A THREE-DIMENSIONAL MAPPING OF FINANCIAL TIME SERIES DATA USING SPATIALISATION

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1. INTRODUCTION

Time series comprises data on some attribute gathered at different points in time which is ordered chronologically [1]. The representation of time series is performed via a two-dimensional profile view, where the x-axis represents time intervals, and the y-axis represents a variable of interest, e.g., the daily closing Bitcoin prices. In this example, the geometric relationship between observations is formed via an irregular horizontal line that directly links the Bitcoin prices at different time intervals, or a mathematical function fitted to the observations.

In the case that there is more than one observation at each time interval, a geometric combination of an irregular horizontal line and a collection of regular vertical lines is typically applied to represent the observation vectors. For example, the daily opening, low, high and closing prices of Bitcoin are represented by candlestick or bar charts. The straight vertical lines along the y-axis are applied to determine the relationship between the values within each observation, namely opening, high, low and closing, at each time interval. Depending on the high and low prices of each observation vector, the lengths of vertical lines vary at each time step. In this structure, the irregular line is formed using the value of the observation vector measured at equally spaced time intervals.

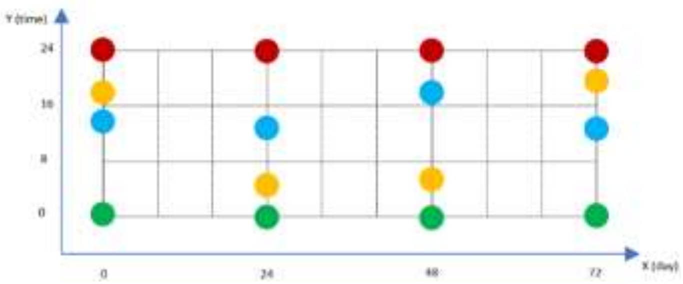
The above algorithms show that regular or irregular lines or curves are the main geometric structure in analysing the dependency between observations in the time series. This structure lacks the necessary geometric tools to directly model the relationships between observations when there is more than one observation at each time interval, e.g., opening, high, low and closing prices. This geometry is also unable to represent data in a three-dimensional space. In this paper, we develop a new method to simultaneously link multiple observations gathered at the same time and represent them in a 3D environment. This enables financial analysers and traders to use new geometric tools, such as 3D graphical projections, in analysing time series data. The proposed method is constructed based on the notion of spatialisation in the Geographic Information System (GIS): that is, modelling a non-spatial phenomenon in a spatial domain [2-3].

2. IMPLEMENTATION

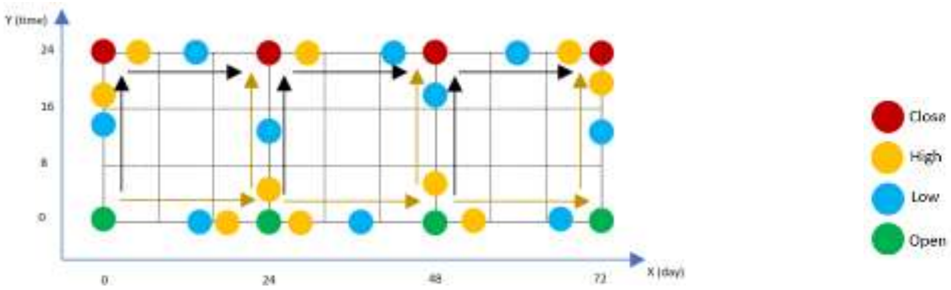
The method is implemented via a linear two-step process: creating a 2D map and constructing a 3D topographic map. We use the daily opening, high, low and closing prices of Bitcoin, downloaded from https://firstratedata.com/i/crypto/BTC, to test the proposed approach.

2.1. Creation of the 2D spatialized map

To transfer the temporal data of Bitcoin prices into a 2D map, we use analytical geometry, where the location of each point in a two-dimensional space is defined by an ordered pair of numbers (x, y). Let $B = \{b_1, b_2, \dots, b_t\}$, t = 1, 2, . . ., N represents a set of Bitcoin observations where $N>1$, and specifies the total number of observation days. b_t values include a pair of numbers (p_i, h_i), i = 1, . . ., 4., where p_i is the price and h_i is the time at which this price is recorded on day t. Here, i is set to four as there are four observations per day. Therefore, each dataset's price has two temporal components: event time and event day. Event times repeat themselves every 24 hours via the opening and closing prices of each day, like the day/night cycle in the real world. We use event time values, h, to define a y value for each price in the 2D map. Event day, t, determines the x-coordinates for each price in the 2D map. In the time-space, they are defined based on the notion of linear time, moving in one direction without repetition. We apply these two components (t, h) to place data samples (Bitcoin price) in a 2D bitemporal map [4] (Figure 1 (a)).



(a)



(b)

Figure 1. (a) and (b) display the events (prices) along the x-axis and y-axis, and (b) the black and brown arrows show different directions in each square to link the open price in one day to the close price in the next day. (b) creates a symmetric 2D space along the southwest to the northeast axis every 48 hours.

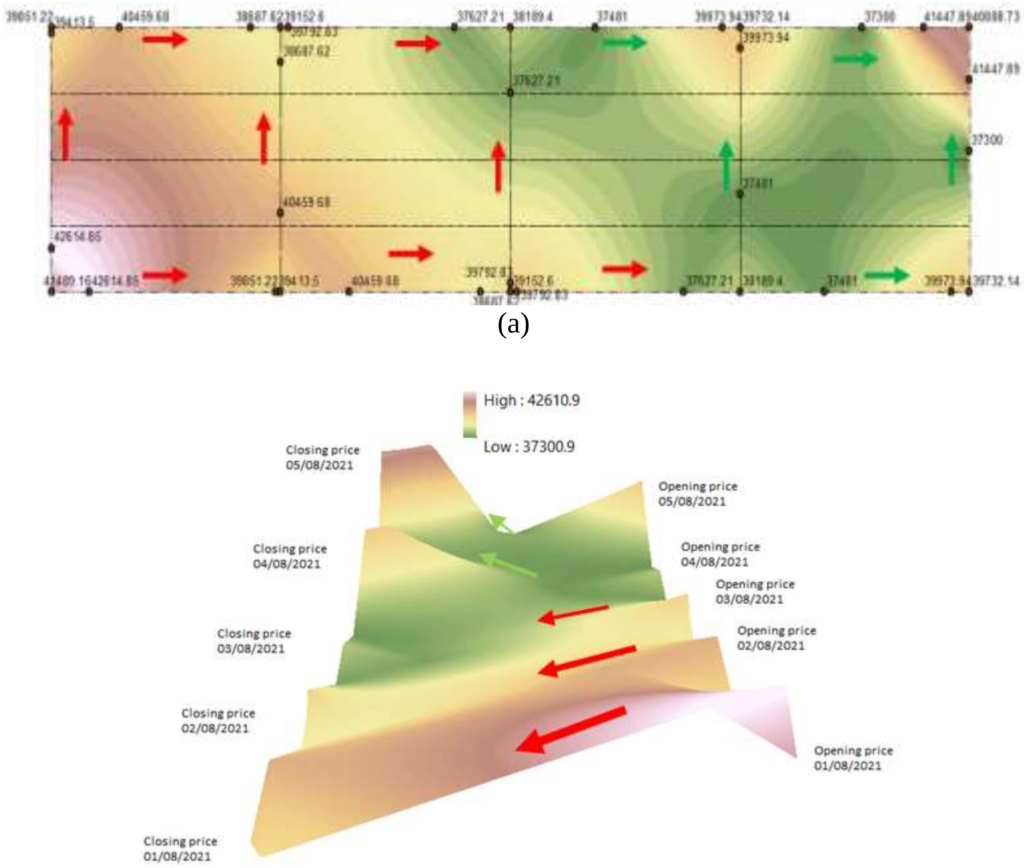
Figure 1(a) provides a framework that can be applied to describe the temporal relation between the red and green points, two intervals, along the x-axis. Figure 1 (b) shows the locations of the data points on the horizontal lines at y=0 (0 minutes) and y=24 (1440 minutes). This figure illustrates a 2D coordinate system that includes a new set of observations $F = \{f_1, f_2, \dots, f_k\}$, k = 1, 2, . . ., S, where $S = 4\times(2N-1)$ and defines the number of point features in the 2D vector map in Figure 1(b). Each point feature f has the coordinate attributes x, y that determine the location of each point (price) on the map. As shown in Figure 1(b), there are two routes in each tile that link opening, high, low, and closing prices of each day to the prices the next day. These two routes form a square of size 24×24 every 24 hours on the x-axis, where time moves from one day to the next. The 2D map in Figure 1(b) provides a 2D planar framework that allows the prediction algorithms to use spatial tools and functions to analyse crypto data.

2.2. Construction of the topographic map

Let $P = \{p_1, p_2, \ldots, p_m\}$ represent a set of m unknown values for price in Set B where m is specified based on the number of cells in the above 2D map. Each p has coordinates determined by (x, y). To calculate the z value of p in the 3D map, the method uses the following equation:

$$p(x, y) = \sum_{i=1}^{n} w_i \times f(x_i, y_i) \, , \tag{1}$$

where $p(x, y)$ is the estimation at (x, y), and n is the number of nearest neighbors used for interpolation. $f(x_i, y_i)$ is the observed data from set $F = \{f_1, f_2, \ldots, f_k\}$, and w_i is the weight associated with $f(x_i, y_i)$. The Natural Neighbor Interpolation (NNI) algorithm is applied to calculate w_i[5]. The weights are proportionate to areas, which are determined via a set of Thiessen polygons formed based on the location of observation and unknown data in the 2D map. In this algorithm, the closest sample points to an unknown point have the highest influence on that point's value in the spatial domain. The method, in fact, indirectly applies Tobler's first law of geography *"everything is related to everything else, but near things are more related than distant things"* [6]. This is similar to the rules that are generally applied in a time domain by conventional prediction algorithms to estimate an unknown price. Figure 2 shows a Bitcoin map generated using Equation 1 via an iterative process.



(a)

(b)

Figure 2. (a) The produced Bitcoin map using the NNI algorithm. Point features are applied to show the location of each price on the map. (b) cross-section view of Bitcoin price.

In Figure 2, annotation via the green arrows indicate when the closing price is higher than the opening price, and the red arrows illustrate when the closing price is lower than the opening price.

3. RESULTS

We use the 3D maps to extract Bitcoin prices each day in order to assess the behaviour of Bitcoin prices. Figure 3 (a-d) illustrates the behaviour of bitcoin prices using the proposed method between the closing price of one day and the opening price of the next day, which have the same value. These graphs, which are represented by the blue lines in Figure 3 (e), have a symmetric shape based on the line x=1018, $\frac{\sqrt{(1440^2+1440^2)}}{2}$. The reason for this is that sample points are repeated along the line y=0 and y=1440, as the line y=0 includes the data from one day and the line y=1440 contains samples of the next day. All values close to the line x=1018 reflects an estimate of the opening prices. The prices near the line x=0 and the line x=2036 are an approximation of the closing prices. Figure 3 (a-d) demonstrates the Bitcoin market is falling in day 1 and day 3, and rising in day 4. Figure 3(b) shows that the opening and closing prices are close in day 2.

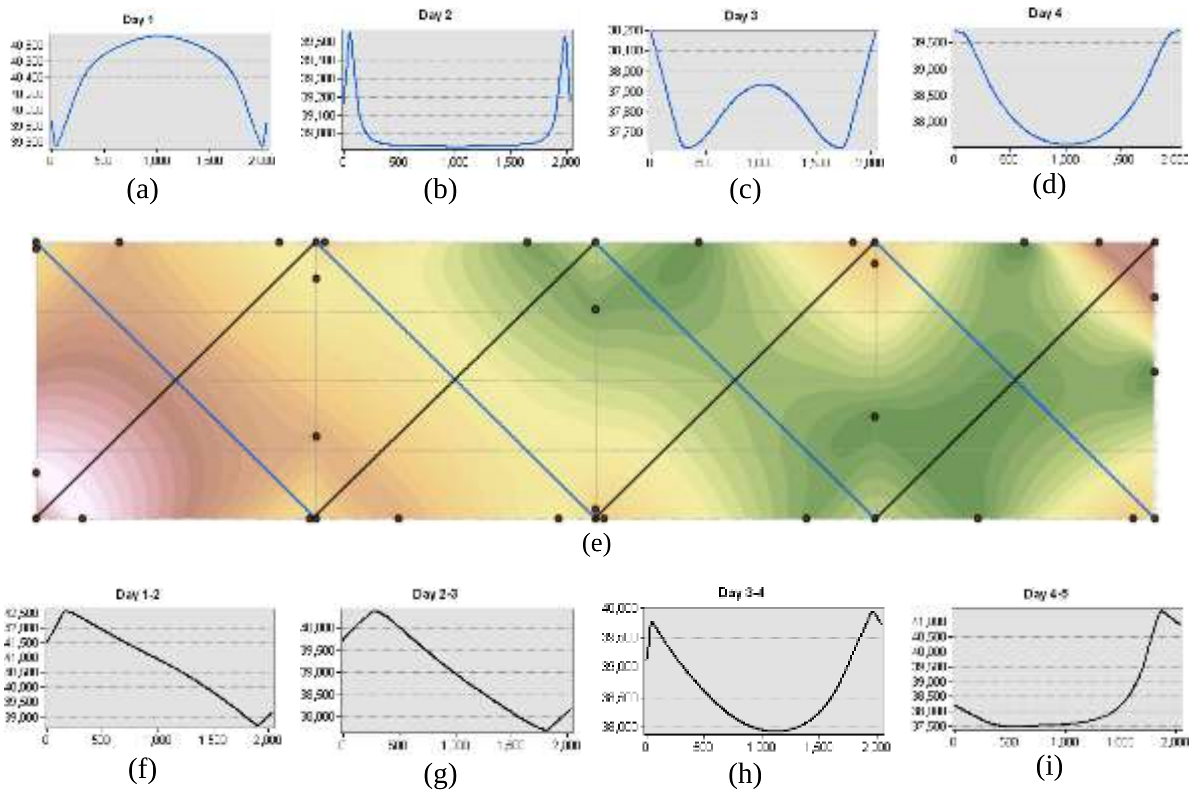


Figure 3. (a-d) profile views of the map (e) along the northwest-southeast line (blue). (f-i) profile views of the map (e) along the southwest-northeast line (black).

Profiles in Figure 3(f-j) are created using the southwest-northeast line. That means these profiles show the change in exchange price from one day to the next. They are a scaled representation of 48 hours of data between two closing prices. In Figure 3(f) and 3(g), there is a steep slope downward that means the prices are falling, which confirms the trend of observed data for the first three days based on the 30-minute data samples. Figure 3(h) shows a pit close to the line x=1018 and two peaks around the end points. This illustrates a transition from a red market to a green market. Figure 3(j) displays that there is a pit around the starting point and a peak near the ending point, which means the prices in day 5 are higher than the prices in day 4.

4. CONCLUSIONS AND FUTURE WORKS

This paper proposed a novel approach for analyzing and visualizing the time series data in a 3D environment using spatialization. The method used the temporal elements of Bitcoin prices first to transfer data into a 2D map and then to create a 3D surface. In this study, we used the NNI algorithm to estimate the price of unknown points in 3D maps based on spatial relationships between known and unknown feature points. The results of the generated 3D map indicate the reliability of the proposed method to analyze and visualize time series data in a straightforward manner. In future research, we will test the usability of spatialisation visualization in financial analysis by using a slope map to assess volatility, or landmarks to track price changes on 3D maps.

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