Improvement of the Identification Rate using Finger Veins based on the Enhanced Maximum Curvature Method using Morphological Operators

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Received: August 2021 Revised: October 2021 Accepted: December 2021

ABSTRACT:
All human biological traits are unique as biometrics, such as fingerprint, palm, iris, palm veins, finger veins and other biometrics. Using these biometrics has always been challenging. One of the challenges in biometrics is physical injuries. Finger vein biometrics is one of the characteristics that is most resistant to physical injuries. Numerous algorithms for authentication have been proposed with the help of this biometrics, which have weaknesses such as high computational complexity and low identification accuracy. In this paper, a new method in identification based on maximum curvature algorithm and morphological operators is proposed. The maximum curvature algorithm extracts image properties using a set of operations based on image returns. This process has been enhanced in the proposed method with morphological operators. What distinguishes the proposed method from other methods is that this algorithm is very accurate in distinguishing images which are similar but belonging to different classes. The proposed method, in addition to having a reasonable computational complexity, has been able to record very good identification accuracy in the challenge of low image quality. The identification accuracy of the proposed method is 97.5%, which compared to other methods has been able to improve more than 3%. Also, the identification speed of the proposed method is 0.84 seconds, which is very fast in its kind.

KEYWORDS: Identification, Biometrics, Finger veins, Infrared, Maximum curvature, Morphological operator.

1. INTRODUCTION

Biometrics are a branch of science used for identification and authentication [1]. Biometrics are basically of two types: behavioral biometrics and physiological biometrics. Characteristics and biometrics are basically fixed and unique, and with the help of which individuals can be identified with each other [2]. Biometric identification systems basically have a complex structure consisting of different parts [3].Biometric authentication systems and identification methods along with other authentication systems can enhance the security aspects of authentication systems [4]. Biometric-based methods of identifying both gender and ethnicity in machine learning consist mainly of preprocessing, feature extraction, feature selection, classification, and finally evaluation. Also, these systems can be based on one biometric or based on several biometrics together [5, 6].

Biometrics are of two types: behavioral biometrics and physiological biometrics [7]. Most biometrics can only be used by living people [8]. While people who have died can easily have their faces, fingerprints, or even their palms forged. Finger veins biometric is not usable after death. It is also very difficult and practically impossible to forge this type of biometrics in living people. Although these two major advantages have attracted the use of this biometrics, it is highly influenced by body temperature. And if a person's body temperature changes, these patterns may change as well [9].In line with the above, a lot of research has been done for identification with finger veins, some of which have had low identification rates and high response time, or high identification rates and low response time. In [10] using the image manifold to identify and authenticate the images of finger veins reached 97.80% accuracy. In [11], simultaneous precedence and segmentation of the desired ROI area are used in the preprocessing section. Steerable filters are used to extract the feature, and finally the nearest neighbor classification was used. In [12] a complex process to preprocess NIR images of finger veins has been proposed. In [13] the Hamming Distance (HD) for

Paper type: Research paper
DOI: https://doi.org/10.52547/mjtd.11.1.1
How to cite this paper: S. A. Mousavizadeh Mobarakeh and M. Emadi, “**Improvement of the Identification Rate using Finger Veins based on the Enhanced Maximum Curvature Method using Morphological Operators**”, Majlesi Journal of Telecommunication Devices, Vol. 11, No. 1, pp. 1-8, 2022.

classification and authentication in this type of biometrics was suggested, [14] Again with a complex process, including preprocessing, feature extraction, and classification. In [15] the Linear Local Binary Patterns(LLBP) is used to extract the feature. In [16] after ROI extraction, Contrast Limited Adoptive Equalization (CLAHE) and normalization in preprocessing stage by KECA Liner Kernel Entropy Component Analysis are used. In [17] complex classifier of Weighted k-Nearest Centric Neighbor (WKNCN) was used along with the PCA kernel feature extractor. In [18] the classifications Violet transform and entropy properties are used. The obtained accuracy is 99.30%. In [19] again, the complex adaptation algorithm is used for classification in the proposed method. In [20],in the method proposed the accuracy has reached 99.85%. In [21] the Linear Local Binary Patterns LLBP and the pulse width modulation are suggested for classification, and LLBP for feature extraction. In [21], edge detection as well as ROI extraction along with softener filtering were proposed in the preprocessing stage. In [22] the hard-adaptation algorithm was used for classification, but in the preprocessing stage only the ROI is extracted, and the feature extractor used in this method is only the Histogram of Competitive Gabor Responses (HCGR), which is a new method in its kind. In [23], a complex pattern matching algorithm for classification in the proposed method was used. In [24] a different classification is used to conclude the authentication with the help of finger vein images. The Sum of Squares Classification was first presented by this research. In [25] machine learning algorithms is used to authenticate finger vein images. In [26], after the same preprocessing process, only PLA is used to make the properties enter the ANFIS-based fuzzy classifier. In [27] various preprocessing processes were used to improve the quality of IR images. In [28] only adapted Gaussian filters have been used to improve image quality in the preprocessing stage, and feature extraction is done using the LBP variance. In [29] the complex preprocessing process includes histogram equalization, contrast enhancement, intermediate filtering, and Gabor filters, and finally the extracted features include global thresholding as well as Gabor filters. In [30] convolution neural networks have been used to classify finger vein images. Convolution neural networks are one of the learning methods which has recently attracted the attention of many researchers.

It seems that presenting a method with features such as high identification rate and low computational complexity is very noticeable. Numerous studies have been performed on the identification using finger veins, based on these studies, the innovations of this article can be announced as follows:

• Improving the maximum curvature algorithm with the help of morphological operators.

• Calculating the maximum curvature of the finger arteries and identifying it by using finger vein images.

• Using morphological operators to improve the information extracted at maximum curvature.

• Creating the obtained distinct feature vectors.

• Low-time complexity of the proposed method.

This article has been categorized as follows:
In Section 2, pattern recognition will be presented as a tool in identification. In section 3, the proposed method will be presented. In Section 4, the proposed method will be evaluated. And finally, in Section 5, the conclusion of the whole article will be presented.

2. IDENTIFICATION BY PATTERN RECOGNITION

Identification systems generally follow a common structure including: imaging, fingerprint zoning, feature extraction, identification, and evaluation [31]. In this research, since morphological operators have been used in the feature extraction stage to improve the maximum curvature descriptor, the two important items will be introduced in the following.

2.1. Algorithm of Morphological Operations

The word morphology usually refers to a branch of science studying the shape and structure of the earth and even animals, and mathematical morphology is a tool that is suitable for extracting different parts of an image, displaying and interpreting it. Interpretation of shapes, borders, concave and convex points and areas with the help of morphological operators is based on the structural element that is usually applied to digital images, although it can be used on gray surface images as well. The two most common operators in morphology are Dilation and Erosion. In Dilation, objects expand based on a suitable structural element, and as a result, the holes are filled, and disjointed areas are connected to each other. This is while the Erosion operator destroys objects based on a structural element. Opening and closing are two other functions used for morphological processes. The function of the opening operator is similar to that of Dilation and Closing is similar to that of Erosion [32].Methods based on morphological operators are of high speed and also resistant to noise in the image. However, these methods cannot correctly identify the intersections of the veins, and also the use of long overlapping structural elements cannot correctly identify the areas of the veins [33]. Structural elements are a major part of the contraction and dilation operators. Two-dimensional or flat structural elements consist of a matrix, which is usually much smaller than the original image. The central pixel is called the main structural element. If it is a pixel determinant, then it should be processed.

Morphological operators are implemented on binary images [34].

2.2. Maximum Curvature Descriptor

This algorithm is the main part of the feature extraction step. The whole process of maximum curvature is divided into three stages: extracting the central positions at the edges, increasing the sensitivity and connecting the central point in improving the edges. To extract the central positions of the edges, first the cross-sectional profile analysis is applied to the image and then the local maximum in the cross-sectional profile are calculated. To further illustrate this method, if $F(x,y)$ is the pixel value of (x,y), Then $P_f(z)$ is a cross-sectional profile obtained from $F(x,y)$. Fig. 1.a shows a cross-sectional profile.

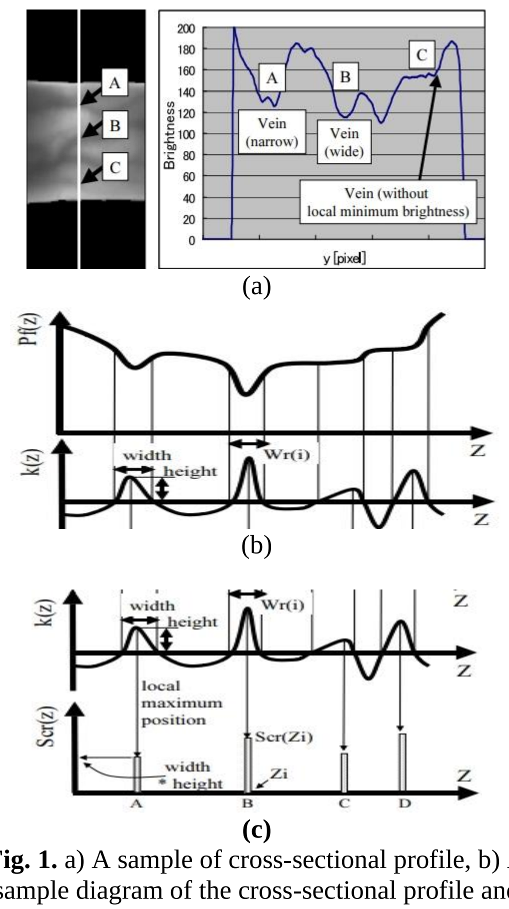


Fig. 1. a) A sample of cross-sectional profile, b) A sample diagram of the cross-sectional profile and maximum curvature, c) A sample of the results of the weighting system.

As shown in Figure 1.a, this algorithm is convoluted as a line on the image at different angles. Then, according to the brightness of the image, a graph is drawn for each column of pixels. In the obtained diagram, convex points are usually recognized as edges. But this diagram is not accurate enough to determine the center points of the edge in the image. Therefore, the maximum values of curvature are calculated using the values of the cross-sectional profile. This transformation is calculated using Equation 1.

$$k(z) = \frac{\dfrac{d^2 p_r(z)}{dz^2}}{\left[1 + \left(\dfrac{d\, p_r(z)}{dz}\right)^2\right]^{3/2}} \qquad (1)$$

In the above equation $P_f(z)$ is a cross-sectional profile, dz is the derivative operator, and k(z) is the maximum valueof the curvature. Then, the obtained diagrams are detected at concave points with a very high probability of the edges inside the image. Figure 1.b shows an example of a cross-sectional profile with maximum curvature. In Figure 1.b, with the maximum transformation of the curves, the edge points are identified approximately, but still there is no necessary accuracy in identifying the edge. To overcome this challenge, a weighting system with concave points of maximum curvature assigns to each point, a kind of probability of being present at the edge points. This weighting system is calculated by the equation 2.

$$S_{cr}(z_i) = k(z_i)\, w_r(i) \qquad (2)$$

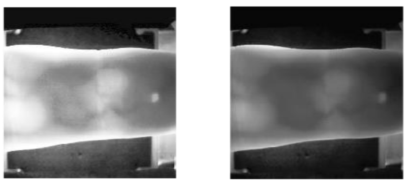
In the weighting system in Equation 2, *i* is one of the maximum points of the maximum curvature diagram,$W_r(i)$ is equal to the result of the width of the concave region multiplied by the value of Z_i. The value of each z_i' is equal to the result of the weight multiplied by the amount of maximum curvature calculated for that point and Figure 1.c is an example of the results of the weighting system. After weighing each of the maximum points and calculating the score of each point, if the score of these points is more than a threshold, it is recognized as the center point of the edge.

3. PROPOSED METHOD

Methods of identifying and segmenting veins using predefined knowledge about pixels and predefined labels for each pixel train the desired classifier. In fact, the rules for training categories are the extraction of features from pixels and areas. In machine learning methods, several features are extracted from the imaging of each pixel. These features can then be minimized by dimension reduction methods to make the classification process easier. There are usually four steps for identification using veins segmentation. 1-Pre-processing 2-Feature extraction 3-Feature selection 4- Classification and finally identification.

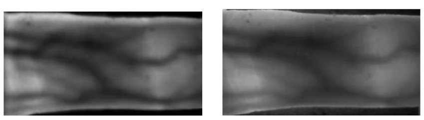
3.1. Preprocessing

To improve the initial edges of the image, a fast local Laplacian filter is created on the image. The created image is an image having both better quality (higher contrast) and better edges for identification than the original image. Fig. (2a) shows the original image and b is an enhanced image. Figure (3a) shows the main image after normalization and (3b) shows the enhanced image after normalization. Filters selected to improve image quality are among the efficient filters, which have shown their quality improvement in various images.



b a

Fig. 2. a) The original image, b) The enhanced image



b a

Fig. 3. a) The main image after cutting the extra area and normalizing, b) The enhanced image after cutting the extra area and normalizing

3.2. Feature Extraction

In feature extraction, each infrared image of veins will be shown with a feature vector containing meaningful numbers. These numbers differentiate people and thus identify them. In this research, edge-based features, transformation-based features of the most enhanced curvature with morphological operators for each image will be extracted. Figure 4 shows the block diagram of feature extraction of blood vein images.

3.2.1 Maximum Curvature Properties

Despite the efforts made to improve the results of blood vein segmentation, due to the challenges ahead to extract features such as random position of veins, low contrast of fingerprint blood vein images, appropriate feature extraction from fingerprint vein images is challenged. Therefore, in this article, geometric methods and maximum curvature properties will be used to extract the feature. The maximum curvature method is one of the most successful methods used to extract features from the image in other biometrics such as the blood veining palm [35]. The maximum curvature method detects small curves in the fingerprint blood veins. Figure (5) shows a feature map of the extraction of veins in a similar image.

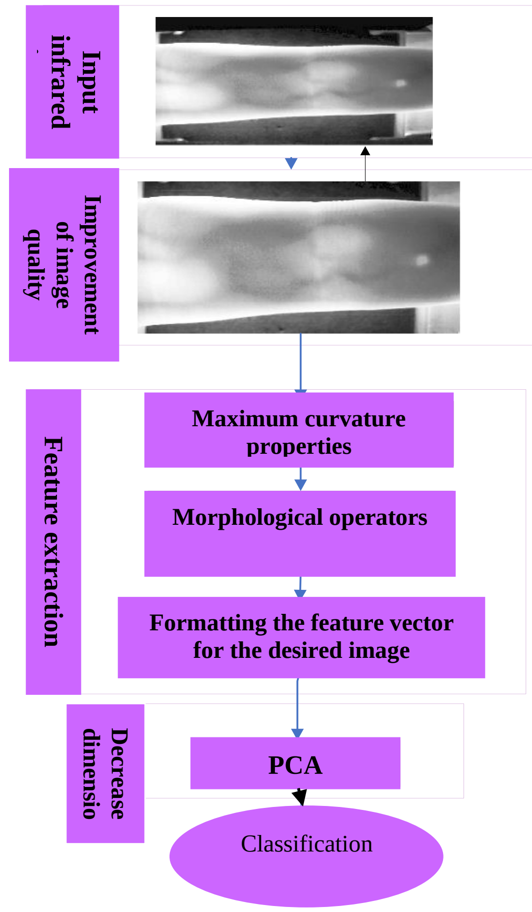


Fig. 4. Complete block diagram of the proposed method extraction and feature extraction.

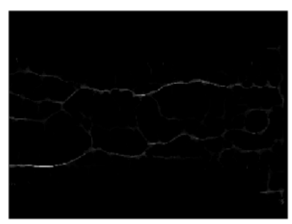


Fig. 5. Feature map generated from the maximum curvature transformation.

3.2. 2 Directional Morphological Filtering

This step is considered very important and vital because after the median filtering, there are still some noisy pixels without status. The binary image is processed using a loading process with a linear structural element in five modes and 5 directions: 0 °, 30 °, 60 °, 120 ° and 150 °. In the linear structural element, the length of M pixels will also be selected accordingly. In order to extract linear structures, the output image of OR of these 5 images will be logical.

3.3. Dimension Reduction

The principal component analysis algorithm is used to improve the feature vectors quantitatively and qualitatively. In mathematical definition, this algorithm is an orthogonal linear transformation that transfers data to a new coordinate system, so that the largest variance of the data is on the first coordinate axis and the second largest variance is on the second coordinate axis and this procedure will continue to analyze all data [36]. Given that the feature descriptors used in this study are of three different types, it is common to generate a large amount of features for each image. However, it should be noted that many of the features produced, do not contain useful and distinguishing information to determine the type of image, so after extracting the feature from the image, for each image, using the principal component analysis algorithm, a feature selection step is performed on the generated feature vectors to reduce the length of the feature vectors and the computational and time complexity in the classification stage.

3.3. Classification

At this stage, two large families of classifiers called backup vector machine and k-nearest neighbors are used. The database of images used is divided into two categories: training and testing. 70% of these images will be used for training and 30% for testing. The desired features will be extracted for each of the relevant images. The features extracted from the training images and the corresponding label for each image will be entered into each category for training, and finally the categories will be trained. It will then be evaluated with one-time test images with the support vector machine classifier, then with the k-nearest neighbor classifier. And finally the person will be identified.

4. EVALUATION OF THE PROPOSED METHOD

The aim of this study is to present a new method for identification using infrared images of fingerprint veins. In recent years, there have been many studies on improving the rate of classification and identification, but in these methods, the identification rate is far from the ideal result. In this study, generating vectors from two-edged descriptors as well as the enhanced maximum curvature with morphological operators, these vectors are combined with each other and the final vector is produced for each fingerprint image. Regarding descriptors, it should be noted that the ideal images are based on veins and edges, and descriptors used for images containing edges should be used. The proposed method will be evaluated below.

4.1. Dimension Reduction

The statistical population used in this research is a database of polyU finger veins, which with the help of the supervisor during the writing of the proposal, official correspondence was done with the author and the database has been received. The database specifications are shown in Table 1.

Table 1. Specifications of the databases used.

	Database	
	TID Database	VERA Database
No. of subjects	110	100
Number of still images per subject (2 hand)	4	18
Distance	Stable	Stable
Resolution	250×665	320×240
ROI Resolution	150×565	160×270
Format	PNG	bmp

4.2. Evaluation Criteria

In this section, the research evaluation criteria, including the criteria of precision and confidence intervals, are introduced. Precision is how many of the selected samples are correct and accuracy is how many of the available correct samples are selected. The relationship between accuracy and precision calculation is given in Table 2.

$$precision = PPV = \frac{TP}{TP + FN} \quad (3)$$

$$Acc = \frac{TP + TN}{P + N} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Regarding equations 3 and 4, TP is true positive, TN is true negative, FP is false positive, and FN is false negative. A range of acceptable values for estimation provides the unknown population parameter. Confidence interval is one of the useful criteria for evaluating the reliability of results. Less confidence interval shows the high accuracy and stability of the proposed method against data change. To calculate the confidence interval criterion, the proposed method is performed ten times with random data. Ten outputs will be calculated as the identification accuracy. Equation 5.shows the calculation of the confidence interval.

$$Confidence\,\text{interval} = [x' - z^* \times \frac{\delta}{\sqrt{n}}, x' + z^* \times \frac{\delta}{\sqrt{n}}] \quad (5)$$

In Equation 5, x' is the mean, z^* is the confidence level, n is the number of observations, and δ is the standard deviation .The constant z^* for confidence level is typically 90% for 1.645, 95% for 1.96, and 99%.for 2.576.

4.3. Evaluation of the Proposed Method

Given that the four stages of preprocessing, zoning, normalization, and classification are common to all identification methods, the proposed method, by achieving higher identification accuracy than the previous methods, has definitely shown that combining descriptors and integrating features from each descriptor can achieve much better results than using only one descriptor. Furthermore, all values in the identification accuracy results are calculated by averaging the results of ten-time implementation of the simulation code so as to calculate the confidence interval for each method in order to evaluate the dependence of the evaluated method on the type of test and training arrangement. After evaluating the results of the proposed method, it is important to note that the desired features on the backup vector machine classifier have a much better result than the k-nearest neighbor classifier.

Table 2. Evaluation the proposed method accuracy by two support vector machine classifiers and K-nearest neighbor.

Accuracy (Support vector machine)	Accuracy (K-nearest neighbor)	Database
97.5%	90%	TID Database
94%	76%	VERA Database

Table 3, compares the accuracy of the proposed method with both the features used and the basic method using the maximum curvature descriptor individually on the both k-nearest neighbor and the support vector machine classifiers. In this table, the features of edge descriptors, maximum curvature as well as morphological operators in the proposed method have a much better result than the use of a descriptor in the base method by the SVM classifier.

Table 3. Evaluation of the accuracy of fingerprint veins identification of the proposed method and the basic method on the databases.

Method	Database	KNN	SVM
Proposed method	TID	90.5%	97.5%
	VERA	76%	54.5%
Basic method	TID	91%	92%
	VERA	89 %	94.5%

In the proposed method, the accuracy of fingerprint veins identification is evaluated and calculated by combining the features of maximum curvature descriptors and morphological and edge operators on the both k-nearest neighbors and the support vector machine. The results of this evaluation are shown in Tables 4 and 5. It is clear that fingerprint veins identification in the TID database has better identification accuracy than the VERA database.

Table 4. Evaluation of the identification accuracy of the proposed method.

Database	SVM	KNN
TID	98%	91%
VERA	100%	71%

Table 5. Evaluation of the identification accuracy of the basic method.

Database	SVM	KNN
TID	100%	91%
VERA	100%	92%

In the following, the confidence level and accuracy of the proposed method and the basic method are evaluated. The confidence interval along with the mean and standard deviation of the proposed method is calculated and compared on the k-nearest neighbor and support vector machine classifiers, which are shown in Table 6 and Table 7

Table 6. Evaluation of the proposed method confidence level.

Confidence interval	Standard deviation	average	Classifier type	Database	Method
[55.86,34.89]	95.1	95.87	KNN	TID	Proposed Method
[82.95,17.97]	94.0	05.96	SVM		
[39.80,70.75]	27.3	05.78	KNN	VERA	
[02.54,87.54]	59.0	45.54	SVM		

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Table 7. Evaluation of the basic method confidence level.

Confidence interval	Standard deviation	average	Classifier type	Database	Method
[13.91,16.93]	41.1	15.92	KNN	TID	Basic Method
[97.69,12.72]	49.1	05.71	SVM		
[23.86,96.88]	91.1	06.87	KNN	VERA	
[52.62,27.67]	32.3	9.64	SVM		

Moreover, the accuracy of the proposed method is compared with the basic method using the maximum curvature descriptor and the SVM classifier. As shown in Tables 6 and 7, using a combination of two descriptors in classifying identity is much better than using a single descriptor. The result of this comparison shows that the proposed method with 97.5% accuracy has the highest classification accuracy compared to the methods presented in [35].

4.4. Comparison with Other Articles

To further evaluate the proposed method based on morphological operators and maximum curvature as well as vein edge detection methods, this method is compared with the methods presented in [24] and [25]. In these articles only precision is presented and this comparison is made in terms of precision. Table 8 shows these results. The superiority of the proposed method is also evident. The reason of superiority of the proposed method is the use of appropriate features, efficient classifications as well as the appropriate integration law.

Table 8. Comparison of the proposed method precision with other methods.

Method	Precision rate
Method in Reference [37]	01.96%
Method in Reference [38]	18.95%
Proposed method	50.97%

4.4. Runtime Comparison

Table 9. shows the comparison of the proposed method with the articles in terms of time. This table shows that the proposed method takes less time for implementing.

Table 9. Comparison of identification time of the proposed method with other articles.

Method	Identification time
Method in Reference [35]	51.1
Method in Reference [37]	69.1
Method in Reference [38]	11.1
Proposed method	95.0

5. CONCLUSION

In this article, a new method of identification in fingerprint biometrics based on morphological operators and the maximum curvature algorithm is presented. The identification system proposed in this study, the same as many methods of identification, consists of four main parts: preprocessing, feature extraction, dimension reduction, and identification. In the proposed method, after pre-processing and improving the quality of the existing images, the relevant properties are extracted with the help of the maximum curvature and edge descriptor as well as morphological operators, and they are classified by SVM and KNN after dimension reduction by principal component analysis. The comparison of the proposed method with the basic method is based on datasets (VERA -TID). Considering the obtained results, it can be concluded that the proposed method using the characteristics of maximum curvature descriptors and morphological operators on the SVM classifier with 97.5% accuracy has better identification accuracy than the basic method using the single maximum curvature on the SVM classifier. Therefore it proves that the use of enhanced maximum curvature with morphological operators has better results than the use of a single descriptor in identification.

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