An Association between Bid Series and Transaction Price Facilitating Trading Decision Making Based on VPIP Algorithm

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54. An Association between Bid Series and Transaction Price Facilitating Trading Decision Making Based on VPIP Algorithm

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Abstract

The stock price has long been an essential issue in stock market analysis, while rarely had any relevant study covered the relational effect of the bidder factor on stock price. Hereby we try to find an association between bid and transaction price time series. The fluctuation of pattern ratios embedded in the bid series affects the fluctuation of transaction price. That means when there is small changed amplitude of pattern occupancy ratio, there is a possibility that small fluctuation of transaction price will occur. And when there is a large changed amplify of pattern occupancy ratio, there is a possibility that large fluctuation of transaction price will occur. Also, we find the boundary value of changed amplify of pattern occupancy ratio which may lead to the relatively large fluctuation in transaction price. The finding contributes to provide reference information for the decision making of trading stock data. Additionally, we propose a new pattern-matching scheme called Visually and Practically Important Point (VPIP), which take the characteristic of the stock data into account. This scheme contributes that more valuable points can be remained in the stock time series after extracting the large number stock time series to small ones. Encouraging experiment is reported from the tests that there is an association between the bid sequence and transaction price time series of selected Chicago Stock Exchange, by using our pattern-matching scheme.

Keywords: Pattern Recognition, Visually and Practically Important Point, Decision Making

Introduction

Finding the factors which affect the stock price is a popular and important research problem (Fama 1965; Lendasse 2000). A popular method is to identify prototype patterns in the charts and forecast the future trend based on these chart patterns (Ge and Smyth, 2000). An even more interesting application of pattern matching in stock market time series data is to learn the frequently occurring patterns directly from the data, and build a model to forecast the stock market. Much work has done for finding the relationship between stock price and other factors for prediction. Such as Tetsuji (1992) used former transaction price for analysis, and Cheung et al. (2000) used the intra-day stock price to analysis and prediction. And Zhang (2005) try to find the relationship between the bid sequences. However, less attention has been paid to finding the relationship between the patterns in bid number sequence and the trading points, that is, whether the occurrence of trading price is related to certain patterns
embedded in the former bid number sequence. So the objective of this paper is to find the answer, in order to facilitating the decision making on stock trading.

On the other hand, there has been much work on defining subsequence-matching methods that try to find subsequences similar to a query sequence within a large time series (Moon et al. 2002). However, most of them did not consider the real meaning and characteristic of the data when doing pattern matching (Ge, 2000; Nesbitt and Barrass 2004). Regarding this, in additionally, we propose an algorithm called visually and practically important point (VPIP) pattern-matching scheme, which consider the characteristic of stock data to find the matched patterns for stock data mining. This scheme contributes that more valuable points can be remained in the stock time series after extracting the large number stock time series to small ones.

Encouraging experiment is reported from the tests that there is a relationship between the parameter, which is derived from the bid series defined by us, and the changing amplitude of trading price. Especially, when the parameter value exceeds a certain boundary level, the trading price will have a high probability to change. It contributes to provide reference information for the decision making of trading stock data.

Using our result found in this paper, we can find the possible fluctuation amplitude-changing trend and use it as the reliable base to make decisions. Thus, we can make an earlier decision on whether to transact stock or not. It can provide as a pre-noticing signal for those investors when large fluctuation in transaction price will occur.

The organization of this paper is as follows. In Section 2, we propose a new pattern-matching scheme based on Visually and Practically Important Points called VPIP. Section 3 introduces the design of each kind of pattern style. Section 4 describes the design of the experiment. The result and analysis are reported in Section 5. And the final section addresses some conclusions of the paper.

**Pattern Matching Scheme Based on Visually and Practically Important Points**
To facilitate evolutionary stock time series segmentation, defining a similarity between time series for fitness evaluation is of fundamental important. In this section, we proposed a new time series pattern-matching scheme that was based on both the fact that frequently appearing pattern are typically characterized by a few critical point points, and the fact that the critical points have the practical meaning for the stock time series. For example, for the head-and-shoulder pattern, the turning points such as the highest and lowest points should be extracted, because these points are visually important in the identification process. In addition, those points that are near the transaction time should have the higher priority to be extracted, because they have more important effect on the transaction and more practically important for the stock time series. The proposed scheme follows the above idea by location the points that considering both the two aspects mentioned above.

**Identification of Visually Important Points**
Firstly, we need to identify the visually important points in the stock time series, which is similar but different with the algorithm proposed by Chung et la. (2004). The following scheme follows the principle of identifying the visually lowest and highest points in a data sequence \( P = \{ P_k | k = 1, \ldots, m \} \), where \( m \) denotes the length of \( P \), in accordance with a query
sequence $Q = \{q_k | k = 1, \ldots, n\}$, where n denotes the length of $Q$ and $n \leq m$. The pseudocode is described in Figure 1.

```
1. Input sequence $P[1 \ldots m]$, length of $Q[1 \ldots n]$
2. Output pattern $SP[1 \ldots n]$
3. Begin
5. Repeat until $SP[1 \ldots n]$ all filled ()
6. Select point $P[j]$ with maximum area to the combination of three points: the adjacent two points in $SP$ and $SP[j]$
7. Add $P[j]$ to $SP$
8. Return $SP$
9. End
```

Figure 1: Pseudocode of Locating the Visually Important Points

The processes of locating the points described in Figure 1 are as the following. The first two points that are found will be the first and last points of $P$. The next visually important point that is found will be the point with maximum triangle area consisted by the three points, the adjacent two points in $SP$ and $SP[j]$. The fourth point that is found will be the point in $P$ with the maximum area that contained with the three points: first point, second point, and point between them, or contained with the three points: second point, last point, and the point between them. The process of extracting points will continue until the number is equal to the $n$. We can calculate the area with following formula by Helen theory.

$$S = \sqrt{l(l-a)(l-b)(l-c)}$$

(1)

$$l = (a + b + c) / 2$$

(2)

where $S$ is the area of triangle consisted by the three points mentioned above. In formula 2,

$$a = \sqrt{(y_3 - y_1)^2 + (x_3 - x_1)^2}$$

$$b = \sqrt{(y_2 - y_1)^2 + (x_2 - x_1)^2}$$

$$c = \sqrt{(y_2 - y_3)^2 + (x_2 - x_3)^2}$$

In the formula, $a$ is the distance from $P_3$ to $P_1$, which consist of one side of triangle area; $b$ is the distance from $P_2$ to $P_3$; and $c$ is the distance from $P_1$ to $P_2$. Through this formula, we can extract the turning points that have the relatively highest or lowest value. To illustrate the identification process, the head-shoulder pattern is used in Figure 2 to show how to extract 4 points ($n=4$) from 7 points ($m=7$).

Identification of Practically Important Points

On the other hand, we should take the practical meaning of the stock data when extract the points from the times series. Those points that closer to the transaction time have the higher
priority than the far ones. In another word, the points have different distance to the transaction points will have different weight to the transaction points. Therefore, we will propose to assign each of the points with a coefficient according to the distance between the point and the transaction point, the closer the distance, the higher weight the coefficient. Respectively, we calculate the distance \( \lambda \) from the following formulation, that is

\[
\lambda = |x_{p_t} - x_{p_o}|
\]  

(3)

To illustrate the process of identification of these points, Figure 3 is used to show.

![Figure 3: Identification of Practically Important Points](image)

From Figure 3 we can find that the \( P_h \) has higher priority to be extracted than \( P_o \) for it is closer to the transaction point time and transaction.

**Identification of Both Visually and Practically Important Points**

Considering both sides of the above, we will propose the scheme that combines the two aspects mentioned in both Section 2.2 and Section 2.3. We will assign a coefficient, represented by \( \zeta \), that include both the area \( S \) and the distance \( \lambda \). The coefficient is calculated by the following formulation.

\[
\zeta = \lambda_i \times S_i \quad 1 \leq i \leq m
\]  

(4)

We call it as Visually and Practically Important Points scheme (VPIP). The pseudocode is described in Figure 4.

```
Function VPIPLocate (P, Q)
    Input: sequence P[1..m], length of Q[1..n]
    Output: pattern S[1..n]
    Begin
        Set SP[1]=P[1], SP[n]=P[m]
        Repeat until SP[1..n] all filled ( 
            Select point P[i] with maximum \( \zeta \)
            Add P[i] to SP
        )
        Return SP
    End
```

Figure 4: Pseudocode of Locating the Visually and Practically Important Points

**Pattern Representation**

In order to obtain the objective of finding the relationship between the patterns in bid number sequence and the trading points, the first step is to find the matched patterns, each of which appear prior to the every trading point in the time domain. Developing a time series pattern
classification is of fundamental importance for the pattern finding and matching. The general manner of design for the pattern classification can be characterized procedurally in the following general manner (Ge and Smyth 2000): (i) To find an approximation and robust representation for a time series; (ii) To define a flexible indexing function that can handle various pattern deformations; and (iii) To provide an efficient scalable and updatable algorithm by using the adopted representation and matching function for massive time series data sets. Several patterns with different numbers of PIP have been introduced. (Fu and Chung 2004). In this paper, we use several major stock patterns that occurred most frequently defined by Zhang et al. (2005), which are based on the point number and the permutation and combination of slope (positive or negative) between two adjacent points.

Suppose that there are four points in sequence from the left to the right: Sp1, Sp2, Sp3, Sp4. Because there are three lines connected each two adjacent points, that is, line 1 connecting Sp1 and Sp2, line 2 connecting Sp2 and Sp3, and line 3 connecting Sp2 and Sp3. We just choose the leftmost line 1 and rightmost line 3 for the design because through this way the patterns can be roughly classified into four shape categories in Table 1, much simpler and more convenient for analyze. Therefore, the combination of slope (positive or negative) can be illustrated as: \( \text{Slope}(k_1, k_3) \in \{ (+, +), (+, -), (-, +), (-, -) \} \), while \( k_1 \) and \( k_3 \) denote the slopes of line 1 and line 3 respectively. The suggested pattern names, the relationships among Sp1 to Sp4, and the pattern figures are shown in Table 1.

### Table 1: Design of 4-point-Pattern

<table>
<thead>
<tr>
<th>Pattern Name</th>
<th>Up-Trapeziform</th>
<th>Up Flag</th>
<th>Down-Trapeziform</th>
<th>Down Flag</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pattern Description</td>
<td>Sp1&lt;Sp2 AND Sp3&gt;Sp4</td>
<td>Sp1&gt;Sp2 AND Sp3&lt;Sp4</td>
<td>Sp1&gt;Sp2 AND Sp3&lt;Sp4</td>
<td>Sp1&gt;Sp2 AND Sp3&gt;Sp4</td>
</tr>
<tr>
<td>Pattern Figure</td>
<td><img src="image" alt="Pattern Figure" /></td>
<td><img src="image" alt="Pattern Figure" /></td>
<td><img src="image" alt="Pattern Figure" /></td>
<td><img src="image" alt="Pattern Figure" /></td>
</tr>
</tbody>
</table>

**Experimental Design**

The purpose of the experiment is to find the relationship between the changing ratio trends of each different four-point-pattern occurrence percentage, which appear prior to the trading points in the bid number sequence, and the change trend of transaction price. In the stock market, there are bid and ask price. The buyer states what price they will pay for the stock – this is the bid price. Under each bid price, there are sequences, which means the total numbers of how many shares are bided. For example, 300 shares are bided under price $15.5.

In order to predict the changing amplitude of transaction price based on the occupancy change ratio for each pattern, we try to find the rule that contained in the relationship between them.

The first step is to find the total number of each pattern between two transaction time. Suppose that \( N_{ti} \) is the matrix, which contain the number of four different patterns. It is calculated as the following:

\[
N_{ti} = \begin{bmatrix} N_{p1l_{t-1}} & N_{p2l_{t-1}} & N_{p3l_{t-1}} & N_{p4l_{t-1}} \end{bmatrix}
\]  

(5)
In (5), \( N_{P\mid t_1} \) is the number of Pattern 1 occur before the transaction time \( t_1 \), and between the two transaction times \( t_{i-1} \) and \( t_i \). \( N_{P_2|t_1} \), \( N_{P_3|t_1} \) and \( N_{P_4|t_1} \) have the same meaning from Pattern 2 to Pattern 4.

In the second step, we will compute the occupancy rate of each pattern between transaction times \( t_{i-1} \) and \( t_i \). The formula is shown as following. We use a matrix, \( P_i \), to represent the four different patterns’ occupancy rate.

\[
P_i = \left[ \begin{array}{c}
N_{P_{1|t_1}} \sum_{j=1}^{k} N_{P_{j|t_1}} \\
N_{P_{2|t_1}} \sum_{j=1}^{k} N_{P_{j|t_1}} \\
N_{P_{3|t_1}} \sum_{j=1}^{k} N_{P_{j|t_1}} \\
N_{P_{4|t_1}} \sum_{j=1}^{k} N_{P_{j|t_1}}
\end{array} \right]
\]

\[
= \begin{bmatrix}
R_{P_{1|t_1}} & R_{P_{2|t_1}} & R_{P_{3|t_1}} & R_{P_{4|t_1}}
\end{bmatrix}
\]

So \( R_{P_{j|t_1}}, j=1,2,3,4 \) is the occupancy rate of jth pattern between the transaction time \( t_{i-1} \) and \( t_i \).

In the third step, in order to find the relationship between changed the four-pattern occupancy ratio trend and the fluctuations of transaction price, we should define a parameter called the vector distance of two vectors, whose coordinates are regarded as four patterns’ occupancy rate derived from the bid sequence, represented by \( \Gamma \). It can be computed in (7). It will represent the changing amplitude of the four-pattern occupancy ratio. And on the other hand, we use \( K_i \) to represent the changing amplitude of transaction price at \( t_i \), and use a vector distance, between two transaction price, to represent the changing amplitude of transaction price between \( t_1 \) and \( t_{i-1} \). It can be computed in (8). Then we can find the relationship between \( \Gamma \) and \( K_i \).

\[
\Gamma = \left| P_i P_{i-1} \right| = \begin{bmatrix}
R_{P_{1|t_1}} & R_{P_{2|t_1}} & R_{P_{3|t_1}} & R_{P_{4|t_1}}
\end{bmatrix} \begin{bmatrix}
R_{P_{1|t_i}} & R_{P_{2|t_i}} & R_{P_{3|t_i}} & R_{P_{4|t_i}}
\end{bmatrix}
\]

\[
= \sqrt{(R_{P_{1|t_1}} - R_{P_{1|t_i}})^2 + (R_{P_{2|t_1}} - R_{P_{2|t_i}})^2 + (R_{P_{3|t_1}} - R_{P_{3|t_i}})^2 + (R_{P_{4|t_1}} - R_{P_{4|t_i}})^2}
\]

\[
\Delta = \left| K_{t_1} - K_{t_i} \right| = \left| K_{t_i} - K_{t_i} \right|
\]

The used data set is taken form the time series of Chicago stock market. 10000 trading points are considered, together with the transaction price and their former bid time series.

**Analysis of Experimental Results**

In order to find the relationship between the \( \Gamma \) and \( \Delta \), firstly, we divide the \( \Gamma \) and \( \Delta \) into different ranges. We divide the \( \Gamma \) into three ranges indicating small, middle and large changing amplitude of pattern occupation, respectively, from 0 to 5, 5 to 7 and 7 to 11.

Similarly, we classify the \( \Delta \) into two kinds, which represent whether the amplitude of transaction price will change or not. Concretely, we divide the changing part into two kinds, the relatively small and large changing amplitude of transaction price. We choose 0 to indicate no change, 1 to indicate relatively small change and 2 to indicate relatively large change for \( \Delta \).

In the experiment, we try to exam the impact of amplitude changing in \( \Gamma \) on the amplitude changing of \( \Delta \) from two aspects. Firstly, we control the \( \Gamma \) changed in a fixed range to find the percentage of how much transaction price will change due to different ranges. The result can
be seen in Table 2. From the table, we can find that the larger value of $\Gamma$ will affect the larger $\Delta$. For example, when $\Gamma$ is in the small range from 0 to 5, there is relatively small percentage of $\Delta$ change, 49.38%. And when $\Gamma$ is in a large range from 7 to 11, there is a relatively large percentage of $\Delta$ change, 76.0%. Also, we find there is a boundary value of $\Gamma$ for the price amplitude that will have obvious change, when $\Gamma = 7$. Also, comparing the two occupation to the changing situation column, we find that the relatively small $\Delta$ is related to the relatively small $\Gamma$ and large $\Delta$ is related to the relatively large $\Delta$. For example, when $\Gamma$ is in the relatively small range from 0 to 5, there are relatively higher possibilities for the occurrence of $\Delta$ in the small range than that in the high range where $\Gamma$ is from 7 to 11, comparing 75.01% and 57.89%. Similarly, when $\Gamma$ is in the relatively high range from 7 to 11, there is a higher possibility for the occurrence of $\Delta$ in the large range than that in the small range where $\Gamma$ is from 0 to 5, comparing 42.11% and 24.99%. In a word, we can find that if there is a higher value of $\Gamma$, there is a higher possibility that larger amplitude change of transaction price will occur.

<p>| Table 2: The Probability of Price-Changing Rate under Fixed $\Gamma$ Range |
|-----------------|-----------------|-----------------|-----------------|
| $\Delta = 0$   | $\Delta = 0$   | $\Delta = 1$   | $\Delta = 2$   | $\Delta = 1$ + $\Delta = 2$ |</p>
<table>
<thead>
<tr>
<th>Occupation to the changing situation (%)</th>
<th>Occupation to the change situation (%)</th>
<th>Occupation to the change situation (%)</th>
<th>Occupation to the change situation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0 = \Gamma &lt; 5$</td>
<td>50.62</td>
<td>37.04</td>
<td>75.01</td>
</tr>
<tr>
<td>$5 = \Gamma &lt; 7$</td>
<td>41.38</td>
<td>41.38</td>
<td>70.59</td>
</tr>
<tr>
<td>$7 = \Gamma &lt; 11$</td>
<td>24.0</td>
<td>44.0</td>
<td>57.89</td>
</tr>
</tbody>
</table>

Secondly, we control the $\Delta$, to find the percentage of how many $\Gamma$ will occur in a range due to whether the transaction price will change or not. The result is shown in Table 3.

<p>| Table 3: The Probability of $\Gamma$ Occurrence Rate under Fixed Price Changing |
|-----------------|-----------------|-----------------|-----------------|
| $\Delta = 0$   | $\Delta = 1$   | $\Delta = 2$   | $\Delta = 1$ + $\Delta = 2$ |</p>
<table>
<thead>
<tr>
<th>Occupation (%)</th>
<th>Occupation (%)</th>
<th>Occupation (%)</th>
<th>Occupation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0 = \Gamma &lt; 5$</td>
<td>43.64</td>
<td>35.67</td>
<td>20.69</td>
</tr>
<tr>
<td>$\Delta = 1$</td>
<td>30.26</td>
<td>33.80</td>
<td>35.94</td>
</tr>
<tr>
<td>$\Delta = 2$</td>
<td>23.80</td>
<td>29.92</td>
<td>46.27</td>
</tr>
</tbody>
</table>

From Table 3, we can find that when $\Delta$ is relatively small, most occurrence percentage of $\Gamma$ is located in the small range of $\Gamma$, seeing 43.64% is higher than 35.67% and 20.69%. And when $\Delta$ is relatively high (e.g. $\Delta = 2$), most occurrence percentage of $\Gamma$ is located in the high range of $\Gamma$, seeing 46.27% is higher than 29.92% and 23.80%. In a word, the situation that transaction price is changed with high amplitude are mostly occur when $\Gamma$ is in a high range. And situations that transaction price is changed with low amplitude are mostly occur when $\Gamma$ is in a low range. This is coincident with the findings mentioned before.

Conclusion

From the experiment result, we find an association between bid series and transaction price. There is a relationship between the changed amplitude of pattern occupancy ratio derived from bid sequence and the fluctuation amplitude of transaction price, that is, when there is the small changed amplitude of pattern occupancy ratio, there is a possibility that small fluctuation of transaction price will occur. And when there is a large changed amplify of
pattern occupancy ratio, there is a possibility that large fluctuation of transaction price will occur. Also, we find the boundary value of changed amplify of pattern occupancy ratio which may affect the relatively large fluctuation in transaction price. The result contributes to provide reference information for the decision making of trading stock data.

On the other hand, we propose a new pattern-matching scheme called Visually a Practically Important Point (VPIP), which consider more characteristic of stock data than other schemes when finding the matched patterns for stock data mining. This scheme contributes that more valuable points can be remained in the stock time series after extracting the large number stock time series to small ones.

References