Improving Accuracy for Authenticity Inspection of Brand Items Using Logo Region Detection Processing

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***Abstract*—In recent years, manufacturing technology of counterfeit brand products has advanced, and it is becoming very difficult for humans to distinguish many counterfeit products. In this paper, we propose an inspection system using two image matching methods to realize authenticity inspection of logo parts of brand items by recognize those images. In the first experiment, we compare the similarity evaluation performance by NCC (Normalized Cross-Correlation) and POC (Phase-Only Correlation) using images of actual brand products. In the next experiment, we propose logo region detection processing using edge images as preprocessing of image matching with the aim of improving inspection accuracy of images containing many background components. Experimental results show that it is possible to separate genuine and fake more accurately by evaluating similarity by POC. Moreover, we confirmed that by adding the logo region detection processing, the background component of the image was reduced and highly accurate inspection was possible.**

***Index Terms*—feature point matching, template matching, NCC, POC, Sobel filter**

I. Introduction

In recent years, the loss of sales opportunities of companies and the decline of brand image due to expansions of counterfeit products are regarded as problems. Manufacturing technology of counterfeit brand products has been sophisticated year by year, and it has been very difficult to distinguish genuine and fake products. Currently, the authenticity inspection of brand items in pawnbrokers and purchasing shops is often done by visual inspection by expert witnesses. However, individual differences can inevitably exist in examination abilities, although they have undergone fundamental training for authenticity inspection. Also, it is difficult to quickly determine the authenticity of counterfeit brand products by only the human senses. So, it is necessary to establish a technology that automates the authenticity inspection of brand items and enables more accurate judgment. On the other hand, many researches have been conducted to realize the authenticity inspection of brand items with the image recognition technology in recent years. If it is possible to identify brand items by utilizing image recognition techniques, it will be possible by a person, whose appraisal ability is not high, to judge whether it is genuine or not. And it can be expected that the time required for its judgment will be greatly shortened. Therefore, in this paper, we propose an inspection system combining two image matching methods with the aim of realizing the authenticity inspection of logo parts of brand products using image signal processing. In the first experiment, we compare the similarity evaluation performance by utilizing NCC (Normalized Cross-Correlation) and POC (Phase-Only Correlation) in order to validate similarity evaluation methods effective for the authenticity inspection of brand items. In the second experiment, we propose partial binarization by utilizing logo region detection in order to improve inspection accuracy of images which can not correctly separate logo and background. Then, we compare the inspection results using binary images obtained by our proposed method and a conventional method.

In this paper, firstly, the outline of our authenticity inspection system is explained in Chapter II, and feature point matching used for deforming correction of brand item images in this system is explained in Chapter III. Next, the outline of template matching and two similarity indexes used to calculate the similarity of logos are explained in Chapter IV, and the logo region detection processing for improving the inspection accuracy of images containing many background components is explained in Chapter V. Finally, the comparison of inspection results using two similarity indexes and the effectiveness of partial binarization by detecting logo region are explained in Chapter VI, and we conclude in Chapter VII [1]-[4].

II. Outline of Inspection System

In this paper, we propose an image matching method as conducting the authenticity inspection of a logo part of a brand item. Fig. 1 shows an algorithm of our inspection system. In the flow of inspection, binarization is first performed to an input image, and the feature point is detected and the feature quantities are described by using the obtained binary image. Next, feature point matching between two images is performed by using the obtained feature quantities. Thereafter, a projective transformation

Manuscript received April 9, 2019; revised August 7, 2019.

doi: 10.18178/joig.7.3.68-75

matrix is calculated based on the matching result, and scale and rotation of the target image are corrected by using the obtained matrix. Finally, similarity score is calculated by subjecting the obtained corrected image to template matching. In this paper, NCC (Normalized Cross-Correlation) [5], [6] and POC (Phase-Only Correlation) [7]-[9] scores are used for calculating similarity in template matching, and the similarity evaluation performance of the two scores is compared for authenticity inspection in the experimental results. In addition, it is difficult to extract logo characters in an image including a lot of background components such as leather patterns of bags or wallets, and image correction by feature point matching may not be performed correctly. There, we compare the processing results of our proposed method and the conventional method in order to ascertain the effectiveness of partial binarization by logo region detection for images in which logo characters and background are not correctly separated by binarization.

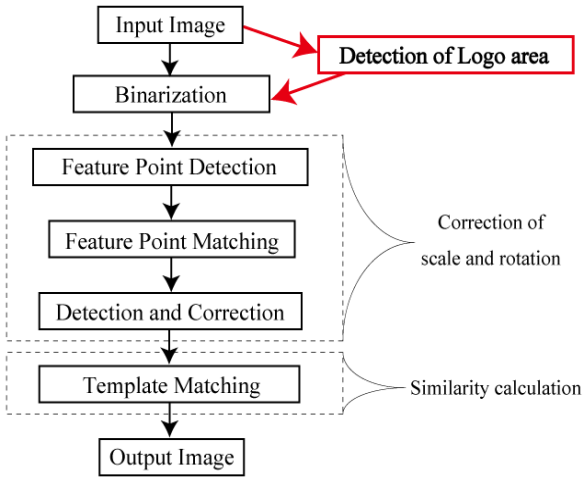


Figure 1. Algorithm of our inspection system

III. Feature Point Matching

Feature point matching [10]-[12] is a method of detecting feature points such as edges and corners from an image and calculating feature quantities from the surrounding regions of correlation images. Our inspection system uses feature point matching when correcting deformation of an input image.

A. KAZE Features

Local feature quantities are used for feature point matching, and they are feature vector obtained by using pixel values or integral value of a region around those points when detecting points with large variation in density from the image. In this paper, the KAZE feature [13]-[15] is used as a local feature quantity. KAZE is a matching method for detecting feature quantities that are invariant to scale change and contrast change in images. It is used not only for specific object recognition but also for many applications such as image synthesis and image classification. In KAZE, a non-linear scale space is formed by the Additive Operator Splitting (AOS) [16], [17] scheme as shown in (1), and feature points are detected by calculating a Hessian matrix as shown in (2) in a plurality of scale spaces.

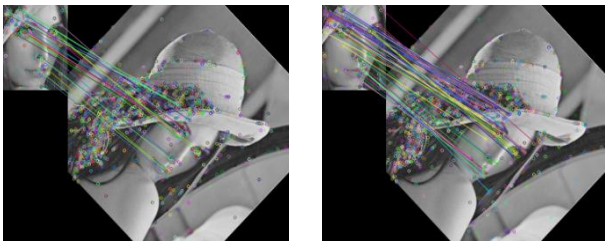
$$L^{i+1} = \left(I - (t_{i+1} - t_i) \cdot \sum_{l=1}^{m} A_l(L^i)\right)^{-1} L^i \tag{1}$$

$$L_{Hessian} = \sigma^2\left(L_{xx}L_{yy} - L_{xy}^2\right) \tag{2}$$

B. Narrowing Corresponding Points

In this paper, after feature point matching using the KAZE feature is performed, and the corresponding points are narrowed down using the following equation as shown in (3), where d_1 is the point with the shortest distance from the matching points, d_2 is the second closest distance, $matchthreshold$ is the threshold of the corresponding point, and d_1 satisfies (3) to obtain good matching points. As the value of $matchthreshold$ increases, the number of matching points increases, but false matching points also increase. The matching results in the cases of $matchthreshold$ = 0.2, 0.8 are shown in Fig. 2. In Fig. 2, it can be confirmed that the number of matching points changes according to the value of $matchthreshold$.

$$d_1 \leq d_2 \times matchthreshold \tag{3}$$



(a) $matchthreshold$ = 0.2 (b) $matchthreshold$ = 0.8

Figure 2. Matching results in two thresholds

C. Robust Estimation

Robust estimation [18], [19] means minimizing the influence of errors on data containing errors. In image processing, a large number of fluctuating factors such as illumination changes and surface conditions are considered to be errors; in robust estimation, the way in which errors occur is used to estimate for a specific model, thus stable processing results are obtained. A major robust estimation method is the RANSAC algorithm [20], [21], and an example of model fitting using this algorithm is shown in Fig. 3.

In this paper, we use the RANSAC algorithm as a method to remove outliers from feature points obtained by KAZE features. In the RANSAC algorithm, the following three procedures are repeated until optimal evaluation values of the model parameters appear.

1. Randomly sample *n* pieces of data determined in advance;
2. Calculate model parameters using *n* sampled data;
3. Evaluate the score of the model parameters using only data within the inlier range which has been determined in advance for the parameters of the obtained model.

By repeating the above processes 1 to 3, it is determined whether only inlier data fit well to the model.

By repeatedly calculating it randomly in this manner, it is possible to obtain an optimum model parameter that successfully fitted only to the inlier data.

IV. Template Matching

Template matching [22]-[24] is a method of scanning a template image on a target image, calculating similarity score at each position on the target image, and detecting a position at which the maximum similarity score is obtained. In template matching, there is a similarity index for checking the similarity score between two images. The similarity index used in this paper is shown below.

A. Normalized Cross Correlation (NCC)

NCC [5], [6] is a similarity index that evaluates similarity by normalized cross-correlation and is calculated by the following equation as shown in (4).

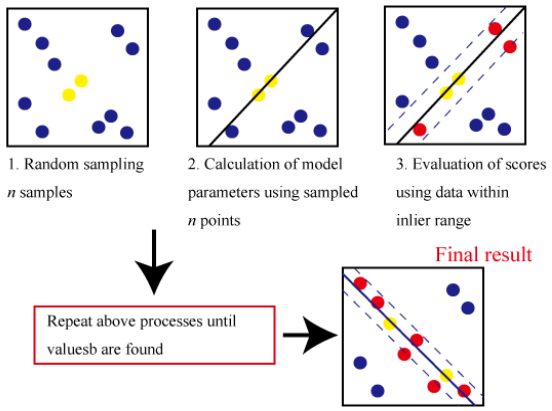


Figure 3. Flowchart of RANSAC algorithm

$$NCC = \frac{\sum\sum\{g(d_x+i,\ d_y+j)f(i,j)\}}{\sqrt{\sum\sum(g(d_x+i,\ d_y+j))^2}\sqrt{\sum\sum(f(i,j))^2}} \quad (4)$$

where f is the pixel value of a template image, and g is the pixel value of a target image. The NCC value lies within the range of 0 to 1.0, and the scanning position closest to the maximum value 1.0 is the position most similar to the template image. Moreover, NCC determines similarity by calculating the inner product and considering the image a vector, and because the value is not affected by the length of the vector, it is hardly affected by illumination change, which is an advantage.

B. Phase-Only Correlation (POC)

POC [7]-[9] is a similarity index that evaluates similarity by correlating phase characteristics. The POC function is an inverse discrete Fourier transform of the normalized mutual power spectrum obtained by a two-dimensional discrete Fourier transform of the image. The following Equations (5) and (6) represent the two-dimensional discrete Fourier transform of the images $f(n_1;n_2)$ and $g(n_1;n_2)$.

$$\begin{aligned} F(k_1,k_2) &= \sum_{n_1,n_2} f(n_1,n_2)W_{N_1}^{k_1,n_1}W_{N_2}^{k_2,n_2} \\ &= A_F(k_1,k_2)e^{j\theta_F(k_1,k_2)} \end{aligned} \quad (5)$$

$$\begin{aligned} G(k_1,k_2) &= \sum_{n_1,n_2} g(n_1,n_2)W_{N_1}^{k_1,n_1}W_{N_2}^{k_2,n_2} \\ &= A_G(k_1,k_2)e^{j\theta_G(k_1,k_2)} \end{aligned} \quad (6)$$

where $A_F(k_1,k_2)$ and $A_G(k_1,k_2)$ are amplitude spectra, and $\theta_F(k_1,k_2)$ and $\theta_G(k_1,k_2)$ represent phase spectra. The normalized mutual power spectrum of $F(k_1,k_2)$ and $G(k_1,k_2)$ is given by following equation as shown in (7).

$$\begin{aligned} R(k_1,k_2) &= \frac{F(k_1,k_2)\overline{G(k_1,k_2)}}{\left|F(k_1,k_2)\overline{G(k_1,k_2)}\right|} \\ &= e^{j(\theta_F(k_1,k_2)-\theta_G(k_1,k_2))} \end{aligned} \quad (7)$$

where $\theta_F(k_1,k_2)-\theta_G(k_1,k_2)$ is the phase difference spectrum of the two images. In image matching, this phase difference spectrum has an important property, and the POC function is defined as a two-dimensional inverse discrete Fourier transform of the normalized mutual power spectrum as shown in (8).

$$\mathrm{r}(n_1,n_2) = \frac{1}{N_1N_2}\sum_{k_1,k_2} R(k_1,k_2)W_{N_1}^{k_1,n_1}W_{N_2}^{k_2,n_2} \quad (8)$$

The POC function has a very sharp peak and is close to the delta function. The height of this correlation peak is useful as a measure of similarity among images and is used for applications such as image collation and image registration.

V. Detection of Logo Region

In our inspection system, binarization is performed to extract only logo portions from brand images as preprocessing of feature point matching. However, images containing a lot of background components such as a leather patterns of bags or wallets do not correctly separate characters and background by binarization. Therefore, in this paper, we propose partial binarization by logo region detection in order to improve the inspection accuracy of images containing a lot of components as the background of the logo. Detection of the logo region is realized by combining edge extraction using Sobel filter [25], [26] and contour extraction. The Sobel filter is a spatial filter used for contour detection. The Sobel filter combines a smoothing filter and a differential filter to extract contours while suppressing the influence of noise. By using Sobel filter, it is possible to extract the vertical and horizontal contours by horizontal and vertical differentiations, respectively. The kernels K_x and K_y used for detecting the contours in the horizontal and vertical derections, respectively in Sobel filter are expressed by the following equation as shown in (9) and (10).

$$K_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad (9)$$

$$K_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (10)$$

The flow of our proposed logo region detection processing is shown in Fig. 4. In the flow of the logo region detection, firstly, luminance components are normalized [27], [28] with respect to an input image in order to eliminate variations in luminance due to illumination fluctuation and edges are extracted by Sobel filter. Edge extraction is performed in the vertical and the horizontal directions, and the sum of the two edge extracted images is output. Next, binarization is performed by discriminant analysis method using the obtained edge image. Thereafter, in order to connect adjacent characters to each other, dilation processing is performed only in the horizontal direction, and contour extraction [29], [30] is performed on the obtained image. Finally, the circumscribed rectangle is calculated based on the obtained contour component, and the logo regions are detected for each row. Output images obtained by each process of our proposed method are shown in Fig. 5. In the detection result of Fig. 5(f), it can be confirmed that the logo regions are detected from the brand image. In the experiments to be described later, in order to ascertain the effectiveness of our proposed method, we compare the partial binarization method using only the logo regions with the conventional binarization method. In addition, we are going to compare the inspection results when using images obtained by each method.

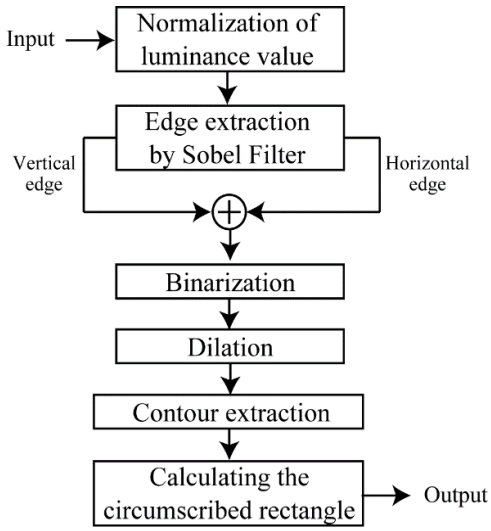
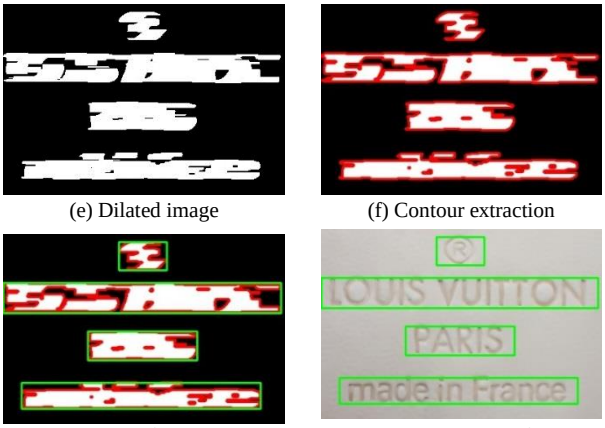


Figure 4. Flow of our proposed logo region detection

(a) Original image (b) Normalized image

(c) Edge image (d) Binary image



(e) Dilated image (f) Contour extraction

(g) Calculation of circumscribed rectangle (h) Detection result of Logo region

Figure 5. Results of each processing of our proposed method

VI. Experimental Results

In order to confirm the performance of our authenticity inspection system, the following two experiments were conducted. In the first experiment, we compare the similarity evaluation performance by NCC and POC using images of genuine brand products and images of counterfeit brand products. In the second experiment, we compare with the conventional method in order to confirm the effectiveness of the logo detection processing proposed in this paper, for images with many background components. In this experiment, the image of the sealed part of the brand bag was used. The experimental conditions are shown in Table I.

TABLE I. Experimental Conditions

Feature Point Matching	
Local features	KAZE
Matching type	Brute-Force
Matching method	knnMatch
Match threshold	0.8
Template Matching	
Similarity index	NCC, POC
Detection of Logo region	
Binarization method	Otsu thresholding
Kernel size of dilation processing	(1, 31)

A. Performance Comparison of Similarity Index

Experiments were carried out to confirm the inspection performance when NCC and POC were used as similarity index in this authenticity inspection system. In this experiment, logo images of actual brand products are used, and 5 images of authentic brand products and 5 images of counterfeit brand products are targeted. Also, similarity scores calculated by NCC and POC will take a value of 0 to 1, and the closer to 1 the higher the similarity of the image. Fig. 6 shows the inspection results when images of authentic brand products are used. In addition, Fig. 7 shows the inspection results when images of counterfeit brand products are used. In Fig. 6, it can be confirmed that in the inspection using the image of

the authentic brand name, the similarity scores show higher values when the similarity evaluation by the POC is performed. In addition, in Fig. 7, it can be confirmed that the similarity calculated by POC shows lower value although the similarity difference between the two indexes is slight in the inspection using the image of the fake brand item. The average similarity index values of genuine and fake images are shown in Table II. Also, in Table III and IV, the similarities of the images calculated by the respective similarity indexes are listed in descending order of similarity. In Table II, it can be confirmed that the average value of the similarity score, when genuine items are used, is less than 0.8 in the evaluation by NCC, but it is about 0.9 in the evaluation by POC. For fake items, the evaluation value by POC is lower than the value of NCC by about 0.04. In addition, it can be confirmed that the difference between genuine and fake items is larger in the evaluation by POC as compared to the case in which evaluation by NCC is performed. In Table III, it can be confirmed that in the evaluation result by NCC, the top four similarities are occupied by authentic brand products. However, the similarity of the real image of image number 5 is lower than the similarity of the fake image of image number 2. On the other hand, looking at the evaluation result by POC in Table IV, it can be confirmed that the degree of similarity of all genuine images is higher than any fake images. From the above, it can be observed that POC is superior to NCC in terms of separation performance between genuine and fake images, and it has been confirmed that it is possible to accurately distinguish between genuine and fake images.

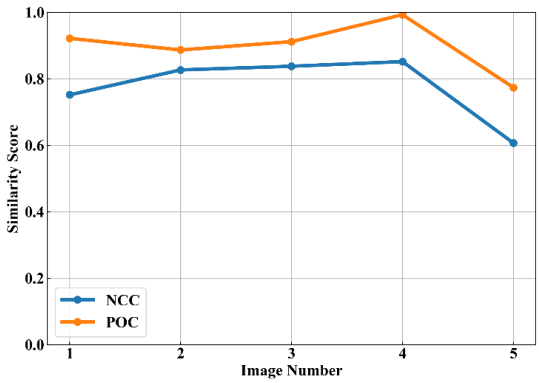


Figure 6. Similarity score of genuine images

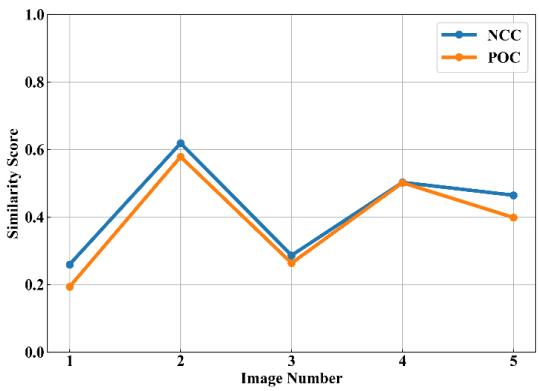


Figure 7. Similarity score of fake images

TABLE II. AVERAGE SIMILARITY VALUES

	Genuine	Fake	Difference
NCC	0.775	0.427	0.348
POC	0.898	0.388	0.510

TABLE III. SIMILARITY SCORE OF EACH IMAGE (NCC)

	Image Number	Similarity Score
1	4 (Genuine)	0.852
2	3 (Genuine)	0.838
3	2 (Genuine)	0.827
4	1 (Genuine)	0.752
5	2 (Fake)	0.619
6	5 (Genuine)	0.607
7	4 (Fake)	0.503
8	5 (Fake)	0.465
9	3 (Fake)	0.287
10	1 (Fake)	0.260

TABLE IV. SIMILARITY SCORE OF EACH IMAGE (POC)

	Image Number	Similarity Score
1	4 (Genuine)	0.993
2	1 (Genuine)	0.922
3	3 (Genuine)	0.912
4	2 (Genuine)	0.887
5	5 (Genuine)	0.774
6	2 (Fake)	0.579
7	4 (Fake)	0.502
8	5 (Fake)	0.399
9	3 (Fake)	0.264
10	1 (Fake)	0.194

B. Evaluation of Logo Region Detection Effectiveness

In our inspection system, after binarizing the input image, image correction by feature point matching is performed using the obtained binary image. However, images containing a lot of background components such as leather patterns of bags and images with sparser brightness due to lighting fluctuation at the time of photographing do not correctly separate characters and background by binarization. As a cause, it is considered that binarization is performed on the entire image in the conventional method, and it is largely influenced by background components unrelated to the inspection. Therefore, for the purpose of confirming the effectiveness of the logo region detection processing, binarization for the whole image and comparison processing result of binarization focused on the logo portions are performed. We also compare the inspection results when using these images. In the experiments, we used genuine images in which binarization of the whole image did not correctly separate the logo portions and the background portions, and image correction by feature point matching failed. A comparison of the inspection results in the case in which the logo detection processing is performed and the case in which it is not performed is shown in Fig. 8. As shown in

Fig. 8, the similarity is low overall in the conventional method, whereas in the proposed method using the logo region detection processing, the similarity of all images is 0.8 or higher, and the improvement in the inspection accuracy is confirmed. Fig. 9, Fig. 10, and Fig. 11 show the binary images obtained by the conventional method and our proposed method and the results of feature point matching when using each binary image. In the output results of the image as shown in Fig. 9, since the matching points in the upper part of the image are obtained in the conventional binarization, the estimation of the plane is performed, but since the logo and the background are not separated correctly in the lower part of the image, It can be confirmed that no matching is done. On the other hand, in binarization by our proposed method, the logo and the background are accurately separated, indicating that the matching points are sufficiently obtained. Further, in the output results of the image as shown in Fig. 10, it can be seen that the number of matching points is small and false matching occurs because the logo and background are not correctly separated in the entire image in the conventional binarization. Moreover, it can be confirmed that the estimation of the plane is erroneously performed by false matching, and the calculated similarity shows a remarkably low value. This is because the shadow at the time of shooting which appeared in the original image, had a bad influence. On the other hand, in the binarization by our proposed method, it can be confirmed that the extraction of the logo character is performed correctly with almost no influence of the shadow. Looking at the output results of the image as shown in Fig. 11, it can be confirmed that according to the conventional method, matching points are obtained at the upper part of the image in which separation of the logo and the background is performed relatively well. However, since no matching points are obtained at the bottom of the image, it can be also confirmed that the estimation of the plane is not performed correctly. On the other hand, it can be seen that our proposed method correctly performs character extraction by binarization and plane estimation by feature point matching. In the above results, it is found that narrowing the range of binarization by detecting the logo region reduces the influence of the background components and enables extraction of the logo character with high accuracy.

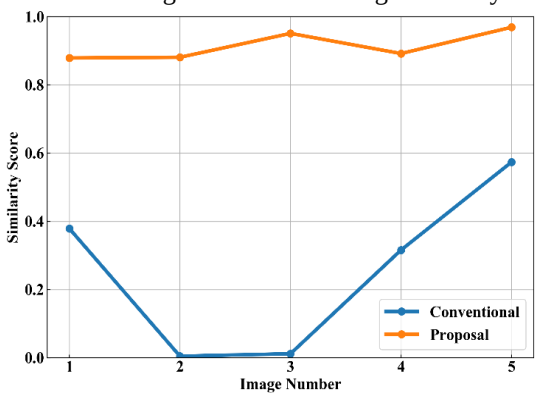
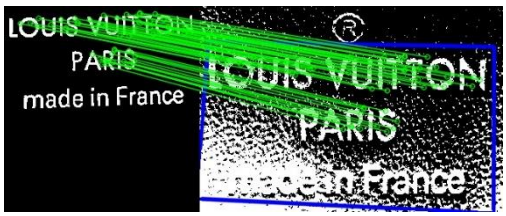
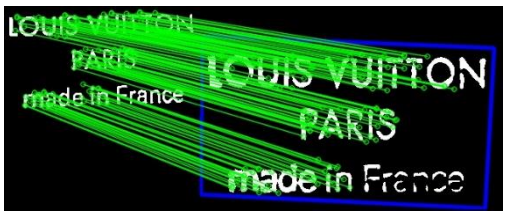


Figure 8. Inspection results of conventional method and proposed method

(a) Binary image (conventional method) (b) Binary image (proposed method)



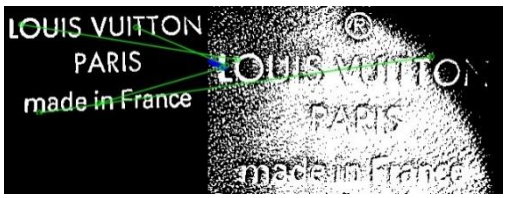
(c) Matching result (conventional method)



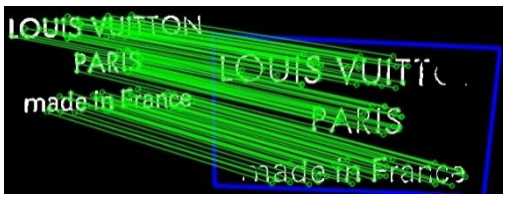
(d) Matching result (proposed method)

Figure 9. Comparison of output results by conventional method and proposed method

(a) Binary image (conventional method) (b) Binary image (proposed method)

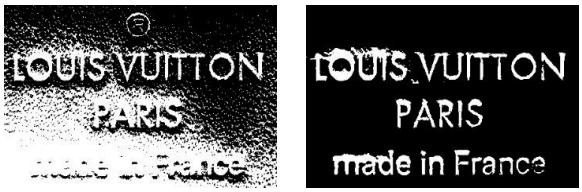


(c) Matching result (conventional method)

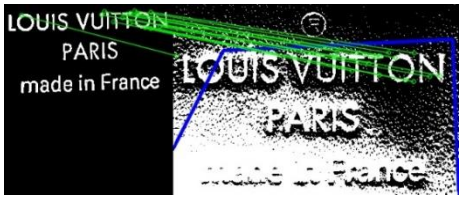


(d) Matching result (proposed method)

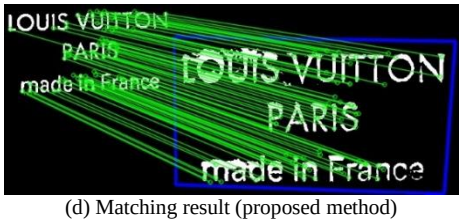
Figure 10. Comparison of output results by conventional method and proposed method



(a) Binary image (conventional method) (b) Binary image (proposed method)



(c) Matching result (conventional method)



(d) Matching result (proposed method)

Figure 11. Comparison of output results by conventional method and proposed method

VII. Conclusion

In recent years, many companies have suffered damage due to the expansion of counterfeit brand products. In addition, the manufacturing technology of counterfeit brand products has become more sophisticated year by year, and it is very difficult to distinguish between genuine and counterfeit products. Therefore, in this paper, we have proposed a novel inspection system using two image matching methods with the aim of realizing authenticity inspection of brand logos based on image recognition processing. In addition, in order to confirm the performance of our proposed inspection system, two experiments were carried out by utilizing images of actual brand items. In the comparison of the similarity evaluation performance by using NCC and POC, we have confirmed that it has been possible to separate genuine and counterfeit more accurately by evaluating similarity score by POC. In experimental results conducted to ascertain the effectiveness of the logo region detection processing, by reducing the range of binarization by detecting logo regions using its edge image, the influence of the background component is reduced and it has been possible to obtain highly accurate inspections. We intend to improve the accuracy of extraction of logo characters by improvement of binarization processing for further research.

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