

The Recognition of Microscopic Images of Ceramics Incorporating Blockchain Technology

Yuanxin Qiu, Minnan Normal University, China*

Xing Xu, School of Physics and Information Engineering, Minnan Normal University, China

Xien Cheng, School of Information Engineering, Jingdezhen Ceramic Institute, China

ABSTRACT

Having summarized the previous research on ceramic identification and anti-counterfeiting, the authors propose a ceramic identification system that combines computer vision algorithms with blockchain technology. The system uses irregular pores on microscopic images of ceramic surfaces as image features, and it applies the SIFT (scale-invariant feature transform) algorithm to extract feature. The images and feature vector sets are then stored by IPFS (inter-planetary file system). When a consumer needs to authenticate a ceramic product, it is only necessary to take a microscopic image of the specified location, and then the SIFT algorithm will compare the picture with the data stored in the IPFS network, previously obtained through the records on a blockchain network. The matching result then determines whether the photographed ceramic is one of those already recorded. Experimental results show that the matching results can be used as a strong basis for identifying the origin of ceramic products.

KEYWORDS

Blockchain, Ceramic Identification, Ceramic Products, Feature Extraction, Image Matching, IPFS Network, Microscopic Image, Sift Algorithm

INTRODUCTION

Research Background

Ceramics are used for a wide range of commodities, such as tableware, tea cups, vases and sculptural ornaments. In addition, there are a significant number of individual collectors of antique ceramics. However, as the pace of development increases, the limitations of the traditional method of visual identification of ancient ceramics become more apparent. It is more and more difficult to meet the needs of ceramic identification by relying solely on manual experience. Methods like chemical analysis (Yi, Feng, et al, 2017; Dogan, Tormo, et al, 2019) and thermoluminescence techniques (Wang, 2009; Trinkler, Christensen, et al, 1998) are often used for the identification of ceramics, but both of them are destructive to a certain extent. Li et al (Li, Guan, et al, 2019) has initiated a method for the identification of ceramics by extracting features from multi-band diffuse reflectance spectra of ultraviolet, visible and near-infrared light. Wu et al (Wu, Guan, et al, 2019) has advanced proposed a

DOI: 10.4018/IJCINI.296728

*Corresponding Author

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

method for classifying and identifying ancient ceramics based on visible-near-infrared spectroscopy. These diffuse reflectance spectroscopy-based identification methods can effectively circumvent the damage to ceramics during the identification process, but they are inconvenient to data collecting and are susceptible to interference.

All the methods mentioned above have involved a number of computer techniques and algorithms to analyse the collected features, such as BP neural networks and k-NN algorithms. In fact, in recent years, computer technology, and in particular computer vision, has been increasingly applied to the identification of ceramics. For example, Mu et al (Mu, Wang, et al, 2019) has studied the artificial intelligence-assisted recognition of ancient ceramics in which three main ancient visual features of ceramics were converted into machine vision features: shape as object outline, decoration as image texture, and inscriptions as handwritten Chinese characters. Yang (Yang, 2014) has proposed an algorithm for feature extraction and classification of ceramic surface images based on artificial neural networks for extracting the shape feature of surface defects.

In the above methods of attempting to integrate computer vision techniques into ceramic identification, all the ceramic features, like shapes and patterns, are easy to collect but, as macroscopic features, are vulnerable to destruction and imitation. While the microscopic features, such as the pores formed on the surface of ceramics during the firing process, have a more stable form and cannot be imitated. Therefore, the computer vision algorithms combined with microscopic ceramic features have become a novel approach to ceramics identification in recent years. Chai et al (Chai, Feng, et al, 2020) proposed a ceramic microscopic fingerprint image generation method, which determines the identity of ceramics based on the microscopic features of a specific areas of ceramics. Due to the stability of micro features comparative rather than the macro features, this type of method tends to achieve better results in practice.

The story of Professor Kevin Ashton, who was inspired by the sale of a lipstick and then developed the concept of the IoT(Internet of Things) in 1999, is a well-told one; the development of IoT technology also provides another direction for the identification and traceability of ceramics: in addition to better defining the characteristics of ceramics, optimizing and improving the extraction methods of ceramic characteristics, and recording the relevant characteristics of ceramics in the network so that they can be accessed, and it is also a way to enhance the credibility of ceramic identification results. In other words, the cost of trust can be greatly reduced if consumers can obtain information about the identity of a ceramic directly from the ceramic itself.

In this process, the issue of what information should be recorded, where to store the information and how to determine the identity of a ceramic product from the recorded information is essential to be discussed. In the previous paragraphs, the question of what information is suitable as identification information for ceramics has already been discussed. The following paragraphs will focus on the latter two topics.

The current status of ceramic anti-counterfeiting traceability-related research is summarised as follows.

1. Identification methods based on chemical feature analysis and spectral feature analysis, although effective, are prone to damaging ceramics and are in need of a high level of expertise in terms of equipment and personnel; the use of computer vision methods allows the visual features of ceramics to be used as the object of identification, effectively circumventing these shortcomings.
2. In addition to better defining the characteristics of ceramics and optimizing the process of feature extraction, recording ceramic information in the network also makes it easier to trace back ceramics to the source of counterfeiting. Decentralised network storage, such as the blockchain, is trusted by consumers and favoured by researchers over traditional centralised network storage.
3. Having been combined with image feature matching algorithms, the microscopic features of ceramics can be used as a good identity marker for ceramics, facilitating identification without damaging the structure and artistic value of the ceramics themselves.

Based on the above three points, in this paper, a method of image matching combined with blockchain technology has been applied to the identification, documentation and traceability of ceramics. Taking microscopic images of ceramics as a reference for ceramic identification, the SIFT algorithm is used to extract the features of the microscopic images, after which the images and the extracted features are saved in a server via the IPFS protocol and their hash addresses are recorded in the blockchain. The security of the data is guaranteed due to the fact that the blockchain records cannot be tampered with and that the hash addresses returned by IPFS uniquely can be corresponded to the saved files. When identifying ceramics, the characteristics of the microscopic images of the corresponding parts of the ceramics are extracted and compared with the existed data to determine whether they are the same as the recorded ceramics by the degree of matching.

Related Work

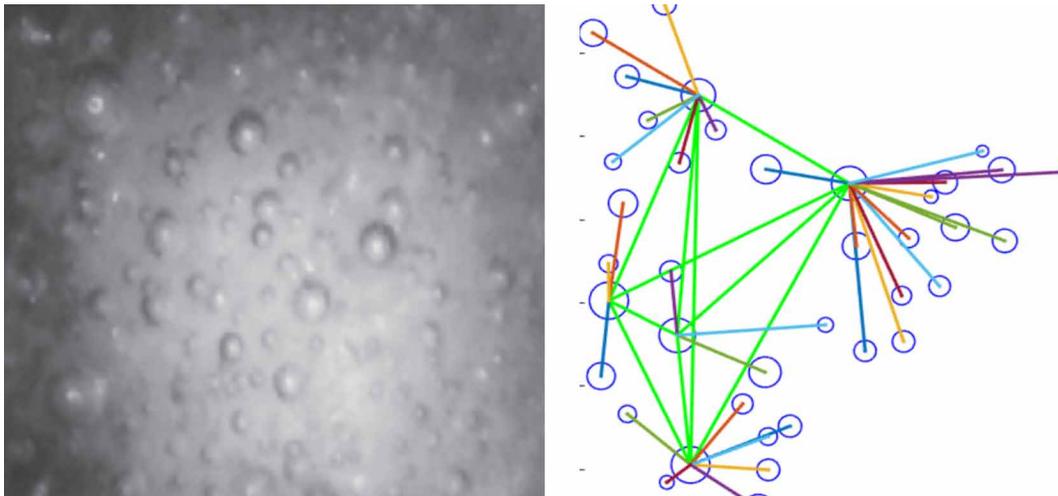
The first topic left to be discussed is where this information is stored. Data security has been an enduring topic since the birth of the Internet, and centralised data storage still takes the dominating place today. There is no doubt that centralised data storage has considerable advantages, especially if the data manager is trustworthy, and that centralised data storage systems have the advantages of large storage capacity and ease of maintenance (Gabriel, Cornel-Cristian, et al, 2019). However, its disadvantages cannot be ignored. The main deficiencies are: 1. the need for a trusted administrator (Corno, De Russis, et al, 2020); 2. the risk that the entire network will be paralysed and disrupted if the centralised server suffers an attack (Mistry, Tanwar, et al, 2020); 3. the failure to guarantee data traceability and non-tamperability (Brous, Janssen, et al, 2020). Encrypted centralised storage solutions (Kopp, Mödinger, 2019) can make some improvements to the deficiency 3, but the first two deficiencies are determined by the centralised structure itself, particularly in deficiency 1. Centralised data storage is extremely unreliable when the administrator of the data lacks trustworthiness, and studies in recent years have shown that consumer confidence in centralised network data storage is on the decline (Wang, Liu, 2019).

The deficiencies of traditional centralised network storage have led researchers to seek alternative network storage solutions. In recent years, blockchain technology has been widely concerned, its main core technology consists of six parts: consensus mechanism, data storage, network protocol, encryption algorithm, privacy protection and intelligent convention (Wang, 2020). The blockchain effectively circumvents the main deficiencies of centralised network storage mentioned above: unlike centralised storage, the transaction process of the blockchain is verified by the participation of multiple users (Morkunas, Paschen, et al, 2019), circumventing the need for trust in administrators in centralised networks; the distributed storage method determines the high resistance of the network to malicious attacks (Bodkhe, Tanwar, et al, 2020); Data is always stored in an immutable manner using timestamps, public audit and consensus mechanisms (Mingxiao, Xiaofeng, et al, 2017), making the possibility of data tampering greatly reduced and achieving data reliability and traceability.

Bhushan et al, (Bhushan, Sahoo, et al, 2019) summarizes various studies in the field of IoT in recent years, and his review shows that BIIoT, i.e., IoT technology combined with blockchain, is receiving increasing attention from researchers, and predicts that research on building IoT networks combined with blockchain technology will become a trend in the coming years. Since blockchain technology has been proposed (Satoshi, 2008), it has experienced very rapid development and has now entered the 3.0 era (Maesa, Mori, 2020), and has been widely used in various industries. A series of explorations on the improvement of storage performance and storage expansion of blockchain have been made by researchers to deal with massive data (Chen, Zhang, et al, 2020). The main means include compressed storage data, collaborative storage, and blockchain storage methods that use the distributed databases as an expansion. In particular, Zheng et al (Zheng, Li, et al, 2018) proposed a blockchain storage structure using IPFS(Inter-planetary File System) (Benet, 2014) as a database,

where the returned hashes are stored as things in the blockchain after storing the data in the IPFS network.

Figure 1. The arrangement of pores on the ceramic surface and its abstract model



The next topic to be discussed is how to determine the identity of ceramic products through this information. While the research on the Internet of Things was still in its infancy, the use of RFID (Radio Frequency Identification) tags as an identifier for things has already been quite well established. However, in the case of ceramic firing, the temperature can reach over 1200 °C, and the common electronic tags made of polymer or paper substrates (Cruz, Rocha, et al, 2018) cannot withstand this high temperature and can only be attached to the surface of the ceramic after firing is complete, which allows for the possibility of tag counterfeiting. Kirtania et al (Kirtania, Riheen, et al, 2020) proposed a high-temperature-resistant ceramic material substrate, and applied it to IoT sensing devices and verified the material's resistance at 300 °C, but this substrate still fail to meet the demand. Moreover, some of the ceramic products are artifacts and such a label could easily damage their artistic value. It is can be summarized that the optimal ceramic identity should meet the requirements of uniquely corresponding to the ceramic and of not damaging the value of the ceramic.

The microscopic features of the ceramic surface have been discussed previously. Fig. 1 shows the arrangement of pores on the ceramic surface and its abstract model, from which the arrangement of these pores can be seen as highly random, and according to Yuan et al (Yuan, Zhang, et al, 2015), these microscopic features remain stable under general wear and tear such as acid corrosion, alkaline corrosion, and natural wear. The random and stable microscopic features on the surface of ceramics meet the requirements of unique correspondence with ceramics and are formed naturally on the surface of ceramics without damaging the value of ceramics, making them suitable as an identity for ceramics. Cheng et al (Cheng, Peng, et al, 2018) registered a certain microscopic partial picture of a ceramic product in the blockchain and made a QR code to be laser printed on the surface of ceramics, so the users can scan the QR code to obtain the information about the ceramic in the blockchain. The users can scan the QR code to obtain information about the ceramic in the blockchain to make comparisons, thus achieving the purpose of anti-counterfeit traceability of ceramics. However, the printing of QR codes can also cause damage to the ceramics, and the local features of the microscopic image of the ceramic are corners or blobs appearing at some distinctive positions in the image, they are not necessarily salient image corners to the human eye, but are distinctive based on some mathematical

model (Chen, Rottensteiner, et al, 2021), i.e., two microscopic images taken from different ceramics are different but very difficult to distinguish the difference with the human eyes, so using a computer vision-based image feature matching method would be a better choice.

The process of image feature matching algorithm is divided into five steps (Chen, Rottensteiner, et al, 2021): feature detection, affine shape estimation, orientation assignment, feature description and matching of the descriptors. Depending on the means of implementation, the algorithms are roughly divided into traditional handcrafted methods and deep learning-based methods. In recent years, with the increasing popularity of deep learning, more and more deep learning models have been applied to affine shape estimation, orientation assignment and feature description in the process, such as LIFT (Learned invariant feature transform) (Yi, Trulls, et al, 2016), Quad-Networks (Savinov, Seki, et al, 2017). Generally, these models outperform traditional handcrafted algorithms in some aspects and can be said to be considerably potential, but the handcrafted methods are not yet obsolete, such as SIFT(Scale Invariant Feature Transform) (Lowe, 2004), ORB (Oriented FAST and Rotated BRIEF) (Rublee, Rabaud, et al, 2011) and other algorithms and their improvements still play an important role in various fields such as Gupta et al (Gupta, Thakur, et al, 2020), Zhou et al (Zhou, Wu, et al, 2020), Yang et al (Yang, Huang, et al, 2021), including the application in ceramic microscopic images (Li, Ding, 2018).

System overview

The system uses the SIFT algorithm to extract and match the image features and then the blockchain to store the data. The innovation of the system lies in the application of the SIFT algorithm to ceramic microscopic images, thus compensating for the slow identification of traditional ceramic identification and combining the almost tamper-proof nature of the data on the blockchain, which greatly increases the credibility of ceramic identification results.

Figure 2. Basic structure of a ceramic microscopic image recognition and matching system combined with blockchain technology

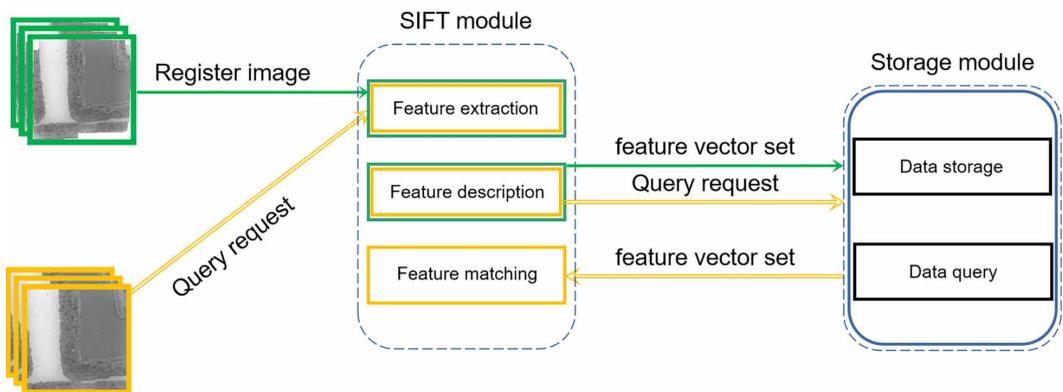
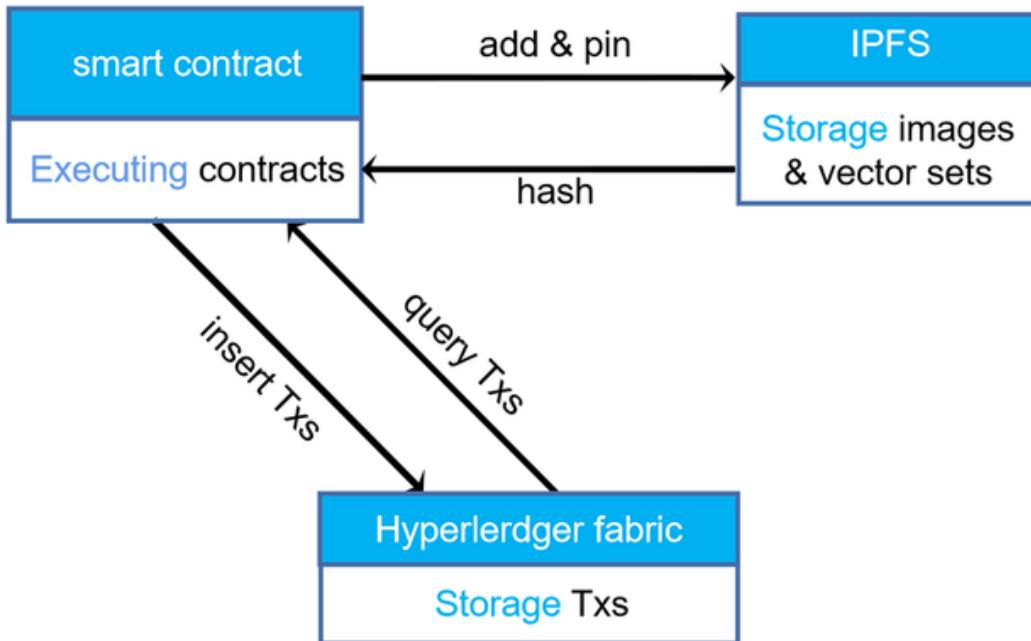


Fig. 2 shows the basic construction of the system, which is mainly composed of two large modules. The SIFT module is primarily responsible for converting images into the feature point description vector sets, as well as the comparison of image features. When registering images, the system passes the images and the feature vector set extracted by the SIFT module into the blockchain storage module. When comparing images, the information extracted by the SIFT module is compared with the information of the registered images to confirm whether the features are in matching or not. The other module is a data storage module based on blockchain technology which is responsible for the storage and querying of images and the corresponding feature vector sets of images.

Figure 3. The internal composition of a blockchain-based storage module



Blockchain-BASED DATA storage

Fig. 3 shows the exact structure of the storage module which consists of three parts, namely the IPFS part, the smart contract part and the Hyperledger Fabric part. Each of these three parts is described in details as follows:

1. IPFS is a peer-to-peer distributed file system that attempts to connect all computing devices to the same file system. Files are transferred to the IPFS network via the add and pin operations. After a successful operation, IPFS returns with a unique string of hashes by which the saved files can be accessed. In theory, the files such as images can be stored as information on the blockchain. But in practice, the storage space of the blockchain has been still very limited so far, and it is expensive to store large files like images directly into the blockchain. It is therefore a common practice to store files off-chain and to store their hashes on the chain (Meng, Morizumi, et al, 2018). This “IPFS + blockchain” approach indirectly enables the storage of large files on the blockchain. At the same time, IPFS embodies the idea of blockchain, where there any modification to the stored file will result in a very different hash value that final been returned. IPFS networks offer the advantages of fast access or download, tamper-proof, and more secured data and privacy protection (Shi, Yi, et al, 2019).
2. A smart contract defines the conditions under which the parties can use the contract. Thus, if the required conditions are met, certain conditions will be automatically executed. Since 2008, when blockchain technology was first introduced with the concept of Bitcoin, the application of blockchain technology has gradually extended from a single crypto-digital currency to the innovative applications in a wide range of industries. In this process, the application of smart contracts has played an important role. As shown in Fig. 3, the functions defined in the smart contract in the system include passing files such as images into the IPFS network, packaging

the returned hashes into transactions recorded in the blockchain, and querying the transactions recorded in the blockchain.

3. Finally, the Hyperledger Fabric, which is an open source blockchain for enterprise federations (Dhillon, Metcalf, et al, 2017), is the blockchain structure used in this system. In this system, the blockchain mainly takes on the role of recording the hash values corresponding to the saved files. Compared to traditional data storage networks, blockchain guarantees the tamper-evident nature of data on the chain by means of decentralised data storage and asymmetric digital encryption algorithms. Commodity anti-counterfeit traceability, which is one of the applications of blockchain, relies on blockchain's data signature and encryption technology to enable tamper-proof, standardised and efficient exchange of information across the chain. Unlike the public blockchains which are open to everyone, Hyperledger Fabric offers to build a consortium blockchain which opens only to users with specific identities and with specific nodes responsible for bookkeeping. So there is no need for participants to waste time on deciding who will do the bookkeeping. However, it is not exactly the same as a private blockchain. In the blockchain network built by Hyperledger fabric, the participants need to be authorized to join or exit the network, and the participating organizations of the network form a coalition of interests to maintain the healthy operation of the blockchain. In the blockchain 3.0 era, the consortium blockchain gradually became the mainstream model of blockchain applications.

To implement such a storage network, it is tested in a Linux virtual machine, using Hyperledger Fabric 2.0 to build a blockchain network with two peer nodes, org1 and org2, which allows data to be stored into the network via the org1 node and then queried via the org2 node, as shown in Fig. 4.

Figure 4. Data storage and querying on the Hyperledger Fabric blockchain.

```
(1) Store data at  
org1 peer node  
$ sshwqyx@ubuntu:~/fabric-samples/test-network$ peer chaincode invoke -o localhost  
:7050 --ordererTLShostnameOverride orderer.example.com --tls --cafile ${PWD}/org  
anizations/ordererOrganizations/example.com/orderers/orderer.example.com/msp/tls  
cacerts/tlsca.example.com-cert.pem -C mychannel -n basic --peerAddresses localho  
st:7051 --tlsRootCertFiles ${PWD}/organizations/peerOrganizations/org1.example.c  
om/peers/peer0.org1.example.com/tls/ca.crt --peerAddresses localhost:9051 --tlsR  
ootCertFiles ${PWD}/organizations/peerOrganizations/org2.example.com/peers/peer0  
.org2.example.com/tls/ca.crt -c '{"function": "InitLedger", "Args": []}'  
2021-07-22 20:16:27.167 PDT [chaincodeCmd] chaincodeInvokeOrQuery -> INFO 001 Ch  
aincode invoke successful. result: status:200
```

```
(2) Query data at  
org2 peer node  
$ sshwqyx@ubuntu:~/fabric-samples/test-network$ peer chaincode query -C mychannel  
-n basic -c '{"Args": ["GetAllAssets"]}'  
[{"ID": "asset1", "color": "blue", "size": 5, "owner": "Tomoko", "appraisedValue": 300}, {"  
ID": "asset2", "color": "red", "size": 5, "owner": "Brad", "appraisedValue": 400}, {"ID":  
asset3", "color": "green", "size": 10, "owner": "Jin Soo", "appraisedValue": 500}, {"ID":  
asset4", "color": "yellow", "size": 10, "owner": "Max", "appraisedValue": 600}, {"ID":  
asset5", "color": "black", "size": 15, "owner": "Adriana", "appraisedValue": 700}, {"ID":  
asset6", "color": "white", "size": 15, "owner": "Michel", "appraisedValue": 800}]
```

Combining this blockchain network with the IPFS module results in a storage network as shown in Fig. 5. In this network, the producers of ceramics firstly upload the ceramic microscopic images and feature vector set to the IPFS network, get the corresponding hash values, then the general information of the ceramic product like name and production date will be packaged together with these hash values and uploaded to the Hyperledger Fabric blockchain network, meanwhile, the buyers of the ceramic product can access the network through the peer node. The hash address of the ceramic's images and feature vector set can be queried through the general information, subsequently, by using the hash address to access the anti-counterfeiting information in the IPFS network, and comparing the anti-counterfeiting information with the images reacquired by consumers themselves, they can complete

the verification process of ceramic products. The above process of data storage and circulation can be realized through smart contracts and IPFS API.

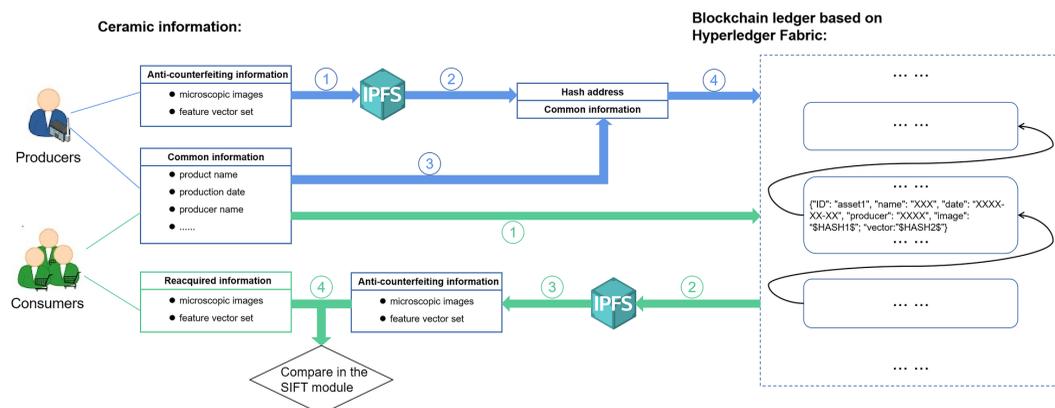
In summary, the overall framework of “IPFS + Blockchain” constitutes the storage module of the system. Both IPFS and blockchain are characterised by decentralised data storage and are difficult to tamper with, which makes this storage system so secured. Trust can be generated without all data on the blockchain. The two modules work with each other through the smart contracts on the blockchain.

SIFT-BASED FEATURE MATCHING

The SIFT module plays a key role in the system for feature extraction and comparison of ceramic microscopic images. Both the distribution of pores formed during the firing process and the irregular shape of ceramic patterns in the microscopic view are highly random and inimitable. This is the reason why it is possible to obtain the very unique microscopic images of ceramics as long as the area for them to be sampled is fixed. A vector set of features can be extract for each ceramic product, which is like a unique ‘fingerprint’ for a ceramic product, and they are a powerful support for anti-counterfeiting identification. Once these ‘fingerprints’ have been recorded, any new microscopic image of a ceramic can be quickly and accurately traced to its authenticity and provenance by simply extracting the SIFT features and matching them to each other. The module uses the SIFT algorithm for feature extraction and comparison of ceramic microscopic images, the SIFT algorithm is one of the classical algorithms in the field of image feature extraction, which extracts feature points from an image and generates a unique description vector for each feature point, and is widely used in the fields of image alignment, image stitching, and image matching because of its sufficient number of extracted feature points and stable localisation and description results. The steps of SIFT-based feature matching include feature point detection, feature point filtering, determination of feature point orientation, feature point description, and feature point matching.

The Difference of Gaussian Scale-Space Extreme Point Detection

Figure 5. Operating process of the blockchain-based ceramic information storage network



For an image, it is of great priority to extract its feature points at different scales. The construction of a Gaussian differential pyramid is the basis for determining the SIFT features. Fig. 6(a) shows a Gaussian pyramid which consists of n octaves from the bottom up; the first interval of the first octave

is the original image and the images in the same octave have the same size and the first image of each octave is obtained by downsampling the third-to-last image of the previous octave.

$L(x, y, \tilde{A})$ represent each picture in the pyramid and It is obtained by convolving Image (x, y) with a two-dimensional Gaussian function

$$G(x, y, \tilde{A}) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where the is the Gaussian ambiguity factor. Let the initial coefficient of octave be and each octave has S layers, then the coefficient of the sth layer of octave is

This allows the ambiguity factor within octave to be expressed as

$$\tilde{A}, k\tilde{A}, k^2\tilde{A}, \dots, k^{S-1}\tilde{A} \quad k = 2^{\frac{1}{S}}$$

Afterwards, a Gaussian difference pyramid is constructed by subtracting the interval in each octave of the Gaussian pyramid in two separate steps. Denoted by $D(x, y, \tilde{A})$, there will be

$$D(x, y, \tilde{A}) = L(x, y, k\tilde{A}) - L(x, y, \tilde{A})$$

Finally, for each pixel point of the rest images in the Gaussian difference pyramid, except for the first and last two images of each octave, comparing it with the nearby 8 pixels and the 18 in the upper and lower interval---a total of 26 pixel points---and extract the ones that satisfy the conditions as preliminary feature points, as shown in Fig. 6(b), comparing the pixel points with the surrounding pixels and filter them as preliminary feature points if the pixel point is the maximum or minimum value among them.

Filtering of Feature Points

After a series of extreme points are obtained through the Gaussian difference pyramids, they need to be further filtered, because the found extreme points are obtained by searching in discrete space, which is the result of sampling continuous space. Therefore, the found extreme points are not necessarily to be the real extreme points. It is thus necessary to eliminate the low contrast feature points and the unstable edge response points by performing the Taylor expansion near the extremes.

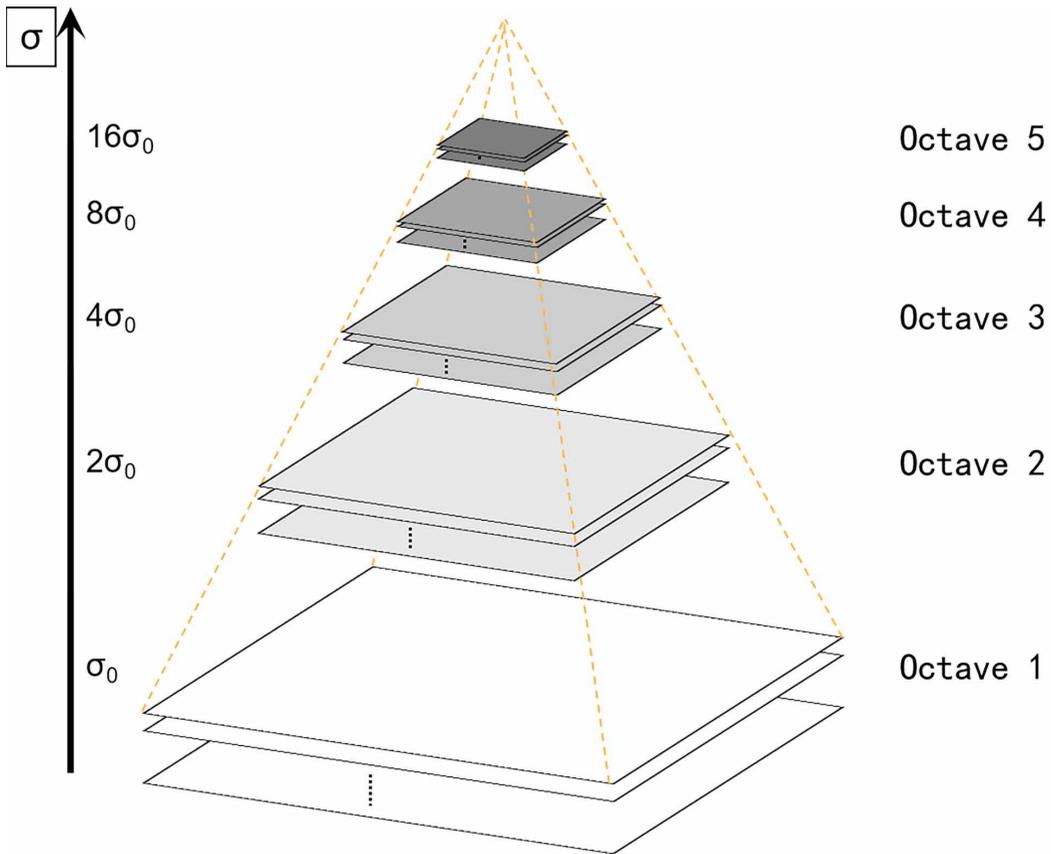
Assigning Directions to Feature Points

Now that the feature points and the scale A corresponding to the feature points have already been obtained, the orientation of the feature points need to be assigned in order to achieve image rotation invariance. The gradient distribution of the pixels next to the feature point is used to determine its orientation parameter, and then the gradient histogram of the image is used to search the stable orientation of the local structure of the key point.

The gradient $M(x, y)$ and the direction $\theta(x, y)$ of the pixel points in a $1.5A$ radius neighborhood centered on the feature point can be found by the following equation

$$M(x, y) = \sqrt{\left(L(x+1, y) - L(x-1, y)\right)^2 + \left(L(x, y+1) - L(x, y-1)\right)^2}$$

Figure 6. Extreme point detection through Gauss pyramid



$$, (x, y) = \tan^{-1} \frac{L(x, y + 1) - L(x, y - 1)}{L(x + 1, y) - L(x - 1, y)}$$

The gradient and direction of these pixel points are counting, the direction with the highest gradient is the main direction of the feature point.

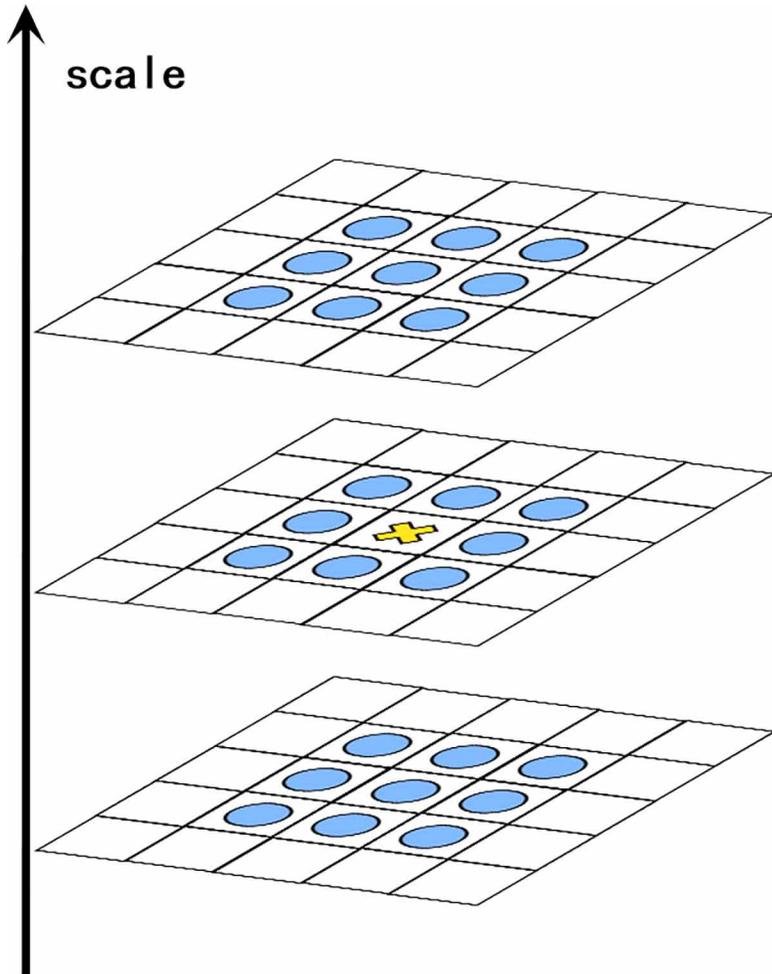
Generating Description Vectors of Feature Points

For each feature point, information about its position, scale and orientation has already been gained. Based on this information, a description vector can be created for each feature point. With the feature point being the centre, a sampling window size of 16×16 is consequently determined based on the A , and the sampling window is rotated according to the orientation of the feature point. The sampling window is divided into 4×4 blocks of pixels and the gradient histogram is calculated for each block in eight directions, so that a $4 \times 4 \times 8 = 128$ dimensional description vector can be generated for each feature point .

Matching of Feature Points

The two images can be referred as the target image and the template image respectively, and the two images would be operated as mentioned above. After that, for a feature point p_0 of the target image,

Figure 7. An example of the template image



find the nearest feature point p_1 and the next closest feature point p_2 in the template image according to the Euclidean distance between the description vectors. Set their distances from p_0 as d_1 and d_2 , compare $\frac{d_1}{d_2}$ with the preset threshold; and if it is less than the threshold, the matching is successful.

TESTING AND ANALYSIS OF MATCHING PERFORMANCE

Test Environment

In order to test the performance of the system, a series of experiments were carried out in the following environments:

- (1) CPU: Intel core i5-9400;
- (2) Operating systems: Ubuntu 16.04;
- (3) Software Versions: IPFS Desktop 0.14.0 & Hyperledger Fabric 1.4.0.

Table 1. Matching results of 20 images with 20 templates.

MR (%)	T ₁	T ₂	T ₃	T ₄	T ₅	T ₆	T ₇	T ₈	T ₉	T ₁₀	T ₁₁	T ₁₂	T ₁₃	T ₁₄	T ₁₅	T ₁₆	T ₁₇	T ₁₈	T ₁₉	T ₂₀
i ₁	70	18.52	12.5	9.4	11.16	6.94	6.67	6.25	9.25	4.55	10	8.43	7.1	5.5	16.67	3.31	2.53	7.69	8.33	6.85
i ₂	8.11	70.37	6.25	5.98	6.25	4.05	3.11	3.57	4.76	1.52	3.33	4.82	4.26	3.21	3.33	2.62	1.52	2.56	3.33	5.36
i ₃	5.41	5.56	75	4.27	4.46	3.47	2.67	3.12	0	1.52	0	2.41	3.65	2.75	3.33	1.8	1.38	1.92	2.5	4.46
i ₄	13.51	18.52	12.5	76.07	8.48	5.78	4.89	5.8	4.76	3.03	6.67	7.23	6.29	5.5	13.33	3.31	2.38	5.77	8.33	6.85
i ₅	5.41	5.56	0	3.42	71.43	2.89	2.22	2.68	0	1.52	0	2.41	3.45	2.75	0	1.38	1.3	1.28	2.5	4.46
i ₆	13.51	14.81	12.5	6.84	8.04	72.25	3.56	5.36	4.76	3.03	6.67	7.23	5.27	4.59	13.33	2.9	1.82	5.77	5.83	6.25
i ₇	2.7	1.85	0	0.85	0.68	0.58	77.78	0.89	0	0	0	1.2	1.83	1.38	0	0.83	0.78	0	1.67	2.68
i ₈	5.41	5.56	0	4.27	4.46	3.47	2.67	78.57	0	1.52	3.33	2.41	3.85	3.21	3.33	1.93	1.41	1.92	3.33	4.76
i ₉	2.7	1.85	0	0.85	1.34	0.58	1.33	1.34	80.95	0	0	1.2	2.23	1.38	0	0.83	0.89	0.64	1.67	2.98
i ₁₀	10.81	11.11	6.25	6.84	8.04	5.2	3.56	4.46	4.76	69.7	6.67	7.23	4.87	4.59	6.67	2.76	1.78	5.77	5	6.25
i ₁₁	8.11	7.41	0	5.13	5.36	4.05	2.67	3.57	4.76	1.52	80	3.61	4.26	3.21	3.33	2.35	1.45	2.56	3.33	5.36
i ₁₂	10.81	11.11	6.25	6.84	7.59	4.62	3.56	3.57	4.76	3.03	3.33	61.45	4.67	4.13	6.67	2.76	1.78	5.13	4.17	5.95
i ₁₃	5.41	5.56	0	5.13	4.91	4.05	2.67	3.12	0	1.52	3.33	3.61	83.57	3.21	3.33	2.21	1.41	2.56	3.33	5.06
i ₁₄	5.41	5.56	0	3.42	3.12	2.31	1.78	2.23	0	0	0	2.41	3.04	75.23	0	1.38	1.3	1.28	2.5	4.17
i ₁₅	5.41	5.56	0	3.42	4.46	2.89	2.22	2.48	0	1.52	0	2.41	3.45	2.75	70	1.52	1.34	1.92	2.5	4.46
i ₁₆	13.51	7.41	0	9.4	4.46	5.78	1.13	3.12	0	3.03	3.33	6.02	3.85	2.75	0	81.91	1.56	3.85	1.67	3.87
i ₁₇	10.81	9.26	6.25	5.98	7.14	4.62	3.56	3.57	4.76	3.03	3.33	6.02	4.26	3.67	3.33	2.76	81.86	3.85	4.17	5.65
i ₁₈	8.11	9.26	6.25	5.98	6.7	4.62	3.56	3.57	4.76	1.52	3.33	4.82	4.26	3.21	3.33	2.76	1.52	84.62	3.33	5.65
i ₁₉	2.7	1.85	0	1.71	2.23	1.73	1.78	1.79	0	0	0	1.2	2.84	2.89	0	1.24	1	0.64	82.5	3.57
i ₂₀	2.7	3.7	0	2.56	2.68	2.31	1.78	2.23	0	0	0	1.2	2.84	2.29	0	1.38	1.08	1.28	2.5	76.19

Note: MR stands for Match rate.

Data Set Preparation

In order to verify the effectiveness of the matching method, 20 groups of microscopic images from different ceramics have been prepared, and each group is sampled from an area of a ceramic. There are 100 images in each group. For easier and quicker comparison, each group of images has been stitched and transformed into one template image. The 20 templates images are named as $T_1 - T_{20}$. Fig. 7 shows one of the template images.

Then, one image has been taken from each of the 20 template images, which are named as $i_1 - i_{20}$. These images have random sizes and rotation angles to simulate the possible position shifts and angle changes that may occur during the second shot sampling in practice.

Prove of the Reliability of the Feature Matching Result

As shown in Table 1, having matched the features of each of the 20 intercepted images $i_1 - i_{20}$ with the 20 recorded images $T_1 - T_{20}$, recorded the matching results obtained, and distinguished them from their own source templates with different colors, then it can clearly be seen that their matches with their own source templates have been much higher than those of the other templates. The match rate of the own-source templates, the highest match and the average match for the non-own-source templates are all recorded, and the three data in a line graph is also plotted, as shown in Fig. 8(a).

From Table 1 and Fig. 8(a), it can be seen that although the control images are all rotated and changed in size to some extent, the matching degree with the template images of their own sources still remains around 70%, in contrast to their matching degree with other templates, which basically remains below 20% at the highest, with an average matching degree of less than 10%. This indicates that the SIFT algorithm possesses stability in feature extraction and is highly resistant to image rotation and size changes; therefore, the matching for images from the same source is much higher than for images from different sources, which is more important than the level of match, as the differences in match determines whether the results produced by the algorithm can be used as a basis for judging the source of the ceramics. As a comparison, Fig. 8(b) intercepts the optimal and sub-optimal results of the two matching results of the ORB algorithm, from which it can be seen that the difference is obviously insignificant, this is due to the fact that the images have undergone the incident scale changes, while is easy to happen in practice, and the ORB algorithm does not achieve well to maintain the scale invariance of the image features, therefore, SIFT can better achieve the purpose of distinguishing ceramic microscopic image sources compared to corner point detection algorithms like ORB and FAST (Rosten, Drummond, 2006).

(a) 20 groups of SIFT matching results, the three curves represent the matching rate of templates from own sources, the highest matching rate of templates from non-own sources and the average matching rate. (b) 2 groups of ORB matching results, illustrating the optimal and sub-optimal results.

A detailed analysis of various types of image feature matching algorithms is presented in a review by Chen et al (Chen, Rottensteiner, et al, 2021), Based on their review and previously research (Jia, Zhu, et al, 2019)(Fan, Kong, et al, 2019)(Li, 2017), the comparison between the SIFT algorithm and some other feature matching algorithms in terms of several aspects including rotation invariance, scale invariance, illumination invariance, and robustness to viewpoint changes is summarized and presented in Table 2. The comparing algorithms include the classical handcrafted methods like FAST and ORB, and deep learning methods such as LIFT and Quad-Networks. Through this comparison, the advantages of SIFT in the proposed ceramic identification traceability system are highlighted, as it has good rotation invariance, scale invariance, and light invariance compared to other hand-craft feature based methods. The SIFT algorithm also does not require a large number of samples as training data, which better meets the needs of identification of small image sets. Of course, other algorithms have their own advantages, the feature matching algorithm is easy to replace as a module in the proposed system.

Figure 8. Comparison of matching results between SIFT and ORB

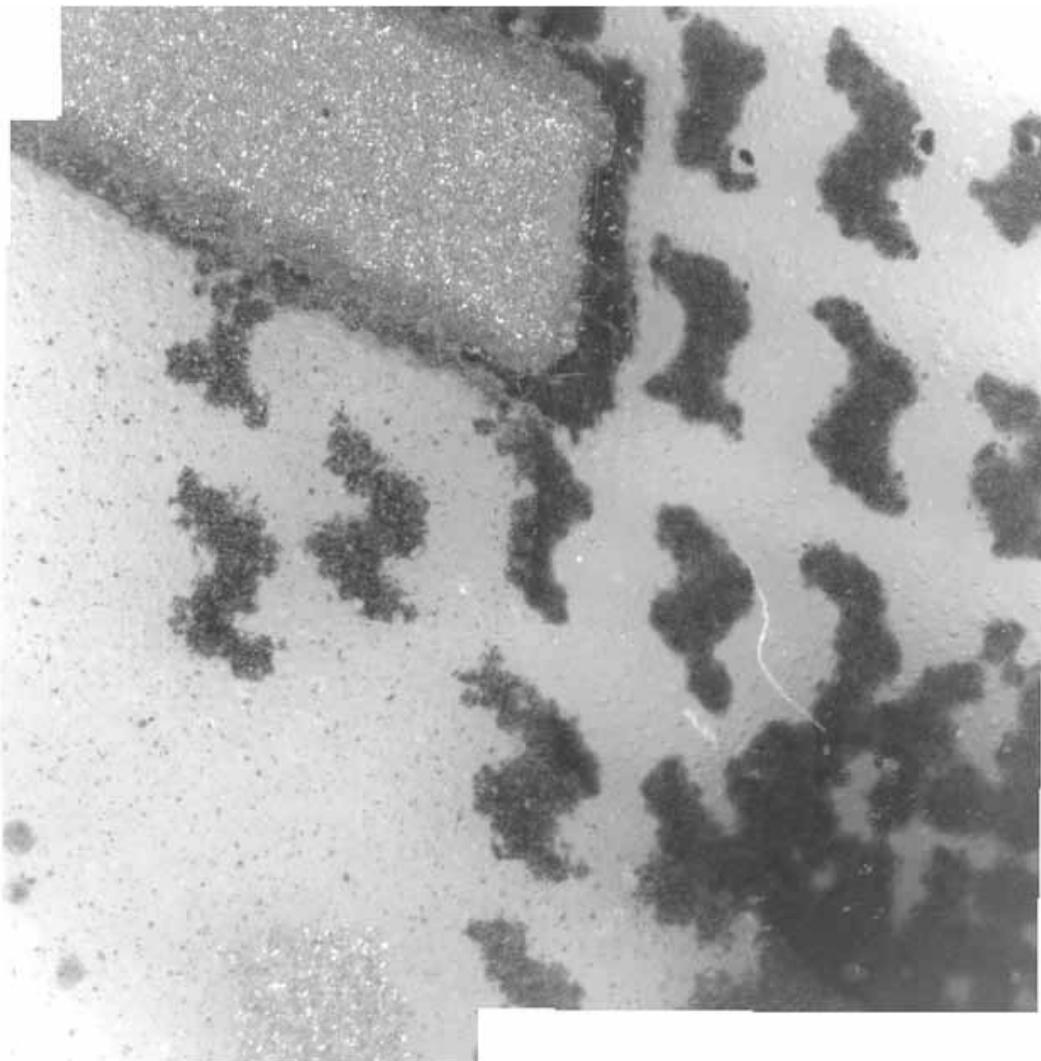


Table 2. A comparison of several feature matching methods

Algorithms	Rotation invariance	Scale invariance	Illumination invariance	Robustness to viewpoint changes
SIFT	Y	Y	Y	High
FAST	Y			Medium
ORB	Y		Y	Low
Quad-Networks	Y	Y	Y	High
LIFT	Y	Y	Y	High

Note: 'Y' stands for algorithm has some advantages in this aspect.

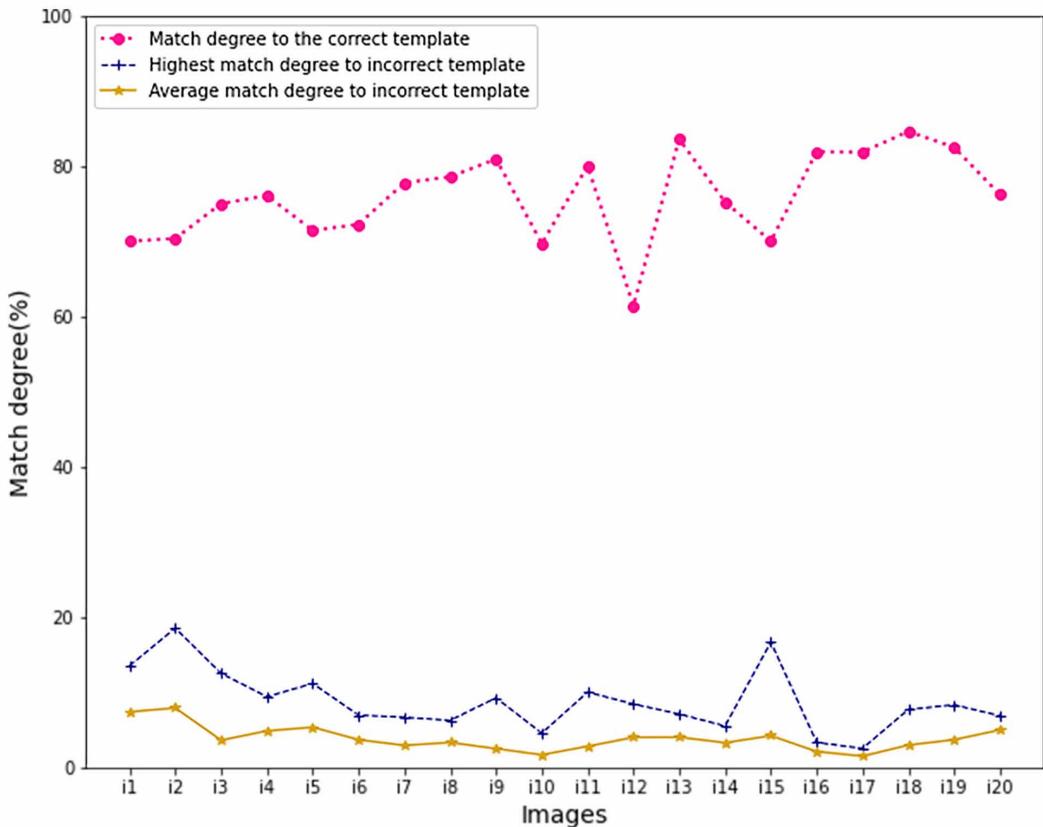
In addition, in the process of extracting ceramic microscopic images, it is likely to have some similar microscopic images, SIFT uses the local features of the images as the basis for feature matching, so it also has a good screening ability for some pictures that hard to distinguish with the naked eye. Fig. 9 shows three groups of ceramic microscopic images and each group has two images that are from different ceramics but are seeming alike with naked eye, in this case, a manual comparison would have made it difficult to reach a correct conclusion. The two images within each of the three groups were matched in both directions using the SIFT algorithm, and Table 3 shows the matching results. Clearly, although the two images appear to be very similar with the naked eye, the difference between the two matches is still huge for the SIFT algorithm to correctly distinguish the origin of the images.

The above experiments demonstrate that the SIFT algorithm can distinguish the origin of ceramic microscopic images very well, and the results of using the SIFT algorithm as recognition to match ceramic microscopic images demonstrate impressive accuracy and stability. In addition, the SIFT

Table 3. Matching of similar images, done once for each of the two images within a set as a template.

Group	Match rate 1	Match rate 2
1	7.81%	8.55%
2	6.47%	9.06%
3	4.25%	4.19%

Figure 9. Three sets of microscopic images of ceramics that look very similar to the naked eye

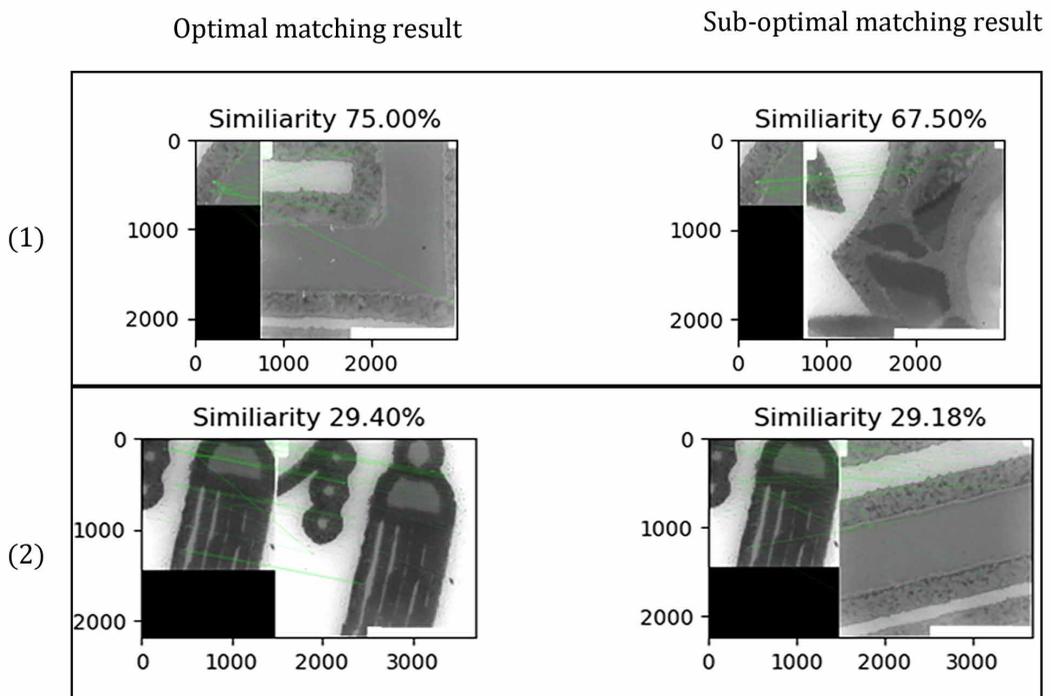


algorithm extracts local features to distinguish the characteristics of the images, making the matching results less susceptible to the interference of overall similar images.

Time Performance Analysis

To illustrate the rapidity of its matching to ceramic microscopic images, the matching time of 400 ceramic microscopic image has been divided into 20 groups as recorded in Fig. 10, and the mean time was 1.499 second with a variance of 0.0063. This time includes the steps of reading the images, extracting and comparing features, and calculating the matching rate. It can be seen that applying the SIFT algorithm to ceramic microscopic images generated very rapid comparison results.

Figure 10. Average response time for 20 sets of matching tests



CONCLUSION

By fusing the SIFT algorithm with blockchain technology, a new anti-counterfeit traceability system for ceramics has been constructed, with the SIFT algorithm extracting and describing the feature points of ceramic microscopic images, storing and returning the hash address through the IPFS protocol, and packaging the hash address as a transaction to be recorded on the blockchain. When inquiring about the authenticity of a ceramic product, simply uploading the ceramic microscopic image and the system will automatically give the available result quickly and automatically based on the information identification on the blockchain. The uniqueness of the ceramic microscopic features, which is inherently impossible to imitate, together with the stability of the SIFT algorithm make the

results highly accurate. And the tamper-evident nature of the blockchain and IPFS further increases the credibility of the results. At the same time, without causing any damage to the ceramics, the proposed method offers better convenience compared to the existing methods for tracing ceramics. Of course, the system still needs further improvement, there is still much room for improvement in the image matching algorithm and it is very unlikely to identify unrecorded ceramics, so the obtained results are still in need of some manual analysis. However, as a secondary method of ceramic traceability, it provides a reliable basis for ceramic traceability. In general, the proposed method is a very promising approach to anti-counterfeiting and traceability of ceramics.

ACKNOWLEDGMENT

This work was supported by the Natural Science Foundation of Fujian Province of China (No. 2021J011007), the National Natural Science Foundation of Zhangzhou(ZZ2020J24), Program for the Introduction of High-Level Talent of Zhangzhou, the National Natural Science Foundation of China (No. 61702239), the Science Foundation of Jiangxi Provincial Department of Education (GJJ170765, GJJ170798), Principal 's Foundation of Minnan Normal University (KJ19015, KJ19009, KJ19005), the Project of Jingdezhen Science and Technology Bureau(20161GYZD011- 011).

REFERENCES

- Benet, J. (2014). *Ipfis-content addressed, versioned, p2p file system*. arXiv preprint arXiv:1407.3561.
- Bhushan, B., Sahoo, C., Sinha, P., & Khamparia, A. (2021). Unification of Blockchain and Internet of Things (BIoT): Requirements, working model, challenges and future directions. *Wireless Networks*, 27(1), 55–90. doi:10.1007/s11276-020-02445-6
- Bodkhe, U., Tanwar, S., Parekh, K., Khanpara, P., Tyagi, S., Kumar, N., & Alazab, M. (2020). Blockchain for industry 4.0: A comprehensive review. *IEEE Access: Practical Innovations, Open Solutions*, 8, 79764–79800. doi:10.1109/ACCESS.2020.2988579
- Brous, P., Janssen, M., & Herder, P. (2020). The dual effects of the Internet of Things (IoT): A systematic review of the benefits and risks of IoT adoption by organizations. *International Journal of Information Management*, 51, 101952. doi:10.1016/j.ijinfomgt.2019.05.008
- Chai, Y. T., Feng, T. Y., Huang, Y. D., & Liu, Y. (2020). Chinese Patent CN201911228202.0, China.
- Cheng, X., Peng, Y. K., & Li, Y. C. (2018). Chinese Patent CN108985413A, China.
- Chen, L., Rottensteiner, F., & Heipke, C. (2021). Feature detection and description for image matching: From hand-crafted design to deep learning. *Geo-Spatial Information Science*, 24(1), 58–74. doi:10.1080/10095020.2020.1843376
- Chen, X., Zhang, K., Liang, X., Qiu, W., Zhang, Z., & Tu, D. (2020). HyperBSA: A High-Performance Consortium Blockchain Storage Architecture for Massive Data. *IEEE Access: Practical Innovations, Open Solutions*, 8, 178402–178413. doi:10.1109/ACCESS.2020.3027610
- Corno, F., De Russis, L., & Sáenz, J. P. (2020). How is open source software development different in popular IoT projects? *IEEE Access: Practical Innovations, Open Solutions*, 8, 28337–28348. doi:10.1109/ACCESS.2020.2972364
- Cruz, S. M. F., Rocha, L. A., & Viana, J. C. (2018). Printing technologies on flexible substrates for printed electronics. In *Flexible electronics*. IntechOpen. doi:10.5772/intechopen.76161
- Dhillon, V., Metcalf, D., & Hooper, M. (2017). The hyperledger project. In *Blockchain enabled applications* (pp. 139–149). Apress. doi:10.1007/978-1-4842-3081-7_10
- Dogan, T., Tormo, L., Akca, S. İ. B. E. L., Kucuk, N., Guinea, J. G., Karabulut, Y., Ayvacikli, M., Oglakci, M., Topaksu, M., & Can, N. (2019). Cathodoluminescence and thermoluminescence of ZnB2O4: Eu3+ phosphors prepared via wet-chemical synthesis. *Ceramics International*, 45(4), 4918–4925. doi:10.1016/j.ceramint.2018.11.191
- Fan, B., Kong, Q., Wang, X., Wang, Z., Xiang, S., Pan, C., & Fua, P. (2019). A performance evaluation of local features for image-based 3D reconstruction. *IEEE Transactions on Image Processing*, 28(10), 4774–4789. doi:10.1109/TIP.2019.2909640 PMID:30969920
- Gabriel, T., Cornel-Cristian, A., Arhip-Calin, M., & Zamfirescu, A. (2019, September). Cloud Storage. A comparison between centralized solutions versus decentralized cloud storage solutions using Blockchain technology. In *2019 54th International Universities Power Engineering Conference (UPEC)* (pp. 1-5). IEEE.
- Gupta, S., Thakur, K., & Kumar, M. (2020). 2D-human face recognition using SIFT and SURF descriptors of face's feature regions. *The Visual Computer*, 1–10.
- Jia, D., Zhu, N. D., Yang, N. H., Wu, S., Li, Y. X., & Zhao, M. Y. (2019). Image matching methods. *Journal of Image and Graphics*, 24(05), 677–699.
- Kirtania, S. G., Riheen, M. A., Kim, S. U., Sekhar, K., Wisniewska, A., & Sekhar, P. K. (2020). Inkjet Printing on a New Flexible Ceramic Substrate for Internet of Things (IoT) Applications. *Micromachines*, 11(9), 841. doi:10.3390/mi11090841 PMID:32911708
- Kopp, H., Mödinger, D., Hauck, F. J., & Kargl, F. (2019). Cryptographic Design of PriCloud, a Privacy-preserving Decentralized Storage with Remuneration. *IEEE Transactions on Dependable and Secure Computing*, 1. doi:10.1109/TDSC.2019.2942300

- Li, J., Guan, Y. P., Li, W. D., & Luo, H. J. (2019). Ancient ceramic kiln non-destructive identification based on multi-wavelength diffuse reflectance spectroscopy. *Guangpuxue Yu Guangpu Fenxi*.
- Li, K., & Ding, G. (2018, July). A novel automatic image stitching algorithm for ceramic microscopic images. In *2018 International Conference on Audio, Language and Image Processing (ICALIP)* (pp. 17-21). IEEE. doi:10.1109/ICALIP.2018.8455766
- Li, S. (2017, September). A review of feature detection and match algorithms for localization and mapping. *IOP Conference Series. Materials Science and Engineering*, 231(1), 012003. doi:10.1088/1757-899X/231/1/012003
- Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, 60(2), 91–110. doi:10.1023/B:VISI.0000029664.99615.94
- Maesa, D. D. F., & Mori, P. (2020). Blockchain 3.0 applications survey. *Journal of Parallel and Distributed Computing*, 138, 99–114. doi:10.1016/j.jpdc.2019.12.019
- Meng, Z., Morizumi, T., Miyata, S., & Kinoshita, H. (2018, July). Design scheme of copyright management system based on digital watermarking and blockchain. In *2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC)* (Vol. 2, pp. 359-364). IEEE. doi:10.1109/COMPSAC.2018.10258
- Mingxiao, D., Xiaofeng, M., Zhe, Z., Xiangwei, W., & Qijun, C. (2017, October). A review on consensus algorithm of blockchain. In *2017 IEEE international conference on systems, man, and cybernetics (SMC)* (pp. 2567-2572). IEEE. doi:10.1109/SMC.2017.8123011
- Mistry, I., Tanwar, S., Tyagi, S., & Kumar, N. (2020). Blockchain for 5G-enabled IoT for industrial automation: A systematic review, solutions, and challenges. *Mechanical Systems and Signal Processing*, 135, 106382. doi:10.1016/j.ymsp.2019.106382
- Morkunas, V. J., Paschen, J., & Boon, E. (2019). How blockchain technologies impact your *business model*. *Business Horizons*, 62(3), 295–306. doi:10.1016/j.bushor.2019.01.009
- Mu, T., Wang, F., Wang, X., & Luo, H. (2019). Research on ancient ceramic identification by artificial intelligence. *Ceramics International*, 45(14), 18140–18146. doi:10.1016/j.ceramint.2019.06.003
- Rosten, E., & Drummond, T. (2006, May). Machine learning for high-speed corner detection. In *European conference on computer vision* (pp. 430-443). Springer.
- Rublee, E., Rabaud, V., Konolige, K., & Bradski, G. (2011, November). ORB: An efficient alternative to SIFT or SURF. In *2011 International Conference on Computer Vision* (pp. 2564-2571). IEEE.
- Satoshi, N. (2008). *Bitcoin: a peer-to-peer electronic cash system*. <http://www.bitcoin.org/bitcoin.pdf>
- Savinov, N., Seki, A., Ladicky, L., Sattler, T., & Pollefeys, M. (2017). Quad-networks: unsupervised learning to rank for interest point detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1822-1830). doi:10.1109/CVPR.2017.418
- Shi, J., Yi, D., & Kuang, J. (2019, December). A blockchain and sift based system for image copyright protection. In *Proceedings of the 2019 2nd International Conference on Blockchain Technology and Applications* (pp. 1-6). doi:10.1145/3376044.3376051
- Trinkler, L., Christensen, P., Larsen, N. A., & Berzina, B. (1998). Thermoluminescence properties of AlN ceramics. *Radiation Measurements*, 29(3-4), 341–348. doi:10.1016/S1350-4487(98)00007-9
- Wang, S. (2020, October). Application of Blockchain Technology in the Field of Network and Information Security. *Journal of Physics: Conference Series*, 1648(3), 032034. doi:10.1088/1742-6596/1648/3/032034
- Wang, W. (2009). Study and progress of the thermoluminescence dating of the ancient pottery and porcelain. *Science in China Series E: Technological Sciences*, 52(6), 1613–1640. doi:10.1007/s11431-009-0106-4
- Wang, Z., & Liu, P. (2019, July). Application of blockchain technology in agricultural product traceability system. In *International Conference on Artificial Intelligence and Security* (pp. 81-90). Springer. doi:10.1007/978-3-030-24271-8_8
- Wu, X. P., Guan, Y. P., Li, W. D. L., & Luo, H. J. (2019). Visible-Near Infrared Spectroscopy Based Chronological Classification and Identification of Ancient Ceramic. *Guangpuxue Yu Guangpu Fenxi*.

Yang, J., Huang, J., Jiang, Z., Dong, S., Tang, L., Liu, Y., Liu, Z., & Zhou, L. (2020). SIFT-aided path-independent digital image correlation accelerated by parallel computing. *Optics and Lasers in Engineering*, 127, 105964. doi:10.1016/j.optlaseng.2019.105964

Yang, L. Q. (2014, June). Ceramic surface image feature extracting and classifying algorithms based on artificial neural networks. In *2014 Fifth International Conference on Intelligent Systems Design and Engineering Applications* (pp. 267-271). IEEE.

Yi, K. M., Trulls, E., Lepetit, V., & Fua, P. (2016, October). Lift: Learned invariant feature transform. In *European conference on computer vision* (pp. 467-483). Springer.

Yi, L., Feng, J., Qin, Y. H., & Li, W. Y. (2017). Prediction of elemental composition of coal using proximate analysis. *Fuel*, 193, 315–321. doi:10.1016/j.fuel.2016.12.044

Yuan, W., Zhang, H., Feng, L. I., Jiang, P., Fang, T., & Ting, Y. E. (2015). *Study on the inspection and verification of ceramic art works based on the characteristics of materials*. China Ceramics.

Zheng, Q., Li, Y., Chen, P., & Dong, X. (2018, December). An innovative IPFS-based storage model for blockchain. In *2018 IEEE/WIC/ACM International Conference on Web Intelligence* (pp. 704-708). IEEE. doi:10.1109/WI.2018.000-8

Zhou, Z., Wu, Q. J., Wan, S., Sun, W., & Sun, X. (2020). Integrating SIFT and CNN feature matching for partial-duplicate image detection. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 4(5), 593–604. doi:10.1109/TETCI.2019.2909936

Yuanxin Qiu, born in May 1997, received Bachelor degree in Engineering from Minnan Normal University in 2019, and is currently a postgraduate student in the School of Computer Science of Minnan Normal University. Research interests: machine learning, blockchain applications.

Xing Xu, born in June 1984, PhD, professor, master's tutor, introduced high-level talents in Zhangzhou City, academic backbone of Minnan Normal University, member of National University Big Data Education Alliance Committee, ACM member, correspondence reviewer of National Natural Science Foundation of China, reviewer of Wuhan University Journal. Research interests: intelligent algorithms, interactive evolutionary algorithms and applications, blockchain applications.

Xi'en Cheng, PhD, Associate Professor of School of Information Engineering, Jingdezhen Ceramic Institute. Research direction: image processing and blockchain technology.