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Quantitative Trading in Visual Finance Based on the Era of Internet of Things Economy

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Abstract: Quantitative trading has a broad development prospect in the future Chinese capital market. The study of quantitative trading strategies and their trading systems is a strategically important layout and a powerful tool and weapon for advanced investors to make trading decisions. The purpose of this paper is to study visual financial quantitative trading analysis based on the Internet of Things economic era. The front-end related technologies required to build the system are selected and the design of smart contracts, private chains and consensus algorithm deployment are completed. Implement the visualisation function in the data trading module, map the sensors into an API interface for the purchaser to call and trigger a smart contract to execute the transaction. The testing of the system and the transaction object matching algorithm was also completed on the built sandbox, and the test results showed that it met expectations.

1. Introduction

There are generally two schools of financial market trading, namely basic analysis and traditional technical analysis, as well as some famous theories, such as combination theory, random displacement theory and investment theory [1-2]. With the development of science and technology, the interaction between disciplines began to strengthen, and quantitative transactions began to appear in the financial market combined with various digital statistical models and computers. Financial quantitative trading is defined as an automatic system that executes transactions without intervention through a specific algorithm model, emphasizing automatic and systematic quantitative trading [3-4].

At present, the application of Internet technology in China's financial transactions is still rare [5]. Kommu Narendra's research aims to visually view financial documents so that even non-experts can understand the meaning they contain. Therefore, a new text display method named Interpretive Gradient NN (giNN) is proposed, which uses the interpretive neural network architecture NN. GINN looked at the sentiment score across the financial documents, as well as the sentiment gradient score in the word and concept units. In addition, GINN can see important concepts provided in the context of various declarations. This perspective helps non-specialists understand financial documents easily. They analyzed the effectiveness of GINN theoretically and tested the text display generated by GINN using actual financial text [6]. As a new economic model, sharing economy has the advantages of improving supply capacity and capital utilization. Christopher Lesner examines performance-based contracts between service platforms and external partners (automobile manufacturers) in the context of the Internet application economy of shared things. The service platform provides manufacturers with an incentive to obtain high quality products. To gain more benefits through better service, manufacturers not only improve product performance by designing high-quality manufacturing processes, but also provide exclusive after-sales maintenance through iot applications. The performance-based contract model between the service platform and the manufacturer aims to provide decision-making consultation for managers [7]. Ajeet Singh discusses the applicability of disasters and nonlinear dynamic theory to predict system risk in the Internet of Things digital economy and systems management. One approach can be nonlinear process modeling based on the concept of disaster theory. Research shows that one of the main indicators of this model is to determine the basic characteristics of disasters. Studies have shown that widely used digital economy process models and Internet of Things software and technology components can be converted into standard assembly equations [8].

In this paper, a transaction object matching algorithm is proposed based on the blockchain visual quantitative financial transaction decision, taking the decentralized Internet of Things trading platform as the background and considering the transaction data itself and the system level comprehensively. Through the data trading module and Echarts visualization technology, a visualization financial quantitative trading system based on the Internet of Things is designed, which verifies the feasibility of the system in the block chain online trading scenario, and solves the visualization problem of the transaction data in the specific application scenario.

2. A Study of Quantitative Trading in Visual Finance Based on the Internet of Things Economy Era

2.1 Technical Solution

In general, in the blockchain-based IOT transaction environment, the decentralized transaction process is:

(1) First, before the transaction, the seller publishes data information, including the basic attributes of the data, the price, and the transaction method, and the buyer initiates the transaction by searching the relevant fields and selecting the required data from the search results and clicking on the purchase, which is then broadcast on the chain to form the transaction request;

(2) In the transaction process, the data is collected and transmitted and needs to be verified by the consensus algorithm, which requires the establishment of a trusted consensus mechanism to verify the true legitimacy of the transaction before the verifier can reach a consensus on the transaction process and then release the transaction to the chain.

(3) Finally, this transaction forms block information and is broadcast to the chain, recorded in the ledger and broadcast to the foreground network to finalize the transaction [9-10].

2.2 IoT-based Visual Financial Quantitative Trading System

In order to meet the specific needs of the data detection of the Internet of Things and the visual financial quantitative trading system based on the block link technology, an architecture of the Internet of Things system that can be called remotely is first proposed, namely, the architecture of the Internet of Things data exchange, as shown in Figure 1.

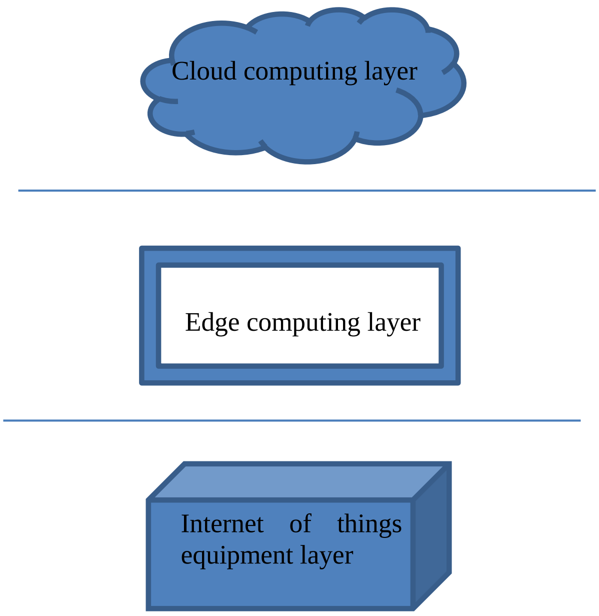

Figure 1: Internet of Things architecture for data sharing

(1) Smart Contracts

Intelligent contract is the core part to ensure the centralized processing of system data transactions. The smart contract parameters specify all elements of the transaction, including price, access data scope, access time, and other information. Data buyers should pre-deposit the assets (usually Ethernet) needed to purchase data into the smart contract account. After data transaction is completed, the assets temporarily stored in the smart contract will be automatically transferred to the data seller until the completion of IOT data transaction [11-12].

The file name of this system smart contract is DataMarket.sol. Smart contracts have a record structure that stores all critical information in a purchase record containing the allocation (address = > purchase) purchase to preserve the data buyer address [13]. The implementation principles of smart contracts are shown in Figure 2.

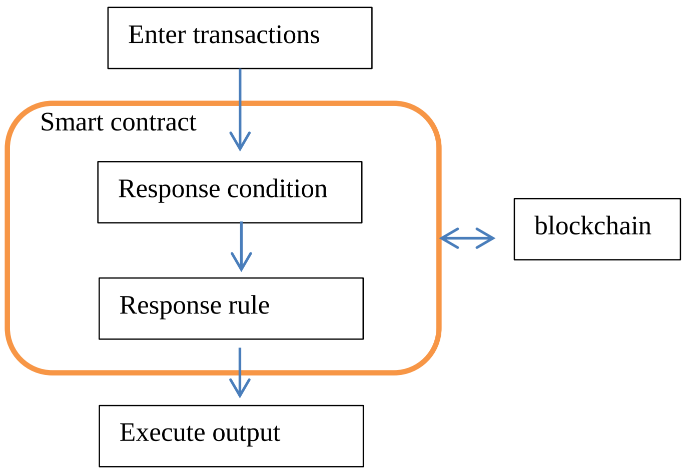

Figure 2: Principle of smart contract execution

(2) Private Chain Deployment

The deployment of an Ethernet private chain is done by Go-Ethereum, the official client provided by the Ethernet Foundation, written in the Go language, or Geth for short. Functions and special effects, it is also a server, and our IoT application platform will access its API interface via RPC and thus obtain data [14].

(3) Consensus algorithm

The authorised proof-of-interest algorithm is similar to a boardroom voting mechanism. The concept of witness is introduced, and the main difference between it and the proof-of-stake algorithm is that instead of having all the people with interests in the system participate in the consensus process, it has all the nodes with interests electing the top N nodes (N is usually 101) as witnesses, so its advantage can be summarised as improving consensus efficiency by reducing the number of nodes involved in the core consensus process.

2.3 Front-end Related Technologies

(1) Echarts

Echarts is a js charting library containing line, pie and bar charts and other interactive shaped visual charts that address the needs related to visualisation head-on, giving users an intuitive, visual experience based on raw data. canva's ZRender is the underlying dependency of Echarts, which runs perfectly on both pc and mobile Echarts, and Echarts is developed by a domestic team and provides complete and comprehensive technical documentation to facilitate learning and use.

(2) Bootstrap

Bootstrap is a front-end development framework developed by Twiter, based on HTML, CSS, JavaScript and written in a simple, intuitive and powerful features to develop Web applications efficiently and easily Bootstrap is written by Less, making HTML and CSS with a certain degree of normality. Bootstrap has a rich library of components, and these components are reusable in different pages, such as drop-down menus, paging components, walk-throughs, pop-up boxes, etc. Bootstrap can also use a rich jQuery plugin to facilitate the writing of business code.

3. Investigation and Study of Quantitative Trading in Visual Finance Based on the Internet of Things Economy Era

3.1 Simulation Test

In order to simulate a realistic blockchain-based data sensing and automatic trading system, a sandbox system was built in a farm scenario. The sandbox contains a total of fifty temperature and humidity sensors deployed in various areas of the farm, and each sensor module is connected to the gateway of the data sharing module to form a data sharing IoT, forming a pool of API interfaces. Accounts are created for all sensors on the application side of the trading system, along with accounts for data buyers.

3.2 Transaction Object Matching Algorithm

Suppose there are n data holders of a certain type of data resource on the trading platform, q={q1, q2, ···; qN} is the data set in which n data holders share data, the offer of the data holder is sellbasei, and the unit price of the shared data of the ith data holder is pbasei. The mathematical relationship between the holder's bid sellbasei and the data unit price pbasei is as follows:

$$sellbase_i = q_i \times pbase_i \tag{1}$$

Suppose there is a data set B={B1, B2, bm} of the data buyer m, indicating that a={a1, a2, aM} is the data demand set of each data buyer m, the data buyer provides buybbasej, and the data buyer requests data through ubasej. The mathematical relationship formula of buybbasej and unit price ubasej provided by the buyer is as follows:

$$buybase_j = a_j \times ubase_j \tag{2}$$

When the data holder Ni registers in the data trading platform, other data information registration entries besides data types include Ni=(sellbasei data cost price, starttimei data collection starttime, qi data volume).

The transaction rate refers to the situation in which the data purchaser requesting a transaction in the system obtains the required data before the deadline. n represents the number of data owners of a data resource type, m represents the number of data buyers who need the data resource, succnum represents the number of transactions, and the total success rate is calculated as follows:

$$closerate = \frac{succnum \times 2}{(N+M)} \tag{3}$$

4. Analysis and Research on Quantitative Trading in Visual Finance Based on the Internet of Things Economy Era

4.1 Data Transaction Module

The data trading module means that the data buyer requests data from the data holder by calling the API, where the API and the transaction price are returned by the transaction object matching module. Through the high transaction rate, more data holders will join the platform to sell their data. The flow design of the data trading module is shown in Figure 3.

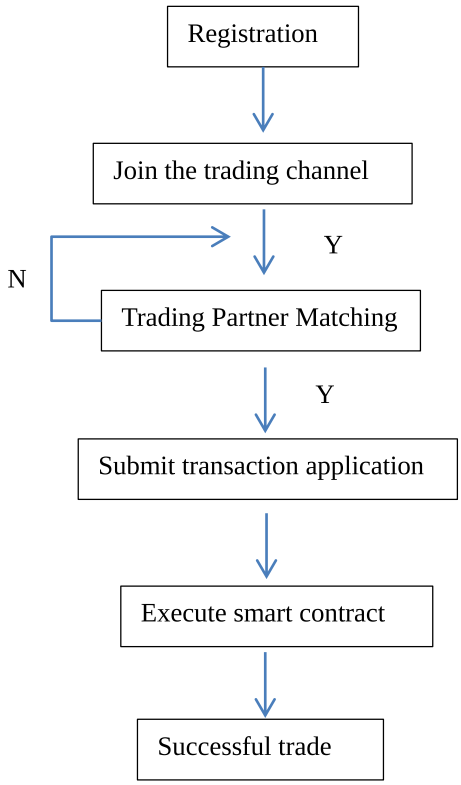

Figure 3: Data transaction module process

First, the data purchaser registers with the client and enters the query criteria for the required data according to the defined entry, which is in the format of:

[data category, data collection area, data price limit, data volume, demand start and end time]

Information about the data query is also stored in both the blockchain and the database. The completed registration is certified by FabricCA, which issues a digital ID certificate in X.509 format, and FabricCA issues the MSP identifier for the data requestor to join the same data trading channel according to the data category required. The blockchain platform creates a wallet for the data requestor, which needs to be pre-funded by the user in order for the transaction to be completed automatically. The user can join the designated channel based on the MSP identifier contained in the digital ID book, and if he wants to purchase a different category of data, he needs to re-authenticate and re-issue the certificate at FabricCA. Afterwards, the transaction object matching module dynamically adjusts the buyer's bid and matches it to the unique optimal adaptation data purchase API. The client invokes the API through the data sharing IoT, while automatically triggering the smart contract Invoke(A, B, Price) function command to pay the data provider the corresponding data cost, and its transaction record exists in the blockchain.

4.2 Test Results

In order to conduct a comparative analysis of the transaction rate of the proposed transaction object matching algorithm, both a fixed pricing algorithm and a continuous two-way auction pricing algorithm were introduced and the original bid price of the transaction was randomly generated. The number of data buyers involved in each round of testing was different, 20, 60 and 100 respectively, and the test values of simulated transactions with different numbers of users were recorded, and then the data were collated and converged into a line graph, as shown in Figure 4.

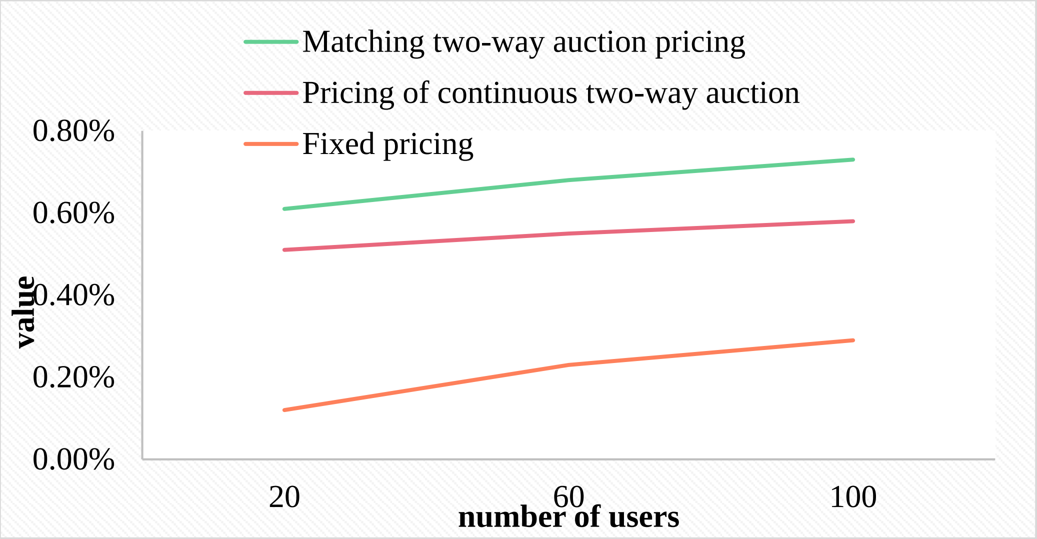

Figure 4: Relationship between number of users and transaction rate

Table 1: Test Results

Number of users	Matching two-way auction pricing	Pricing of continuous two-way auction	Fixed pricing
20	0.61%	0.51%	0.12%
60	0.68%	0.55%	0.23%
100	0.73%	0.58%	0.29%

From the top to the bottom of the graph, line 1 represents the turnover rate relationship for the object matching algorithm proposed in this paper, line 2 represents the turnover rate relationship for the continuous two-way auction pricing algorithm, and line 3 represents the turnover rate relationship for the fixed pricing algorithm. Based on the line graph, it can be concluded that the transaction rate using the transaction object matching algorithm is significantly higher than the transaction rate using the fixed pricing algorithm. Comparing the two dynamic pricing algorithms, it can be seen that the transaction rate using the object matching algorithm is higher than the transaction rate using the continuous two-way auction pricing algorithm, and the transaction rate increases as the number of users increases, and the test meets the expected results, as shown in Table 1.

5. Conclusions

Our economic market is moving towards prosperity, and financial quantification platform has become an inevitable trend. The biggest contribution of this paper is the visual modeling and system design, which means that investors can more easily engage in quantitative trading without dragging and dropping. Today, the volume of transactions is growing across the country, which only considers the tip of the iceberg, but it is not enough compared to the complexity of actual business decisions. As the details become more and more detailed, any data test can be verified in the simulation solution to truly solve the problem of data authenticity in real de-centralized applications.

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