

EigenNail for Finger Force Direction Recognition

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Abstract—This paper presents a technique termed EigenNails to classify fingertip force during contact based on the coloration patterns in the fingernail and surrounding skin. Fingertip force is classified into six directions: no force, normal force only, two directions (left/right) of lateral shear force, and two directions (forward/backward) of longitudinal shear forces. Based on the face recognition technique Eigenfaces, a small number of EigenNails are sufficient to express the color pattern features for shear force direction classification. Results show that 98% of 960 fingernail images of 8 different subjects are correctly classified. The lowest imaging resolution without sacrificing classification accuracy is found to be 10-by-10.

I. INTRODUCTION

Coloration changes in fingernails have been shown to be useful for measurement of fingertip forces [6]. Due to the interaction between the fingernail, bone, and tissue, the blood pools under the fingernail are affected by the pressure at the fingerpad. The blood pools create color patterns in the nail and surrounding skin that provide a surprisingly good transduction of fingerpad force [7]. Shear forces as well as normal forces can be measured, although there is coupling between them [8].

To measure the color change in the fingernail, Mascaró and Asada [6] developed a *photoplethysmograph sensor*, comprised of an array of 6 LEDs to illuminate the fingernail and an array of 8 photodetectors to measure the coloration. These components were embedded in epoxy, which was shaped to an individual's fingernail and attached for close fit and controlled lighting environment. A strength of this design is portability. With a linear model, the sensor predicted normal force to within 1 N accuracy in the range of 2 N and shear force to within 0.5 N accuracy in the range of 3 N. Considering that the photodetectors are located close to the surface of the fingernail and there are a limited number of photodetectors, to fully measure these color patterns, the locations of the photodetectors are critical. Human factors such as differences in fingernail size, in the underlying biomechanical structures of the fingertip, and in blood circulation dynamics make it difficult to design a sensor with fixed photodetectors to best suit all fingernails for force measurement.

In previous work [10], [11], we used instead a high resolution video camera to image the full back of the fingertip.

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A detailed analysis of the static and dynamic color response of each pixel (0.04-by-0.04 mm area) in the fingernail was carried out for all regions of the fingernail and surrounding skin. The complex color response was characterized by a Bayesian model trained for each individual. The result was that the normal and shear force on fingertip could be estimated in isolation with around 0.3 N accuracy and 6 N measurement range.

The previous studies also provided some characterization of the coloration patterns for different directions of shear force. [7] displayed and thresholded the average fingernail color patterns for 16 subjects to show the different color patterns for different force and finger postures. [9] showed that after cropping and normalization according to the length and width of the fingernail, the fingernail coloration patterns under various force conditions (no force; normal force = -3; longitudinal shear forces = ± 2 N; lateral shear force = +2 N) are different in a statistically significant sense and common to all people. [10] quantitatively showed that different areas in the fingernail respond differently. Some areas respond well to all components of force, other areas are unique to a force component, particularly for lateral shear where skin areas are strongly involved.

Identifying the coloration patterns in the fingernail and surrounding skin, related to the directions of the shear force on the fingertip, is a pattern recognition problem. Since the coloration patterns are complex and high dimensional, it is quite difficult to apply traditional recognition methods to decide on the direction of shear force. A similar problem is encountered in face recognition. [13], [14] presented a method called Eigenfaces that has been successfully used in face recognition. Face images are decomposed into a small number of characteristic feature images, which are the eigenvectors (principal components) of the training face images, called Eigenfaces. An image is projected into the subspace spanned by the Eigenfaces. In the subspace of the Eigenfaces, the classification can be made by comparing the distance from the projection of the new image to the projections of the known faces.

Using the same idea, we decompose fingernail images into a small number of eigenimages, which we call them EigenNails. The coloration pattern of a new fingernail image is recognized in the EigenNail space. The EigenNails, which are the characteristic features of the training images with different color patterns, represent the response feature areas in the fingernail and surrounding skin.

In the remainder of this paper, after presenting the EigenNail method, we present experiments that show a very high accuracy of classification with very few training images. We

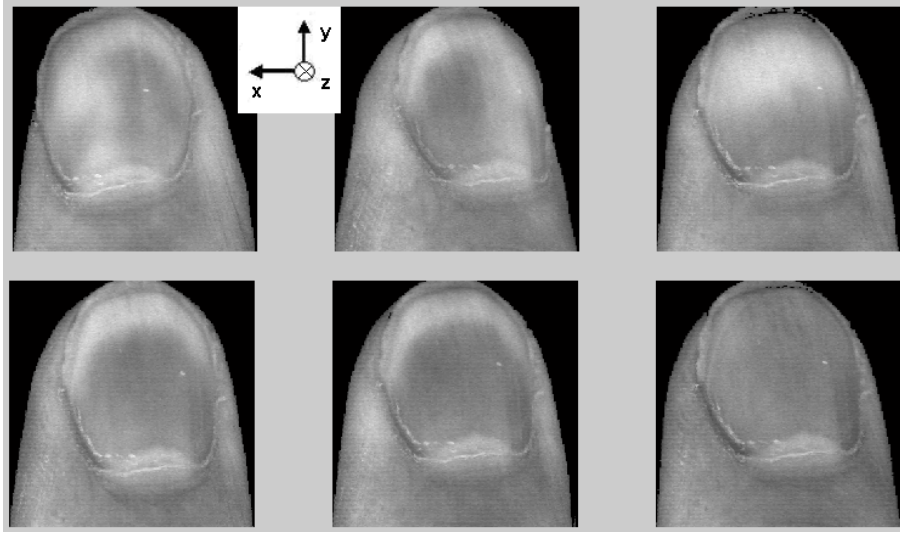


Fig. 1. Fingernail images with different directions of force on the fingertip. The top row are $+F_x$, $-F_x$ and $+F_y$. The bottom row are $-F_y$, F_z , and zero force.

also determine the minimum image resolutions required for accurate classification.

II. EIGENAIL

From our previous study, we found that there are areas having significant color changes in the fingernail corresponding to the force direction changes on the fingertip. If we view each image as a point in a very high dimensional space, the significant color changes cause data scattering in the space. Using principal component analysis (PCA) to obtain primary directions of the scatter, we drastically reduce the dimensions of the space by using just a few principal components to represent the color changes.

A. Calculating EigenNail

Suppose a fingernail and surrounding skin are imaged by an N -by- N photo sensor array. For each image I , the N^2 area of intensity values can be reshaped into an N^2 dimensional vector. For example, a 300-by-300 image has 90,000 dimensions, and so the the image space is a 90,000 dimensional space. Images with different color patterns are a set of points in space $\mathbf{R}^{N \times N}$. The principal components or eigenvectors of the data set in the space $\mathbf{R}^{N \times N}$ are orthogonal vectors representing the distribution of the image data [5].

Let the training set of fingernail images be $\mathbf{I}_1, \mathbf{I}_2, \dots, \mathbf{I}_M$. The mean and covariance matrix of the images are

$$\bar{\mathbf{I}} = \frac{1}{M} \sum_{i=1}^M \mathbf{I}_i \quad (1)$$

$$\Sigma = \frac{1}{M} \sum_{i=1}^M (\mathbf{I}_i - \bar{\mathbf{I}})(\mathbf{I}_i - \bar{\mathbf{I}})^T \quad (2)$$

We can write $\Sigma = \mathbf{A}\mathbf{A}^T$. Since Σ is a $N^2 \times N^2$ matrix, it is computationally infeasible to find its eigenvectors.

Fortunately, [13] has proved that if \mathbf{v}_i is an eigenvector of $\mathbf{A}^T\mathbf{A}$, then $\mathbf{A}\mathbf{v}_i$ is an eigenvector of $\Sigma = \mathbf{A}\mathbf{A}^T$.

The following is the procedure to calculate the EigenNails relative to different directions of force for one subject's fingernail.

- 1) Take images of the fingernail and surrounding skin for 6 known force directions on the fingertip: no force, normal force F_z only, 2 lateral shear force directions $\pm F_x$, and 2 longitudinal shear force directions $\pm F_y$. The force level on each direction is around 2-3 N. For the shear force, subjects apply approximately a 2-3 N normal force to prevent slip. There are 10 images of each force direction, and so the size of the training data set is $M = 60$.
- 2) Preprocess the images to size 300-by-300 (discussed later), using the green color channel from the camera. The green color channel has previously been found to be better than the red or blue channels. Each image is reshaped to a 1-by-90,000 vector \mathbf{I}_i .
- 3) Calculate the 60 by 60 matrix $\mathbf{A}^T\mathbf{A}$ and its eigenvectors \mathbf{v}_i with singular value decomposition (SVD) [5].

$$\mathbf{A} = [\mathbf{I}_1 - \bar{\mathbf{I}} \quad \mathbf{I}_2 - \bar{\mathbf{I}} \quad \dots \quad \mathbf{I}_M - \bar{\mathbf{I}}],$$

where $\bar{\mathbf{I}}$ is the average of all images.

- 4) Calculate the eigenvectors $\mathbf{A}\mathbf{v}_i$ of the covariance matrix $\Sigma = \mathbf{A}\mathbf{A}^T$. These eigenvectors are the EigenNails.

With a high resolution (1024-by-768) color video camera (Flea camera from Point Grey Research), we have collected 10 images for each of the 6 force directions for 8 subjects. All the auto adjustment functions of the camera were turned off to make sure the internal condition of the camera does not change over images. All images are taken in a controlled lighting environment.

Figure 1 shows one image for each training group of a typical subject. Figure 2 shows the top 20 EigenNails from

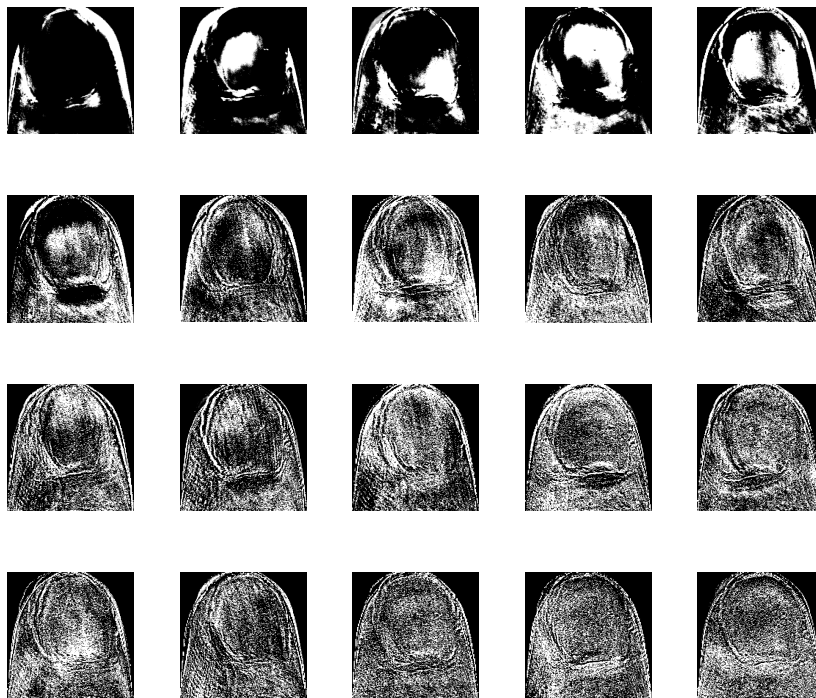


Fig. 2. Top 20 EigenNails

the 60 training images.

There are several strategies to select the most adequate set of principal components from training data space. We used the well-known “knee” method, which examines the plot of the descending ordered normalized eigenvalues and then searches for the “knee” where the values fall sharply. Defining λ_i as the eigenvalue corresponding to eigenvector $\mathbf{A}\mathbf{v}_i$, the normalized eigenvalues are calculated as $\lambda_i / \sum_{i=1}^M \lambda_i$. Figure 3 shows that the knee is at 5. The first 5 eigenvectors captures the major features of the color patterns due to different directions of force on the fingertip. It is consistent with the look of the EigenNails. The first five EigenNails highlight the areas with clear color patterns relative to force directions. The areas are also consistent with the good linear response areas to different directions of force found in [10].

Figure 4 shows an original fingernail image and its projections onto the subspace constructed by 5 EigenNails. We can see that the projection onto the EigenNails space keeps the major color patterns of the original image.

B. Recognizing Force Directions

The hope is that the training images \mathbf{I} will cluster into six different regions of the image space, corresponding to the 6 force directions. For classification of a new image, the task then is to see if the image is close to one of the six clusters.

Rather than attempt this classification in the high-dimensional space $\mathbf{R}^{N \times N}$, the EigenNails method reduces the image space dimension to a small number r , based on the number of principal components selected. Each training

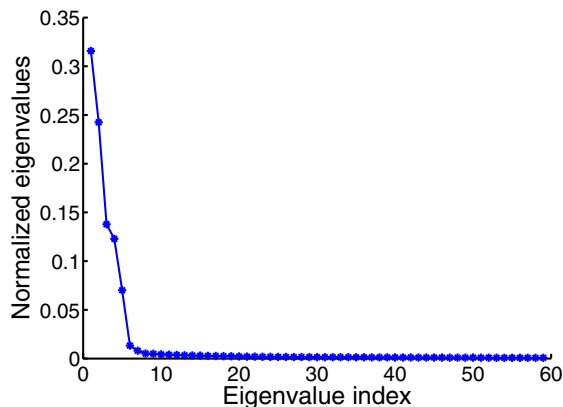


Fig. 3. Normalized eigenvalues

image is projected to the r -dimensional EigenNail space as a point $\mathbf{P}^T = [p_1 \cdots p_i \cdots p_r]$, where p_i is the projection value on EigenNail i . The EigenNail images in the same group form one cluster. The L_2 norm distances (Euclidean metric) between its projection and the centroids of all 6 clusters are used for classification.

To demonstrate the process, Figure 5 shows 6 clusters using just two EigenNails; the 6 clusters are quite well separated. The subject produced a new image by exerting force in the $+F_y$ direction. The projection of this new fingernail image into the 2D EigenNail space clearly shows

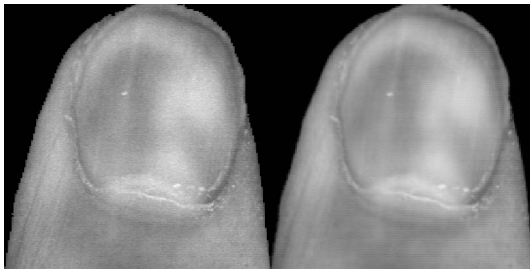


Fig. 4. An original fingernail image and its projection on the space spanned by 5 EigenNails.

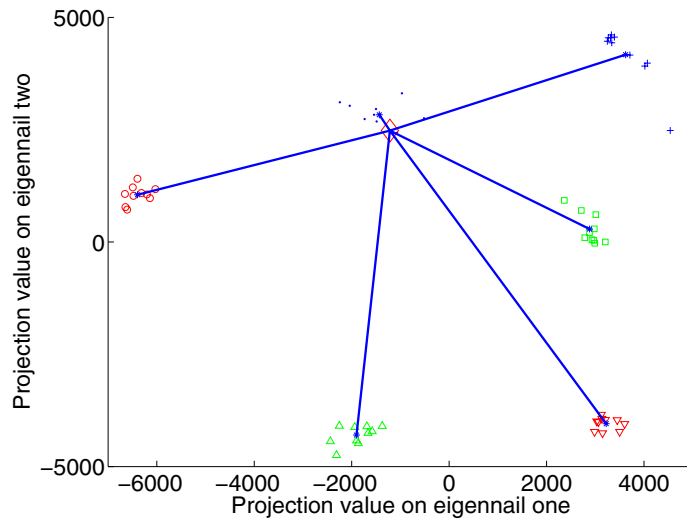


Fig. 5. Six clusters represent the lateral shear force directions $+F_x$ (\circ 's) and $-F_x$ (\triangle 's), the longitudinal shear force directions $+F_y$ (\cdot 's) and $-F_y$ (∇), normal force F_z only (\square 's), and no force ($+$'s). The centroids are indicated by '*'. The projection of a new image is marked as ' \diamond '. The distances between the new image point to the centroids of each cluster are shown. The shortest distance is the one to the centroid of $+F_y$ cluster.

that this image belongs to the $+F_y$ cluster as it should.

Figure 6 shows the recognition accuracy with different numbers of EigenNails. There are 10 fingernail images for each group used as training data. The recognition accuracy is calculated based on 20 new fingernail images for each group. The result shows that the EigenNail method works well when the number of EigenNails is equal to or larger than 2 and works perfectly when the number is equal to or larger than 5.

Running the EigenNail method for all 8 subjects, Table I lists the subject index, skin color, sex, EigenNail number, and accuracy. 5 out of 8 subjects have 100% recognition accuracy. The average recognition accuracy is 98.1%. The minimum EigenNail numbers for best recognition accuracy are from 2 to 6. The EigenNails can efficiently characterize and distinguish the color patterns for different directions of force. According to our experimental results, there is no evidence that the sex or race plays a role in force direction recognition by imaging.

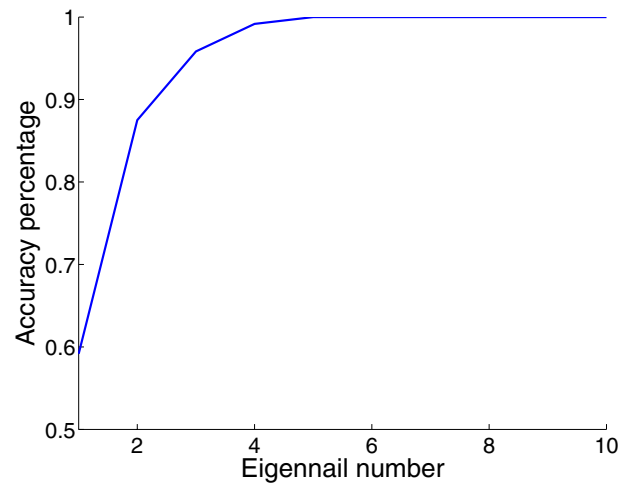


Fig. 6. The accuracy of the recognition increases with the number of EigenNails. There were 60 training images and 120 verification images.

Subject	Skin color	Male/Female	EigenNail number	Accuracy
2	White	M	3	100%
3	White	M	2	100%
4	White	M	5	93%
5	White	M	2	100%
1	Yellow	M	5	100%
6	Yellow	M	5	100%
7	Yellow	F	6	92.3%
8	Black	F	4	100%
Average			4	98.1%

TABLE I

THERE ARE 8 SUBJECTS VARYING IN RACE AND SEX. THE "EIGENNAIL NUMBER" COLUMN LISTS THE MINIMUM EIGENNAIL NUMBERS FOR BEST ACCURACY. THE ACCURACY LISTS THE PERCENTAGE OF CORRECT RECOGNITION FOR 120 NEW FINGERNAIL IMAGES FOR EACH SUBJECT.

III. PREPROCESSING

The EigenNail approach is very sensitive to the fingernail size and its orientation. For example, when the orientation of the fingernail changes 10 degrees, the recognition accuracy decreases to 60%. Preprocessing is very important to correct for orientation and to normalize for size.

The orientation of the fingernail can be obtained by estimating the orientation of the whole finger, located by background subtraction. There are many ways to estimate the orientation of an object in computer vision [12]. For our problem, since as shown in Figure 7, the shape of a finger is symmetrical, the center line of the finger can be obtained by calculating the average of the columns of finger pixels along each row. The orientation of the finger is the orientation of the center line. A typical bilinear image rotation is used for orientation correction.

Assuming there is no tilting or rolling, the size of the fingernail can be normalized according to the width of the undeformed portion of the orientation-corrected finger. After the normalization, a bounding-box is determined for the full back of the fingertip by finding the very front tip and pre-



Fig. 7. The original finger and the finger after orientation correction.

define the length and width.

IV. RESOLUTION

The results show that just a low-dimensional EigenNail space can express the color patterns efficiently. This suggests that a high-resolution camera image is not necessary. To determine what the lowest-resolution camera image might be that still gives good results, the image resolution was gradually increased from 2-by-2 (Figure 8). The result is that the recognition accuracy increases with the resolution until it reaches 100% at 10-by-10.

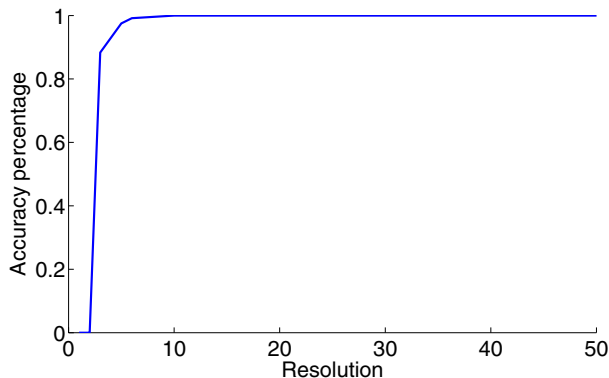


Fig. 8. The relation between the recognition accuracy and the resolution of the fingernail images. The row and column of the images are equal. The x-axis shows the row/column resolution.

Figure 9 shows the top twenty EigenNails when the image size is 10-by-10. The top five EigenNails in Figure 9 contain all the feature areas as the top five EigenNails in Figure 2. 10-by-10 is the lowest resolution that is still sufficient for force direction recognition. This finding holds for all 8 subjects.

V. APPLICATION

The finger imaging force direction recognition technique is potentially useful for human-computer interfaces, by conveniently adding the detection of fingertip force without requiring a force sensor. At the same time that a camera tracks finger position [2], [3], [4], it can also measure contact force.

One example is to use finger tracking to position a mouse icon and the EigenNail technique to detect mouse clicking. Instead of recognizing 6 different directions of force, it only needs to distinguish zero force from normal force F_z .



Fig. 9. The top twenty EigenNails for 10 by 10 fingernail images with 6 different directions of force on the fingertip.

One application of this idea is as a virtual switch panel as illustrated in Figure 10. Fingertip pressing is interpreted as pressing on a virtual panel to control a virtual PUMA robot. This application was tested on several subjects; all were easily able to use this interface to control the virtual robot in real-time. A demo video is included.

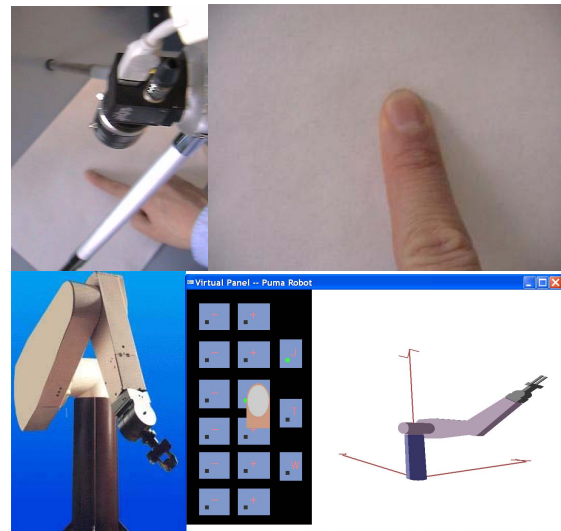


Fig. 10. A camera is used to track the position of a finger and to detect whether the finger is pressing down. The finger input is used to control a virtual robot by a virtual switch panel.

VI. DISCUSSION

The coloration patterns in the fingernail and surrounding skin in response to fingertip force have been studied with principal component analysis. In terms of recognizing six different force directions (left/right lateral shear, front/back longitudinal shear, normal force only, or no force) a highly reduced set of principal components termed EigenNails is

sufficient for high accuracy. For 8 subjects varying in race and sex, the average accuracy is 98%.

This method currently is limited to recognizing 6 discrete color patterns due to orthogonal forces. We found that the color pattern in the fingernail and surrounding skin changes continuously with the changes of force direction on the fingertip. Since the principal component analysis is a linear projection, the continuity property remains in the EigenNail space. In the future, we will further investigate the possibility of using the continuity property and Euclidean distances to centroids to continuously estimate the force direction.

After comparing the EigenNails of 8 different subjects, we found that they are not that different. [9] showed that from a statistical point of view the fingernail coloration patterns are common to all people after normalization. In the future, we will study the data scattering in the EigenNail space for a general population, with a view towards developing a recognition method that can be used for all people without individual training.

The lighting in the experiments was fully controllable to be uniform and consistent. For more general usage, the lighting environment is not controllable. The eigenface method does not work as well for varying illumination. A method called “Fisher linear discriminant analysis” (FLDA) or “Fisherfaces” can tolerate lighting changes [1], at the cost of additional complexity.

An image resolution analysis showed that the lowest resolution fingernail image sufficient for fingertip force direction recognition is 10-by-10. This resolution analysis provides a guide for camera and lens selection, finger positioning, and finger tracking resolution (there is a conflict between the resolution of the fingernail and the resolution of the finger tracking).

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