FINANCIAL TIME SERIES REPRESENTATION USING MULTIRESOLUTION IMPORTANT POINT RETRIEVAL METHOD

Chaliaw Phetking[1], Mohd Noor Md. Sap[2], Ali Selamat[2]
[1,2]Faculty of Computer Science and Information System
Universiti Teknologi Malaysia, Johor, Malaysia
[1]chaliaw_utm@hotmail.com, [2]{mohdnoor,aselamat}@utm.my

Abstract: Financial time series analysis usually conducts by determining the series important points. These important points which are the peaks and the dips indicate the affecting of some important factors or events which are available both internal factors and external factors. The peak and the dip points of the series may appear frequently in multiresolution over time. However, to manipulate financial time series, researchers usually decrease this complexity of time series in their techniques. Consequently, transforming the time series into another easily understanding representation is usually considered as an appropriate approach. In this paper, we propose a multiresolution important point retrieval method for financial time series representation. The idea of the method is based on finding the most important points in multiresolution. These retrieved important points are recorded in each resolution. The collected important points are used to construct the TS-binary search tree. From the TS-binary search tree, the application of time series segmentation is conducted. The experimental results show that the TS-binary search tree representation for financial time series exhibits different performance in different number of cutting points, however, in the empirical results, the number of cutting points which are larger than 12 points show the better results.

Keywords: Financial time series , Multiresolution , TS-binary search tree, SB-binary search tree, Segmentation

1. INTRODUCTION

Time series analysis is become one of the most popular data mining tasks and is widely applied in many research areas; for example, economics, finance, medicine, chemistry, bioinformatics, etc. For financial time series, the data are generated from the complex and dynamic system with noisy, non-stationary and chaotic data series [1]. Financial data such as stock prices or currency exchanges are discrete time series of prices data. A financial time series demonstrates its movement in a fluctuant way due to some important factors or events which are available both internal factors (e.g. company news) and external factors (e.g. politics, economic growth). These important factors usually reflect to stock prices or exchange rates directly.

Financial time series researches usually relate to following tasks; pattern matching[3], segmentation[4], dimensionality reduction[5], clustering[6], and forecasting[7]. As with all time series data mining problems, the key to effective and scalable algorithms is choosing a suitable representation of the data [2]. Many researchers propose the representation techniques of time series data as found in reference [2],[8],[9],[10]. Authors in [8] propose an Extended Symbolic Aggregate ApproXimation(ESAX) which is a symbolic representation of financial time series. ESAX was adapted from the original SAX[2]. In reference[9], the author presents a generalized model in financial time series by the utilizing of turning points in financial data. Turning points can be considered as the important points in a study done by Fu et al. [10].

In the study of Fu et al.[10], they propose a financial time series representation based on the Perceptually Important Points(PIPs)[11] which are mapped to SB-Tree data structure. These PIPs are collected by measuring the distance between the series points and their trend. The point that has the largest distance is chosen. Alternatively, the important points exist in the series usually occur in as both the peak points and the dip points with the equivalent importance priority. Thus, it is better to collect both the most peak point and the most dip point in the same time or in the same iteration.

In this paper, we introduce a TS-binary search tree for financial time series data based on a Multiresolution ImportaNt pOits Retrieval (MINOR) method. MINOR is used for collecting the most important points (MIPs) which comprises of the most peak (MP) point and the most dip (MD) point. The MIPs are collected in multiresolution views and used for constructing the TS-binary search tree. The financial time series segmentation is conducted as an implementation.

This paper is organized as following. Section II, we introduce the MINOR method. Section III the TS-binary search tree for financial time series representation is proposed. Section IV, an example of trend based financial time series segmentation is conducted. The last section, the conclusion and recommendation for future works are described.

2. RETRIEVALS OF THE MOST IMPORTANT POINTS

In this section, the retrieval of the most important points of financial time series is focused. Firstly, the multiresolution important point retrieval method is conducted, and the second section, the method of finding the most important points is described.

2.1 MINOR method

Given time series $S = \{s_1, s_2, s_3, \ldots, s_m\}$, where m is the length of time series. First, finding the global trend of the time series sequence is processed by drawing a trend line which connects the first point and the last point of the time series. Next, the MIPs which comprises of MP and MD points are recorded. To retrieve the MP and the MD points from the time series, we apply the *Finding the Most Important Points* (FiMIP) *method.* Consequently, the MP and MD points are used as cutting points, then, the time series is divided into three subsequences. For each subsequence, starting from the first subsequence, finding the trend of the subsequence is conducted and then finding MP and MD points of the subsequences are determined and recorded.

The algorithm is performed recursively until the final condition is met. The final condition is the length of final subsequences which is designed by user. However, the smallest length of a subsequence that can be used as the final condition is 3. The pseudo code of the MINOR method is depicted in figure 1.

```
Function MINOR(S,cond)
Input   sequence S[1..m]
Integer cond
Output  list MIPList
Begin
Repeat while length(S) >= cond
MIP = FiMIP(S,cond)
Add MIP to MIPList
Divide segment S into S1, S2 and S3 at MIP
Recursively call to MINOR for all S1,S2,S3
End
End
Return MIPList
End
```

Figure 1 Pseudo code for MINOR method

2.2 FiMIP method

Given a time series segment $S = \{ s_1, s_2, \ldots, s_{m-1}, s_m \}$, the algorithm of FiMIP can be illustrated as following.

MIP is a set of the most important points obtained from a sequence. Two kinds of points are collected; MP and MD points. Each pair of MP and MD is retrieved from a sequence in iteration. The MP point is the point that has the largest distance away up from the trend line of the sequence and the MD point is the point that has the largest distance away down from the trend line of the sequence. Measuring of the distance can be determined by various methods; for example, Euclidean distance(ED), perpendicular distance (PD), and vertical distance (VD).

Actually, the distance value is positive for MP point and negative for MD point. In particular, in this paper vertical distance measurement is selected because of the better results in capturing of the highly fluctuated points [10]. The illustration of the method is depicted in figure 2.

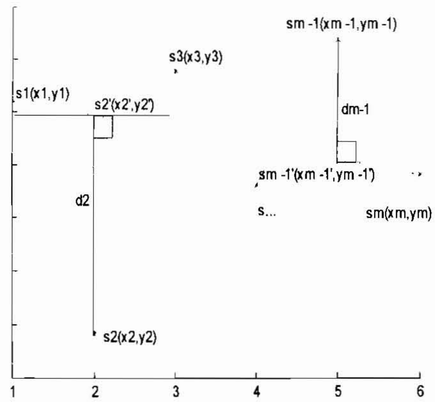


Figure 2 VD height measuring

As can be seen, figure 2 illustrates a vertical distance measurement. The method is started from making a trend line connecting between the first and the last points, we can see as the line s_1s_m in figure 2. From the trend line, we can see that peak points appear up higher than the line s_1s_m, and conversely, the dip points appear lower down from the line s_1s_m. Different points correspondingly give different distance far away from the line s_1s_m. Every point around the line s_1s_m must be measured its distance. In figure 2., for example, the point s_2 appears lower than the line s_1s_m and the point s_{m-1} appear higher than the line s_1s_m. In case of the point s_2, the distance d_2 is measured. As can be seen above, d_2 is a straight line connecting between s_2 and s_2', thus d_2 is a distance between s_2 and s_2' or y_2-y_2' or we can say d_2 is a VD of s_2. For the point s_{m-1}, we can find its VD in similar way. In general, the distance of the ith point is y_i-y_i' can be calculated as equation 1.

$$d_i = y_i - y_i' = y_i - \left(y_s + (y_e - y_s)\frac{x_i - x_s}{x_e - x_s} \right), \qquad (1)$$

where x_i and y_i are the coordinate of the ith point and $1 \le i \le m$, y_s, y_e are the value of the time series at the first point x_s and the end point x_e respectively.

In figure 2, supposedly, if VD of s_2 is the smallest value and if VD of s_{m-1} is the largest value, thus, we can record s_2 and its VD as MD point and record s_{m-1} and its VD as MP point.

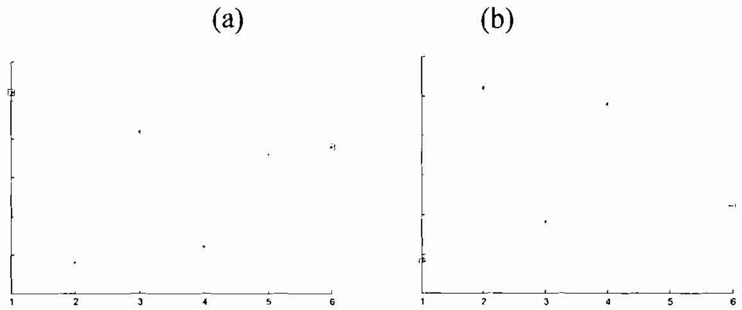


Figure 3 All points are lower than the trend line(a) and all points are lower than the trend line(b).

Nevertheless, there are other two special cases of FiMIP method. These two special cases are depicted in figure 3 and figure 4.

Finding the MPD points in other two cases, their calculations have a little bit of difference. In figure 3(a), all points appear as dip points; the MP point is not available. Thus, in this case we can record MD point information but MP point cannot be recorded, so it is set to be NULL. Similarly, in figure 3(b), all points appear as peak points, thus, the MP point is recorded while MD point is set to be NULL.

3. TS-BINARY SEARCH TREE REPRESENTATION

TS(Time Series)-binary search tree is designed as a variety of binary search tree with additionally special nodes and their arcs information while the binary search tree properties are kept. As can be seen, in binary search tree, if x is a node with key value key[x] and it is not the root of the tree, then the node can have a left child (denoted by left[x]), a right child (right[x]) and a parent (p[x]). Every node of a tree is constructed under the following binary search tree properties:

(1) for all nodes y in left subtree of x, key[y] < key[x]
(2) for all nodes y in right subtree of x, key[y] > key[x]

The additional nodes in TS-binary search tree are the two special nodes; one is the first element of the time series, which is placed at the first node of the tree, and the other one is the last element of the time series which is placed as the right child of the first node. These two nodes, their iterations and their distances equal to zero.

To construct the next node of the TS-binary search tree, the founded MIPs are adopted. The first used point is the peak point which is a member of the pair of the peak and the dip points, however, if the peak is not available the second point—the dip point is determined. The construction of the tree is performed recursively. From the root node, let *root* is the pointer points to the root, and *newNode* is the node, which is formed by the current MIPs.

For more detail, following is an example of the representation demonstration with the ten-point time series data. The data is transformed into the range of 0 and 1. The graphical illustration of the time series is shown in figure 4.

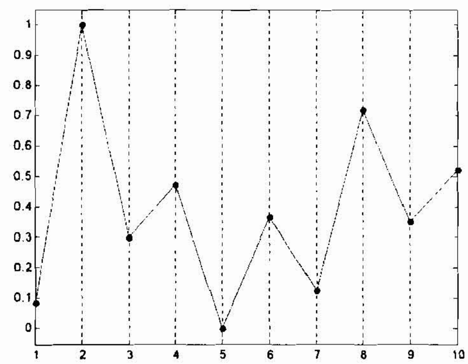


Figure 4 A sample time series.

From the sample time series, by utilizing of the MINOR method and FiMIP method the peak and the dip points are collected in different iterations and depicted in table 1. The step of collecting the dip and the peak points in iteration 1, 2 and 3 are shown in figure 5, 6, 7 respectively.

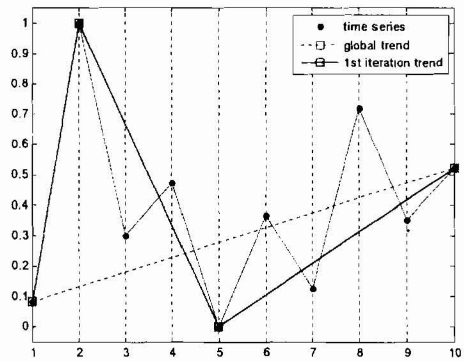


Figure 5 The first iteration trend

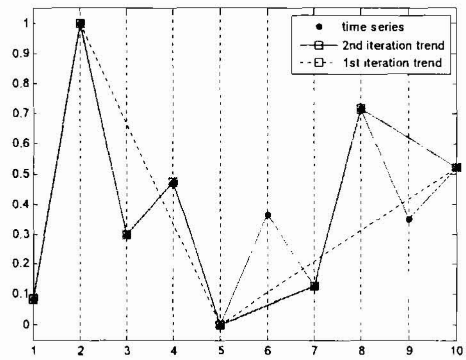


Figure 6 The second iteration trend.

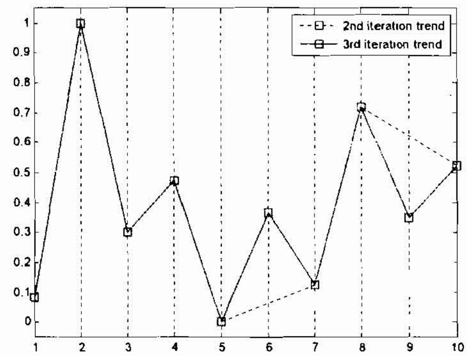


Figure 7 The third iteration trend.

Table 1. The most important points list.

iteration	Segment		peak point		dip point	
	start	End	X	VD	x	VD
1	1	10	2	0.86	5	-0.30
2	2	5	4	0.14	3	-0.37
2	5	10	8	0.38	7	-.02
3	5	7	6	0.26	n/a	n/a
3	8	10	n/a	n/a	9	-0.20

The collection of MP and MD points are used for constructing the TS-binary search tree by using TS-binary search tree algorithm. The demonstration of tree representation of the sample time series is shown in figure 8.

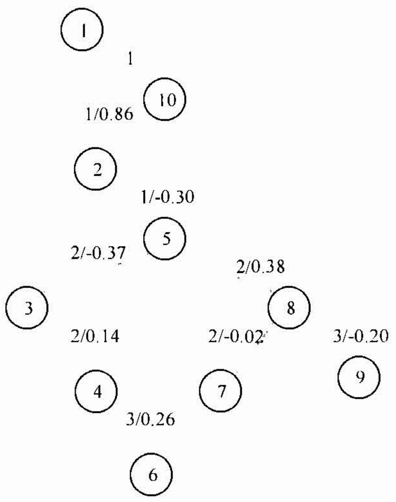


Figure 8 A TS-binary search tree of a sample time series.

4. TREND BASED SEGMENTATION USING TS-BINARY SEARCH TREE

In this section, the implementation of trend based time series segmentation is conducted. By considering trends of the time series, trends have been changed overtime, but, however, in different resolutions, the time series exhibits different trends. With this concept, we aim to propose a segmentation method based on the time series trends by using TS-Binary Search Tree by adapting from reference [10]. The algorithm of trend based time series segmentation using TS-binary search tree depicts in figure 9.

The algorithm firstly considers the MIP in the lowest resolution by accessing the tree from root. The first-two nodes are retrieved from the first and the last points of the time series. Consequently, accessing the next node is determined by the node iteration and its VD. From the time series in figure 4 and its tree in figure 8, the next node to access is the node x=2 this shows the result of segmentation in figure 9(a). Next,the node x=5 is retrieved since its iteration is 1 and it has a largest VD after previous node, this makes the time series is segmented into three segments as shown in figure 9(b).

The next accessing node is considered with the node with iteration 2, but, in this iteration there are 4 choices, the largest VD node should be retrieved first, thus, node x=8 is retrieved. With the 3 accessed nodes, the time series is segmented into 3 segments as shown in figure 9(c). By considering in the similar way, the following nodes should be retrieved are node x equals to 3, 4, 7, 9, and 6 respectively.

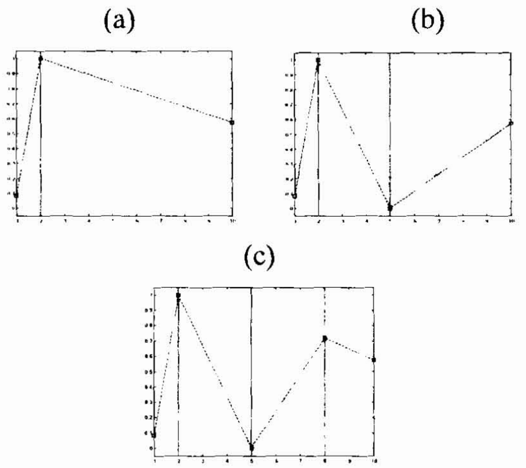


Figure 9 A sample time series with 1 cutting point(a), 2 cutting points(b) and 3 cutting points(c).

5. EXPERIMENTAL RESULTS

In this section, we experiment the segmentation algorithm with 2725 data points of closing prices of Hang Seng Index (HSI) since January 2, 1997 until December 31, 2007. The results of segmentation are reported in different number of segments and comparing between the results done by our method and the results done by the method proposed in reference [10].

The segmentation results of our experiments are done by using our proposed method and comparing to the SB-Tree based method [10]. The comparisons are conducted by the segmentations in different number of 3, 4, 6, 8, 10, 12, 14, 16, 18, and 20 cutting points.

The performance of segmentation is measured by the root mean square errors (RMSE). The RMSE can be calculated from the distances between the original time series and its segment trends. Table 2 shows the results of the experiments and figure 10 demonstrates the comparison of those two methods.

(a)

(b)

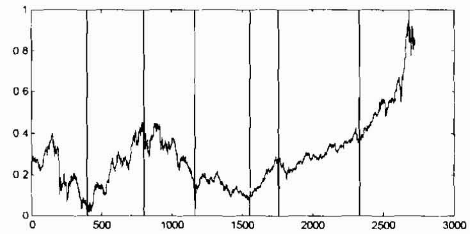
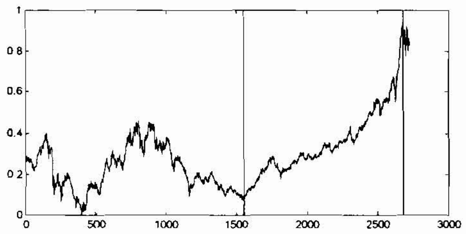


Figure 10 Segmentation of HSI index using: SB-Tree based segmentation in 3 and 7 segments respectively (a),(b) , and TS-Binary Search Tree based segmentation in 3 and 7 segments respectively(c),(d).

(c)



(d)

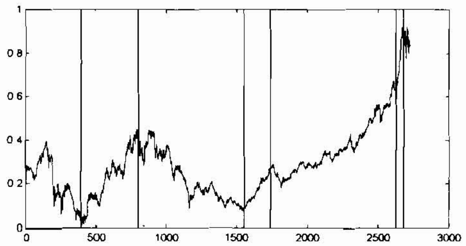


Figure 10 Segmentation of HSI index using: SB-Tree based segmentation in 3 and 7 segments respectively (a),(b) , and TS-Binary Search Tree based segmentation in 3 and 7 segments respectively(c),(d). (Cont'.)

Table 2. Numbers of cutting points and the errors

No. of cutting points	RMSE	
	TS-BS tree	SB- tree
3	0.1263	0.1263
4	0.1714	0.1325
6	0.1081	0.0678
8	0.0677	0.0647
10	0.0648	0.0770
12	0.0633	0.0881
14	0.0636	0.0849
16	0.0635	0.0688
18	0.0644	0.0675
20	0.0630	0.0650

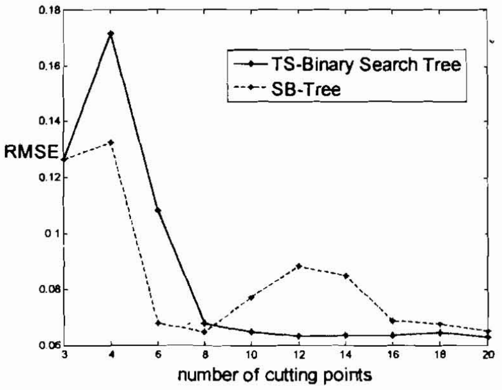


Figure 11 Performance comparison of segmentation based on TS-binary search tree method and SB-binary search tree method

As can be seen in table 2 and figure 11, the RMSE of the segmentation the errors show sharp peaks at 4 cutting points on both two methods and dramatic falls until number of cutting points are 8. At the 8-cutting points, the graph show almost the same error values. However, from the 8 cutting points, SB-tree based methods gradually increases until number of cutting points is 12, then, the graph slightly declines and remain stable. While the errors of SB-tree based method between 8 to 12 cutting points, the graph show a remain constant and less errors comparing to the SB-tree based method.

6. CONCLUSION

In this paper, we have proposed a method for financial time series representation based on the most important points retrieval method. The idea of the method is based on finding the most important points in multiresolution. These retrieved important points are recorded in each resolution. The collected important points are used to construct the TS-binary search tree. From the TS-binary search tree, the application of time series segmentation is conducted. Our experiments have been tested on the real stock market time series.

The proposed method shows that the performance of the method is better when using the segmentation with number of segments more than 6 cutting points and the results show very poor performance when using the cutting points less than or equal to 6. Future works the method should be applied in other dataset and with different size of the dataset.

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