 4. In such cases, the latter portion is 0.382 of the total distance when wave 5 is not extended. This guideline explains why a retracement following the fifth wave often has double resistance at the same level: the end of the preceding fourth wave and the 0.382 retracement point (Frost and Prechter 2001).

We used the backpropagation method for the adaptation with the following parameters: first 5000 iterations havethe learning rate value 0.5, and for the next 2000 iterations the learning rate value is 0.1, momentum is 0. The conducted experimental studies also showed that in each cycle of adaptation is to present an adequate network of training patterns mixed randomly to ensure their greater diversity, but also acts as a measure of system stability. Uniform system in a crisis usually collapses entirely, while in the diversion system through a crisis of its individual parts, but the whole remains functional. The condition of end of the adaptation algorithm specified thelimit value of the overall network error, E <0.07. It concernsthe perfectthetraining set adaptation.

The second neural network of the proposed multi classifier simulates the knowledge system. Knowledge modelling is the concept of representing information and the logic of putting it to use in a digitally reusable format for purpose of capturing, sharing and processing knowledge to simulate intelligence. A knowledge base is designed in the form of rules. Each rule consists of a conditional and a consequential part. All rules are expressed in the following form: *IF a THEN b.* The left side of each rule represents a conditional part of the rule whereas its right side represents consequential part of the rule. For our purposes, it was essential to create suitable form of rules which should include all important features of the designed knowledge system. The rules in our system were presented in the following form:

IF *found pattern* & *fulfilment of consensus of similarity* THEN *trend direction*

There are two basic variables in the antecedent. It means fulfilment of consensus of similarity and found patterns which we gained as results (outputs) from the first part of classifier. After prediction of trend direction the consequent is composed like thisupward trend or downward trend. Consensus of similarity was set at 90% or more. In summary, the topology of neural network contains 12 input, 6 hidden and 2 output neurons. In the active phase, outputs of the first of neural networks are entering, which represent the degree of consensus of recognized Elliott wave pattern. The parameters of the backropagation algorithm (Fausett1994, Hertz et al. 1991) are the following: first 1000 iterations have learning rate value 0.5, and for the next 3000 iterations the learning rate value is 0.1, momentum is 0. These learning rates were set according to the experimental study. Calculation is halted after every 1000 cycles and the coefficient of the learning rate is set to a smaller value, resulting in subsequent weight gain soft. The Condition of the end of the adaptation algorithm specified the limit value of the overall network error, E < 0.07. It concerns the perfect the training set adaptation. Error function history (E) of both parts of multiclassifier during adaptation is shown in figure 5 (Kotyrba et al. 2012).

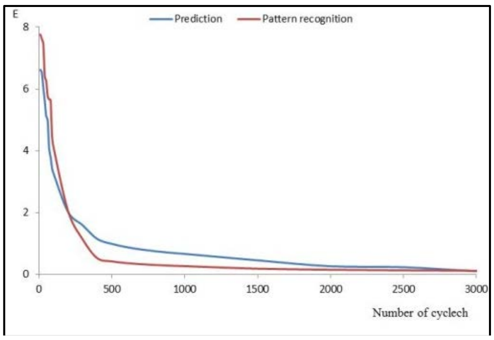

Figure 5: Error function history

METHODOLOGY OF RECOGNITION OF STRUCTURES WITH FRACTAL DYNAMICS

Aim of the proposed methodology is to propose a procedure for automatic pattern recognition in the systems with fractal dynamics in order to predict the trend. Using the proposed methodology, in the context of this articleis limited tothe stock market, but the area of application is much wider character, such as the prediction of sunspots or volume wave forms etc. The proposed methodology represents a sequence of actions whose implementation will help in the recommended sequence recognition of individual parts of structures Elliott waves, which can be used to predict the trend of the analyzed time series. The sequence of these activities is shown in Table 1.

Table 1: Steps of methodology

	Name of activity methodology	Character activities within publications	Selection tool
1	Obtaining data- time series with fractal dynamics.	It is essential to have appropriate data representing the solved problem.	World Wide Web.
2	Selection of structures for the purpose of detection and analyzing their characteristics.	Elliott wave analysis for identification of characteristic structures.	Elliott's theory.
3	Choice of classification methods and setting its parameters.	Settings of the first neural network topology, type of transfer function and adaptation parameters.	Neural network.
4	Preparing data for the first part of multiclassifier which realizes pattern recognition.	Preparation of standard training set patterns which represent individual parts Elliott waves.	Neural network, Elliott´s theory.
5	Application of methods.	Adaptation of the first neural network.	Neural network.
6	Proposal of knowledge system, preparing the base rules. Implementation of knowledge system in a form of the second part multiclassifier.	Preparation of normalized patterns for the training set for the second neural network that represents a rules-based knowledge system, designed to predict the trend line. Settings of the second neural network topology, type of transfer functionand adaptation parameters.	Neural network, Knowledge modeling.
7	Analysis and data processing and their preparation for further use.	Selection of test data series and its standardization. Adapted neural network recognizes patterns in test data with different degrees of compliance. Real outputs of the first neural network, also represents the inputs to the second neural network.	Neural network.
8	Evaluation of the solution results.	Validation of the results and their comparison with existing methods for overall evaluation.	Analytic Programming, Box-Jenkins methodology, Refined Elliott Trader, etc. Fuzzy logic toolbox etc.

ANALYSIS AND EVALUATION OF THE RESULTS

During our experimental study we applied a database from the area of financial forecasting [8] that is a set of data that reflects the situation on the market. Data shows volume behavior of Ebay corp.

In the first phase, a set of values with the found degree of consensus that is assigned to each recognized pattern from training set in test set is the output from the first neural network. It is important to realize what can be considered as an effective criterion. Whether there is about 90% agreement with the original pattern or is sufficient 70% for us? The proposed boundaries of the degree of consensus, comes from results of the performed experimental studies and it was set to at least 90%. The neural network is able to find dependences which are unobservable for humans. Therefore it may be a situation where the degree of consensus marked with neural networks is more than 90% and the visual evaluation of the expert is much less. Figure 6 shows the degree of consensus more than 78% even if expert could not determine such a real similarity with the original pattern. The performed experimental study shows success of the proposed methodology.

We examined a total of 10 data sets. Each of them contains 300 values. A propose methodology allows to recognize 5421 patterns with consensus of similarity greater than 70%, next 4852 patterns with consensus of similarity greater than 80% and 1752 patterns with consensus of similarity greater than 90% (Kotyrba et al. 2012).

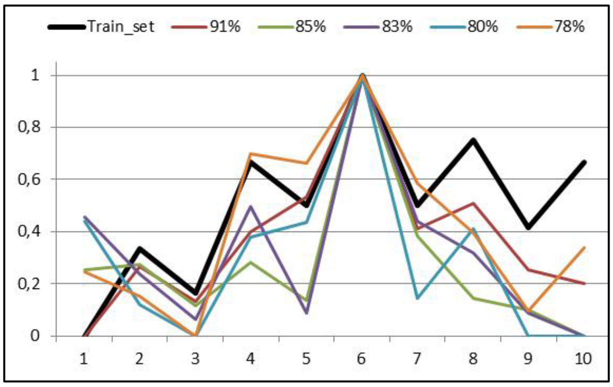

Figure 6: Similarities with degree of consensus more than 78%

Trend prediction was verified only for patterns with consensus of similarity greater than 90% and their number is 1189, what is 67.8 % successful prediction in total. In this case, the proposed multi-classifier is justifiable because the prediction percentage greater than 50% means success in the case of predictive exchange software.

CONCLUSION

In this paper, a short introduction into the field of time series pattern recognition using our methodology based on neural network has been given. According to the results of experimental studies, it can be stated that Elliot wave's patterns were successfully extracted in given time series and recognized using the suggested method as can be seen from the figures in the result section. The proposed methodology is based on an interdisciplinary approach that combines various methods of artificial intelligence. Experimental results show that the methodology can also be used on a wider class of problems than just detection of Elliott waves in the price charts and achieving successful prediction.

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