High-speed Retrieval and Authenticity Judgment using Unclonable Printed Code

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Abstract: The distribution of counterfeit products such as food packages, branded product tags, and drug labels, which are easy to imitate, has become a serious economic and safety problem. To address this problem, we propose a method to judge counterfeit products from commonly used inkjet-printed codes. To judge authenticity, copies of printed matter of an inkjet printer are used as they are difficult to duplicate. In this study, we propose a new authenticity judgment system that combines the locally likely arrangement hashing (LLAH) system, which performs high-speed image retrieval, and Accelerated-KAZE (A-KAZE), which matches the features of inkjet-printed matter with high accuracy to verify accuracy.

1 INTRODUCTION

In recent years, information and manufacturing technologies have been advancing at an extremely fast pace. While this has increased convenience in daily life, determining the authenticity of information and distinguishing between genuine and counterfeit products have become increasingly difficult due to its elaborate production. According to OECD/EIPO (2019) survey the amount of counterfeit and pirated goods traded worldwide trade is approaching $500 billion, which is equivalent to approximately 2.5% of the world's total trade. Counterfeit goods range from branded goods and airline boarding passes to pharmaceuticals and food products. According to WHO (2010) report a wide range of counterfeit products, with the increased Internet penetration rate, provide a dizzying array of both branded and generic drugs. In more than 50% of cases, medicines purchased online from illegal sites that conceal their physical address were found to be counterfeit; many of these products are labeled and packaged to look genuine, making it difficult to distinguish between counterfeit and genuine products at a glance. In addition, counterfeit medicines have a tremendous impact on society, not only in terms of economic damage but also as a threat to the health and safety of consumers, infringement of intellectual property rights and trademark rights, and as a source of income for illegal organizations.

In the field of security printing, holograms (Lim et al., 2019) and security inks (Song et al., 2016) are used, and artifact metrics using transmitted light images (Matsumoto et al., 2000, Matsumoto et al., 2004) have been used in Japan for some time.

Other methods have been proposed, such as the use of unique random patterns created by imperfections on the surface of objects, such as paper plant fibers or industrial products (Yamakoshi et al., 2007, Ito et al., 2004, Ito et al., 2018 and Fuji Xerox Co., 2018), or the use of double-encoded codes, in which the black cells of a barcode are encoded with both normal and special black ink (Pacific Printing Co., 2018).

In terms of productivity and cost, we think that the inkjet printing method is best suited to the trend of small-lot, multi-variety printing in the printing industry, where the life cycle of products on the market is short, consumer needs are diversified, and high added value is sought. This research is focused on the fact that the method is optimal in terms of productivity and cost, and that it is possible to print on various media such as film, cloth, plastic, and wood, which is not possible with the electrophotographic method.

This research aims to construct a system that enables producers and consumers to judge product authenticity by cross-verifying the printed codes on labels and tags at the time of manufacture production and delivery.

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Under a microscale, ink grains can be observed on inkjet printouts. The shapes and positions of these grains are slightly different for each print, and the combination of these grains can be regarded as their unique feature. Herein, we developed a system to embed ink grains in a part of a printed code, which can be enlarged and captured and verified that its features (shape and position of the ink grains) are registered in a database. The code can be authenticated via highly discriminative color matching.

Herein, we propose such a system by combining Locally likely arrangement hashing (LLAH), a high-speed image retrieval system that utilizes ink variation in inkjet printing, and Accelerated-KAZE (A-KAZE), which realizes the feature matching of inkjet-printed materials.

2 PHYSICALLY UNCLONABLE FUNCTION OF INKJET-PRINTED CODES

The shape and positional relationship of the ink on the paper can be a unique feature of materials printed by an inkjet printer that can't be observed by laser printer. The following factors can cause differences in the shapes and positions of the ink.

1. Slight airflow on the paper surface
2. The direction in which the header moves when the ink is fired
3. Air resistance of the ink in flight
4. Differences in the fiber quality of the adherend.

These properties can be used for authenticity determination, as the uniqueness of these object fingerprints (Physically unclonable function properties), which each print possesses, makes it difficult to reproduce maliciously. These properties are independent of the printer type and apply to all printers.

In this study, QR codes, typically used for airline tickets and pharmaceutical labels, are used as an embedding medium to obtain characteristics unique to inkjet printing. Specifically, a single color (grayscale information) with a density of 200 (Max 255), as shown in Figure 1, is embedded in the white area in the upper left corner of the QR code to an extent that it does not interfere with its use, and then printed.

Figure 1: Embedded grayscale (density 200) (Max 255) and QR code after embedding.

As an example, Figure 2 shows enlarged images of three QR codes printed where the upper left white area of each QR code was embedded with a single color. But the same URL can be read from each QR code.

Figure 2: QR codes and an enlarged photo of the upper left corner.

The figure shows that, for the printed QR codes with embedded grayscale information, the shape and position of the printed ink differ greatly, and the same ink arrangement can be difficult to reproduce exactly on a microscopic level. Therefore, the characteristics of printed material can be treated as features for authenticity determination. And this study has shown that these features are not lost after three years of storage.

3 METHOD OF HIGH-SPEED RETRIEVAL AND AUTHENTICITY JUDGMENT ALGORITHM

3.1 Overview of the System

The outline of the proposed system is shown in Figure 3, which can be classified primarily into the following processes.

1. Capturing the QR code and saving the image
2. Image preprocessing for LLAH
3. Fast retrieval by LLAH
4. Authenticity judgment by feature matching using A-KAZE

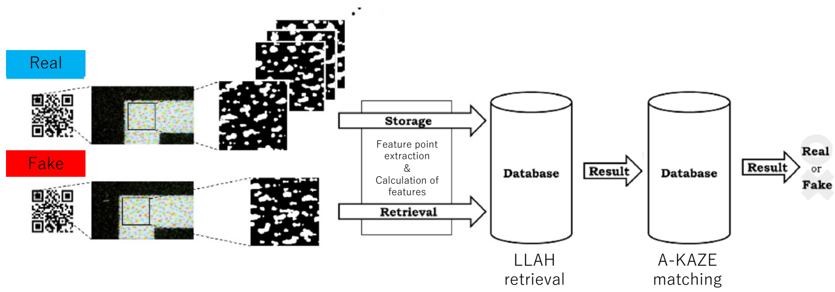

Figure 3: Outline of the proposed new system for determining authenticity.

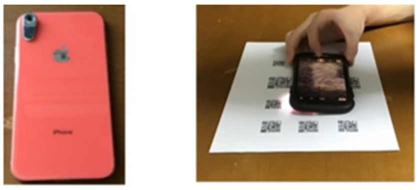

Figure 4: The capturing environment used and the actual capturing scene. Left: The phone and microlens used. Right: The image capture set up.

3.2 Image Preprocessing

We applied image preprocessing to extract feature points for the LLAH system using the captured images. The following procedure was used to preprocess the image and produce a binary image in which the ink hues were extracted from the grayscale part by dividing it into three colors: cyan, magenta, and yellow. Each color was extracted by setting a range in the Hue, Saturation, Value (HSV) color system. Which is calculated by using OpenCV3.30 library with threshold value.

1. Hue

Cyan: 90 to 150,
Magenda: 150 to180,
Yellow: 20 to 40

2. Saturation All: 90 to 255
3. Value All: 120 to 255

Figure 5 shows the cropped image immediately after capturing and the ink colors extracted. (Colors are added for clarity).

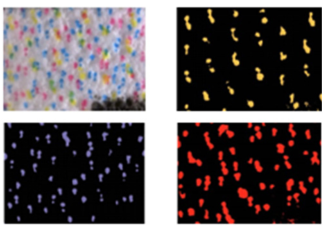

Figure 5: Comparison before and after preprocessing.

The process for image preprocessing is as follows.

1. Cropping of the input image to 100 × 100 pixels along the right and bottom edges.
2. Shrinkage processing.
3. Detect the outline of the QR code and the boundary line between black and white.
4. Determine the angle of the above boundary line and correct the angle of the captured QR code.
5. The origin of the boundary line is calculated using a new algorithm that adds assistance to the approximation.
6. Crop the image further to the size of 700 × 500 pixels.
7. Adjust contrast.
8. Extract the three ink hues.
9. Grayscale conversion.
10. Adaptive Binarization.
11. Smoothing by Gaussian filter.
12. Re-binarization.
13. Invert bits to create an image for input into LLAH.
14. Shrink the image again to remove the noise.

3.3 Fast Retrieval by LLAH

The feature matching system A-KAZE was introduced into the proposed system to judge the authenticity of printed matter. Even though the system is very accurate in judging the authenticity of inkjet-printed matter, it takes approximately 0.4 to 1.0 s for a one-to-one match. To match 100,000 images with Only A-KAZE, the system would take approximately 27 h, which is far from our goal within 10s ,so it is impractical for a real system. Therefore, in the proposed system, we used a technique called locally likely arrangement hashing (LLAH), which was proposed by Nakai et al., 2006, Iwamura et al., 2007, and Takeda et al., 2011, that can retrieve matching images as quickly as 0.02 to 0.04 s regardless of the number of images registered in the database.

Previously, the LLAH technique was used for document image retrieval. Document image retrieval is a technique where images similar to the input image are retrieved. For example, by taking a picture of a paper article with a digital camera and inputting it into the retrieval system, the user can retrieve pre-registered documents and their references. Web services for this technique are also available.

LLAH does not use the image information as is but a unique index value obtained from the image for the registration and matching process, thus reducing the data size and realizing high-speed and high-performance retrieval.

3.3.1 LLAH Extraction of Feature Points and Calculation of Feature Values

Since LLAH judges the match of images based on the arrangement of feature points, the same feature points must be extracted even in the case of projective distortion, noise, or low resolution. Therefore, the center of gravity is used as a feature point and obtained from the ink portion of the binary image generated during preprocessing.

The positions of the obtained feature points are indicated by coordinate information. These positions will change with the angle during capturing changes. To obtain the same feature values even in such a situation, the feature values are not calculated from a single feature point but calculated based on the positional relationship between feature points. In addition, since the images captured by the camera are subject to projection transformation, we used affine invariants as the feature values, which was proposed by Nakai et al., 2006, and which are robust to changes in the position of the feature points as geometric invariants robust to such changes. Figure 6 is shown to explain affine invariants.

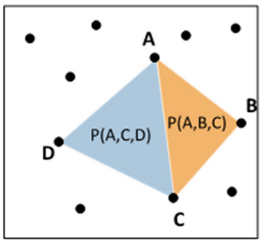

Figure 6: Calculation of affine invariants.

When there are four points A, B, C, and D on the same plane as shown in the above figure, the affine invariant for point A is calculated by the following equation:

$$\frac{P(A,C,D)}{P(A,B,C)} \tag{1}$$

where P (A, B, C) is the area of the triangle formed by the three points A, B, and C. This feature is calculated and discrete-valued from the nearest point to a point. When obtaining m points in the vicinity of a certain point, it is simplest to set m = 4; however, if this is the only method used, the same feature value may be calculated for features in different images and result in an incorrect match. Therefore, to further improve the discriminability, we can set m ≥ 4, find all combinations of four points out of m points, and use the sequence of discretized values of affine invariants computed from the combinations as feature values. In this study, we set m = 6. Each sequence was uniquely determined by moving in a clockwise direction.

3.3.2 Registration with the Database

When registration the extracted features in the database, we obtained the index, H_{index}, and quotient, Q, from the extracted features so that they can be uniquely retrieved using the following equation:

$$\left(\sum_{i=0}^{{}_{m}C_{4}-1} r_{(i)}\, d^{i} \right) = QH_{size} + H_{index} \tag{2}$$

where r_(i) is the discrete value of the i-th affine invariant, d^i is the number of discrete value levels, and H_{size} is the size of the hash table. In this study, we set d = 10 and H_{size} = 1086. In other words, in two matching images, the same index, $H_{index,}$ and quotient Q can be obtained from the same feature vector. Therefore, during retrieval, for features with the same H_{index} (when collisions occur at the same index), quotient Q is used for comparison instead of the feature values. Therefore, as shown in Figure 7, the image ID, feature point ID, and quotient Q are registered in the database. The image ID and feature point ID are the image and feature point identification numbers, respectively. When a collision occurs in the index, a list is added.

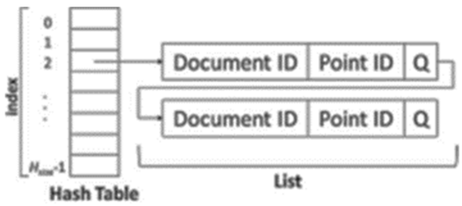

Figure 7: Configuration of the database (Takeda et al., 2006).

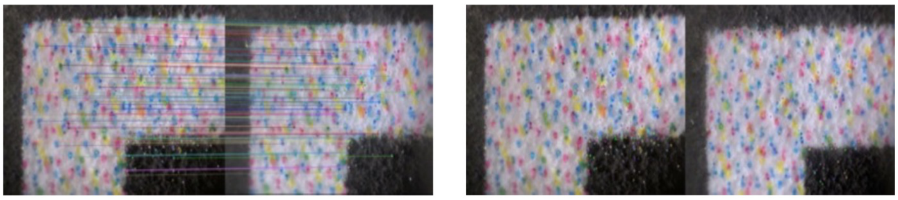

Figure 8: Comparison of registered data with collation data (right) and fake data (left).

3.3.3 Retrieval from Database

Matching is performed by voting on registered images using a voting table. First, as in the registration process, the index of the database is calculated for each feature point, and the obtained index is used to refer to the list shown in Figure 7. For each item in the list, we checked if the quotient matches, and if it does, we increment the image ID item in the voting table. Finally, the results were sorted by the number of increments, and the images were outputted as the retrieved results.

3.3.4 Need for Additional Feature Matching

By setting a threshold value at the "Retrieval from database" stage in the LLAH system introduced in Section 3.3, the system can determine the authenticity of collation and fake data. However, since the LLAH system uses binary black and white images for matching, a high threshold value is required to reject all fake data when the dataset is large. Therefore, we proposed combining color matching with LLAH to make a more powerful system for judging authenticity, instead of using LLAH alone.

3.4 Judgment of Authenticity by A-KAZE

To solve the above problem, we introduced A-KAZE matching, which can perform highly discriminative verification using color images, while LLAH, which can independently determine authenticity, is used for verification from the database without setting a threshold.

A-KAZE was introduced (Tareen et al., 2018, Chien et al., 2016) as a feature matching method that has high robustness, similar to SIFT and SURF, and is good at extracting feature points on a plane; therefore, is resistant to rotation and illumination changes. Figure 8 shows the results of the A-KAZE matching. Figure 8 (right) shows the comparison of registered data collation data using A-KAZE, and Figure 8 (left) shows the comparison of registered and fake data. As can be seen, more than 200 features were matched to the collation data, whereas none were matched to the fake data. In addition, the maximum number of matches for the fake data was only four points, and the genuine data matches were over 50 times higher.

However, although the feature matching A-KAZE is very accurate for inkjet-printed materials, as mentioned earlier, it takes approximately 0.4 to 1.0 s for one-to-one matching, and when applied to an assumed scale of 100,000 sheets, it takes approximately 27 h per sheet. This is not practical for real systems. Therefore, in this system, we will continue to use the LLAH system, which is capable of high-speed retrieval. So, we can accurately judge authenticity within 10s, which is our target time and does not burden the user. In the proposed system in this research, the feature matching of A-KAZE is introduced as follows: For each image divided into three colors (cyan, magenta, and yellow), the top three candidates for each color are retrieved using LLAH, and a total of nine candidates (three colors × three candidates) are selected. We then perform A-KAZE matching on each of the three candidates per color to obtain a highly accurate judgment of authenticity.

4 VERIFICATION

4.1 Verification Outline

In this study, we printed 2,000 QR codes for verification. The images were taken in an environment using a smartphone as described in "3.2 QR Codes Capturing." The captured images were categorized as follows:

1. Registration data: data taken for registration of 1000 QR codes.
2. Collation data: The same 1000 QR codes were re-captured and used to match with the registration images.
3. Fake data: data taken from the second 1000 QR codes without registration.

A total of 3000 images were collected in this manner. To show that the method does not depend on the environment in which the images are taken, the images were taken on different days.

To verify the accuracy of the judgment of authenticity, we changed the size of the datasets registered in the database. Specifically, verifications were conducted in four dataset sizes: 20, 100, 400, and 1000 registered, collation, and fake data. Furthermore, the effectiveness of the proposed method combined with A-KAZE matching was verified by comparing the results achieved using only the LLAH system with those using LLAH with A-KAZE and to compare with other feature detectors, a comparison with ORB is also shown to demonstrate the superiority of A-KAZE.

4.2 Equipment

The following list shows the instruments used for the verification

1. Printer:
   IP8730 (print resolution 9600dpi) by Canon Japan
2. Smartphone:
   iPhone XR (camera resolution 12 million pixels) by Apple America
3. Microlens:
   i micron pro (maximum magnification 800x) by Qing Ting E&T LLC Japan
4. Computer:
   Magnate IM (Intel Core i5-9400 @ 2.90GHz, 16GB RAM) by THIRDWAVE Japan

5 RESULTS

5.1 Verification Results

Table 1 shows the results of the verification of authenticity for each dataset size. The upper part shows the results of the verification of the authenticity using only the LLAH system, LLAH with ORB and the lower part shows the results of the proposed authenticity determination system combined with A-KAZE.

Table 1 shows that the correctness rate for the collation data was very high, exceeding 98%, for all dataset sizes. In addition, the proposed system is sufficiently accurate to be used in the real world.
Furthermore, a comparison of the accuracy of the proposed system with that of the LLAH system alone showed that the accuracy of the proposed system was over 95% for small datasets of up to 400 images. However, when A-KAZE was included, the accuracy was further improved for the small dataset of up to 400 images, and it was confirmed that the accuracy did not decrease and remained high even when the number of images were increased to 1,000, which was a point of concern.

The high accuracy can be attributed to the LLAH being used only for the retrieval function without a threshold value, which is a key feature of the new method. This allowed data to be considered positive, where previously it would have been excluded because the threshold value was not reached when judged by LLAH alone.

Furthermore, the accuracy of the A-KAZE matching system was confirmed to be 100% for

candidates of the collation and fake data, given as arguments. On the other hand, compare with the accuracy of LLAH with ORB, one of the feature detectors for corner, can be seen that there is almost no improvement in accuracy, and instead the accuracy decreases.

In summary, the results confirm that A-KAZE is a suitable feature matching system for the authenticity determination of the inkjet-printed matter.

As for the average processing time, the following breakdown was obtained for 1000 registered images.

LLAH (retrieval function): 0.25 s.
A-KAZE (authenticity judgment function): 8.42 s

Total: 8.67 s

Therefore, this system enables fast retrieval of images by LLAH and judge for high accuracy authenticity by A-KAZE within 10seconds, which is the target time and fast enough for practical use. In the case of ORB, the speed is 0.89s, which is very fast and slow compared to that, but this is the target time and is fast enough for practical use.

In addition, the storage usage of the system with 1000 registered images was as follows:

LLAH (retrieval function): 87 MB
A-KAZE (authenticity judgment function): 492 MB

Total: 579 MB

This breakdown shows that the database for A-KAZE matching is approximately 6.6 times that used for LLAH alone because it uses color images as they are. Therefore, in real-world applications, the color images for A-KAZE should be stored on a server in the cloud rather than the user terminal, and responses should be sent in response to requests.

5.2 Discussion

From the results of the verification described in Section 5.1, we verified that if the correct candidate is passed to A-KAZE as an argument, the system can determine the authenticity with 100% accuracy.

Table 1: Judgment results for each dataset size of the authenticity judgment system (Numbers in red show where the accuracy of the proposed method was better than LLAH only and LLAH with ORB).

LLAH only

	20			100		
	Positive judgment	False judgment	Undecided	Positive judgment	False judgment	Undecided
Dataset size	20	0	0	100	0	0
Collation data	20	0	0	98	0	2
Fake data	0	0	20	0	0	100
	400			1000		
	Positive judgment	False judgment	Undecided	Positive judgment	False judgment	Undecided
Dataset size	400	0	0	1000	0	0
Collation data	385	0	15	846	0	154
Fake data	0	0	400	0	0	1000

LLAH with ORB

	20			100		
	Positive judgment	False judgment	Undecided	Positive judgment	False judgment	Undecided
Dataset size	20	0	0	100	0	0
Collation data	20	0	0	94	0	6
Fake data	0	0	20	0	0	100
	400			1000		
	Positive judgment	False judgment	Undecided	Positive judgment	False judgment	Undecided
Dataset size	400	0	0	1000	0	0
Collation data	388	0	12	932	0	68
Fake data	0	0	400	0	0	1000

LLAH with A-KAZE (Proposed method)

	20			100		
	Positive judgment	False judgment	Undecided	Positive judgment	False judgment	Undecided
Dataset size	20	0	0	100	0	0
Collation data	20	0	0	100	0	0
Fake data	0	0	20	0	0	100
	400			1000		
	Positive judgment	False judgment	Undecided	Positive judgment	False judgment	Undecided
Dataset size	400	0	0	1000	0	0
Collation data	398	0	2	986	0	14
Fake data	0	0	400	0	0	1000

Therefore, observed that the accuracy of LLAH is directly related to the correctness of the judgment. Table 2 summarizes the results of the first, second, and third candidate retrievals for cyan, magenta, and yellow for a total of three sets of 1000 images of registration data.

Table 2: Retrieval accuracy by color (1000 registered data).

	First candidate	Second candidate	Third candidate
Cyan	827	848	854
Magenda	868	885	893
Yellow	834	869	880

The table shows that the result for the three sets combined is 98.6%, which is very high, but the result for the authenticity judgment of each color is between 85% and 90%, which means that there is room for improvement. This is because when extracting the inks in the image preprocessing stage, the specular reflection of the flash during capturing prevents accurate extraction of some colors, resulting in misalignment of the center of gravity and different feature values, leading to matches with more images.

Figure 9 shows three examples, one of which was retrieved correctly, whereas the other two failed.

Figure 9: Comparison of successful and unsuccessful images for determining authenticity.

The correctly retrieved image (left) is clear, but the failed images have problems, such as red due to the flash of the smartphone (center) and blue (right). For the practical use of the system, numerical analysis and verification of the images must be analyzed and verified before image preprocessing. This will prevent registration and judgment of authenticity on images where it is difficult to extract ink colors, obtain the center of gravity, and calculate feature values.

6 CONCLUSIONS

In this study, we proposed a high-speed and high-accuracy authentication system by combining LLAH, which can perform high-speed image retrieval, and A-KAZE, which can perform high-accuracy feature matching for inkjet-printed matter.

Our evaluation verification using a large dataset of 1,000 images showed a correct judgment rate for collation data exceeding 98%, and a positive judgment rate of 100% for fake data within 10s, which is exceptional even considering its use in the real world.

As mentioned in the Discussion section, there is still room for further improvement in accuracy of the retrieval system. Further, the image preprocessing needs to be enhanced to improve the accuracy of the entire system.

In addition, we consider the introduction of a verification step before the preprocessing stage to detect images that are unsuitable for registration and authenticity judgments (Figure 9) by getting the average hue of the image. and to prompt the user to re-capture the image.

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