Finger Force Direction Recognition by Principal Component Analysis of Fingernail Coloration Pattern

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Abstract

A method based on Principal Component Analysis of the fingernail coloration pattern is presented to infer fingertip force direction during planar contact. Images from 7 subjects were registered and normalized to each other. Results show that the fingernail coloration patterns are similar for the 7 subjects, but the feature centroids vary. It is concluded that there are common features for all people. But accurate detection of fingertip force direction requires individually calibrated centroids.

1. Introduction

Due to the interaction between the fingernail, bone, and tissue, the pools of blood under the fingernail are affected by the pressure at the fingerpad during contact with a surface. The blood pools create color patterns in the nail that provide a surprisingly good transduction of fingerpad shear and normal force [8, 9]. To measure the color change in the fingernail, Mascaro and Asada [8] 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. 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.

In previous work [13, 12], we used instead a high resolution video camera to image the full back of the fingertip. 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 results were that the normal and shear force on the fingertip could be estimated in isolation with around 0.3 N accuracy and 6 N measurement range. We have also showed that different areas in the fingernail respond differently [13]. 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.

[11] showed that after cropping and normalization according to the length and width of the fingernail, the average patterns of fingernail coloration corresponding to various states of applied forces were common to all people and distinguishable in a statistically significant sense. The fingernails of fifteen human subjects were imaged for 6 different fingertip force states. At the point of contact, the force vector $F = [F_x \, F_y \, F_z]$ is defined such that F_z is the normal force, F_x is the lateral shear force, and F_y is the longitudinal shear force (positive direction forward). The six force states were: zero force = $[0\ 0\ 0]N$, normal force = $[0\ 0\ -3]$, left shear = $[-2\ 0\ -3]$, right sheer = $[+2\ 0\ -3]$, backward sheer = $[0\ -2\ -3]$, and forward sheer = $[0\ 2\ -3]$. (To produce a shear force without slipping, subjects were asked to produce 3N of normal force.) One image per force state per person was taken. Pixel by pixel correlation showed that all of the images from one force state correlated best to the average image of the true force state with better than 99% confidence, with the exception of normal force and backward shear force which had similar patterns of coloration.

Observations and previous studies all indicate that there are common patterns in the fingernails that are related to force directions on the fingertip. The development of a technique that can successfully identify fingertip force direction by monitoring the color pattern change in the fingernail will reveal a great potential use in human-computer-interaction (HCI).

This paper presents a technique called EigenNails based on Principal Component Analysis (PCA) to extract linear features in the fingernail and use them to identify 6 force directions. The force level for each direction is no longer restricted as in [11]. Instead, subjects are instructed to apply arbitrary force levels as they prefer. To make a comparison

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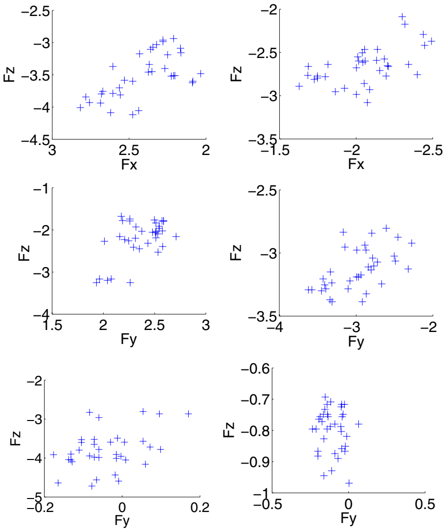


Figure 1. From the top left to bottom right, they are the force readings of F_x, $-F_x$, F_y, $-F_y$, $-F_z$, and F_{zero}.

between images, registrations between images and subjects are carried out.

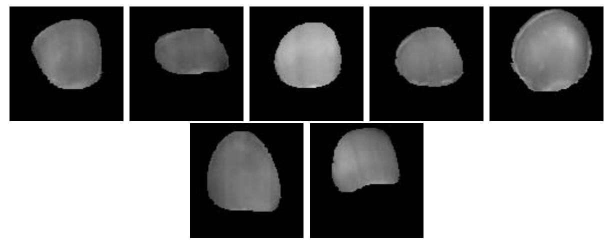
2. Experimental Setup

With a 1024-by-768 color video camera (Flea camera from Point Grey Research), we collected 10 images for each of the 6 force directions for 7 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. A lighting dome [13] was used to provide a consistent uniform lighting condition.

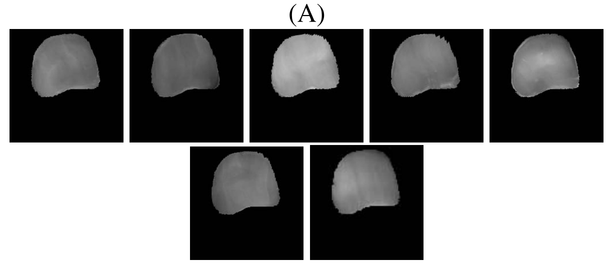
As in [11], this paper focuses on the case where the fingerpad is pressed against a large, uniformly flat surface parallel to the bone of the distal phalanx. As mentioned before and on the contrary of [11], subjects were allowed to apply different levels of shear and normal force according to their comfort. The subjects were given visual feedback about the magnitudes and directions of the fingertip force components using a graphical display as in [13], so that they could hold their chosen force levels. For directional shear forces, the subjects needed to exert some normal forces to prevent sliding. For zero force, the subjects were asked to rest their fingers on the force sensor to yield a small normal force. An example for one subject is shown in Figure 1. Subjects were asked to remove their fingers from the force sensor between recordings.

One zero-force image of each subject is selected to be the reference images. Figure 2 (A) shows the zero-force images after automatic segmentation for all 7 subjects. All the other nail images for each subjects are registered to the reference nail images by means of feature detection [4], feature correlation, the RANSAC algorithm [7], and a 2D homography mapping model [5].

The last nail image on the bottom row in Figure 2 (A) is defined as the standard fingernail. All the normalized images of other subjects are registered to this standard fingernail with an elastic registration model [2, 10]. The registration results of the normalized nails are shown in Figure 2. After the registration, the color pattern features in different images of different nails can be compared.



(A)



(B)

Figure 2. (A)The zero-force nail images for all subjects. (B)The nail images after registration and normalization for all subjects.

3. EigenNail Method

Identifying the coloration patterns in the fingernail in relation to the shear force directions is a pattern recognition problem. Since the coloration patterns are complex and high dimensional, it is difficult to apply traditional recognition methods to decide on the direction of shear force. A similar problem is encountered in face recognition. [14, 15] 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

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projections of the known faces.

Using the same idea, we decompose fingernail images into a small number of eigen images, which we call 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.

For an N-by-N fingernail image, the pixels are recast as an N^2 dimensional vector. For example, a 200-by-200 image leads to a 40,000-dimensional vector space. Images with different color patterns are points in space $\mathbf{R}^{N\times N}$. The principal components or eigenvectors of the data in the space $\mathbf{R}^{N\times N}$ are orthogonal vectors representing the distribution of the image data [6]. Let the training set of fingernail image vectors be $\mathbf{I}_1, \mathbf{I}_2, \cdots, \mathbf{I}_M$. The mean and covariance matrix of the images are

$$\bar{\mathbf{I}} = \frac{1}{M}\sum_{i=1}^{M}\mathbf{I}_i \tag{1}$$

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

We can write $\mathbf{\Sigma} = \mathbf{A}\mathbf{A}^T$. Since $\mathbf{\Sigma}$ is a $N^2 \times N^2$ matrix, it is computationally infeasible to find its eigenvectors. Fortunately, [14] 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 $\mathbf{\Sigma} = \mathbf{A}\mathbf{A}^T$.

To recognize the force direction with fingernail images, 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. There are several strategies to select the most adequate set of principal components from the 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 $\lambda_i / \sum_{i=1}^{M} \lambda_i$.

Each training 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.

4. Results

To fully understand the color pattern in the fingernail for force direction recognition purpose, recognition is carried out in 3 scenarios.

4.1. Common EigenNail and Common centroids

With 420 training images from 6 force directions of 7 subjects, we obtained a set of EigenNails. The top 20 EigenNails are shown in the Figure 3. Since the EigenNails are trained from all subjects, we call them the *common EigenNails*.

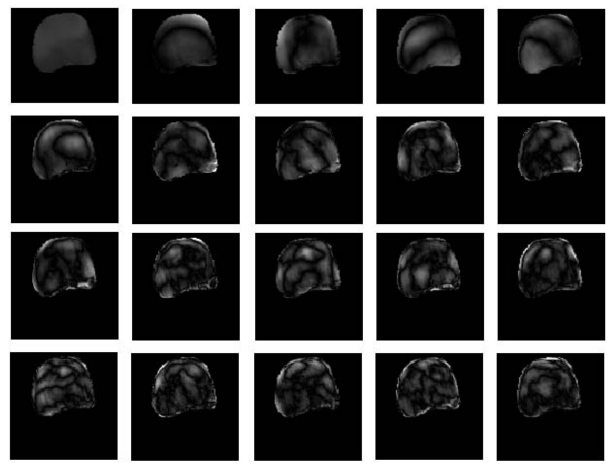

Figure 3. The top 20 common EigenNails for 7 subjects.

The EigenNails are eigenvectors that are the principal components of the distribution of the nail space. The EigenNails put weights on the pixels. The regions that change the most will be given highest weights. Thus the EigenNail images highlight the areas that have the biggest response to the force direction changes. Those areas are the color pattern feature areas. The top EigenNails in Figure 3, except for the first one, highlight the areas consistent with color patterns that we observed in the fingernails. The first EigenNail highlights the whole nail, and indicates that there are big difference between the nails from difference subjects.

Recognition is made in a 10 dimensional space spanned by the EigenNail 2 to EigenNail 11 (we also tried the top 10 EigenNails, but they gave worse results). Each force direction of the data is a cluster. The centroids of the 6 clusters are called the *common centroids*, since they are trained from all subjects. A new image projected to the 10 dimensional space is classified based on the L_2 norm distances to the

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1	2	3	4	5	6	7	Ave
47%	65%	43%	62%	61%	69%	51%	57%

Table 1. The identification accuracies for all 7 subjects and the average.

Index	All	No $-F_y$	Force	All	No $-F_y$
1	77%	95%	x	88%	93%
2	86%	94%	x-	99%	100%
3	79%	98%	y	97%	98%
4	89%	100%	y-	62%	—-
5	77%	96%	z	70%	97%
6	90%	98%	zero	88%	91%
7	91%	99%	—-	—-	—-
Total	84%	96%	**Total**	84%	96%

Table 2. The accuracies when using the *common EigenNails* **and the** *individual centroids***.**

centroids of the 6 clusters. The recognition results for 840 images of 6 force directions of 7 subjects are shown in Table 1. The accuracy of this approach is relatively low, below 70% for all subjects.

4.2. Common EigenNail and Individual Centroids

After we looked into the clusters of different subject, we found that from the training data, if we only look at the clusters of one subject, even with just 2 EigenNails as shown in Figure 4.2(A), the clusters can almost be well separated. But if we look at the clusters of all subjects together as shown in Figure 4.2(B), they are heavily overlapping.

Using the same *common EigenNails* as in 4.1, but using the centroids of each individual subject, we call them *individual centroids*, the new approach is tested on the 840 verification images. The recognition results are shown in Table 2. Comparing with the results in 4.1, the accuracies have been dramatically improved.

For recognition including $-F_y$, the average accuracy is 84%. There are 4 out of 7 subjects with accuracy larger than 85%. The $-F_x$ and F_y directions have 99% and 97% accuracies respectively. The $-F_y$ and F_z have the lowest accuracy and more than 80% of those misclassifications are between them. It is consistent with the observation that the color pattern of $-F_y$ and F_z are similar.

For recognition without considering $-F_y$, the average accuracy goes as high as 96%. All subjects have larger than 94% accuracy. For subject 4, all the force directions are correctly recognized. All force directions are recognized with more than 91% accuracy. All images with $-F_x$ direction have been correctly recognize for all subjects. The result indicates that the features extracted with EigenNails are common to all subjects but the centroids are not.

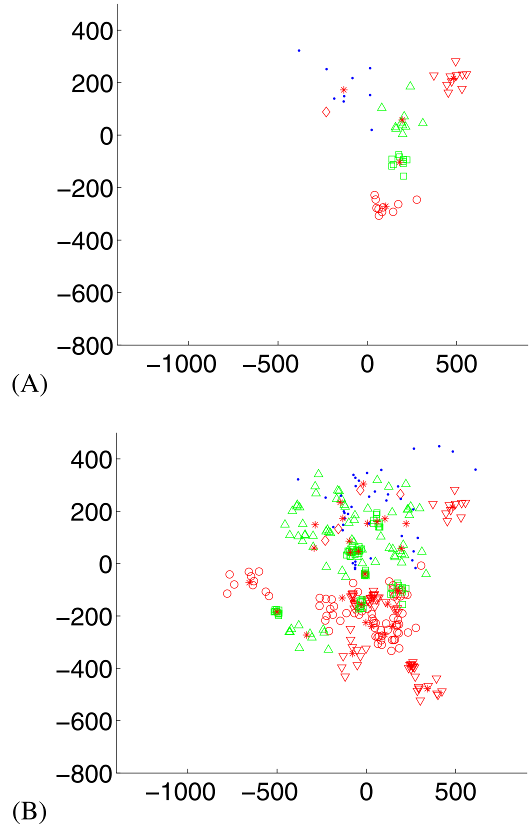

Figure 4. Six clusters represent the lateral shear force directions $+F_x$ (o's) and $-F_x$ ($\triangle$'s), the longitudinal shear force directions $+F_y$ (.'s) and $-F_y$ ($\triangledown$), normal force F_z only ($\square$'s), and no force ($+$'s). The centroids are indicated by '*'. The projection of a new image is marked as '$\diamondsuit$'. (A) The training data of one subject projected onto 2 EigenNails. (B) The training data of all subjects projected onto 2 EigenNails.

4.3. Individual EigenNail and Individual Centroids

We also looked into the differences between the *individual EigenNails* trained from each individual, and the *common EigenNails*. Figure 5 lists the top 6 EigenNails for each subject row by row. We can say that they are not very different.

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Figure 5. The EigenNails trained from each individual. From the top, row i has 6 EigenNails trained from each subject i, $i = 1, \ldots, 7$.

Index	All	No $-F_y$	**Force**	All	No $-F_y$
1	99%	100%	x	90%	94%
2	97%	97%	x-	99%	93%
3	85%	100%	y	96%	100%
4	85%	99%	y-	74%	—-
5	94%	87%	z	94%	99%
6	95%	97%	zero	99%	100%
7	87%	100%	—-	—-	—-
Total	92%	97%	**Total**	92%	97%

Table 3. The force direction recognition accuracies using the EigenNails and the centroids trained from each individual.

Using the 6 *individual EigenNails* and *individual centroids*, the new approach was tested on the 840 verification images. The recognition results are shown in Table 3. Compared to the results in 4.2, the accuracies have been improved somewhat.

With individually trained EigenNails and centroids, the recognition accuracies for all subjects are higher than or equal to 85%. The average accuracy for all subjects and all force directions is 92%. All directions other than $-F_y$ have larger than or equal to 90% accuracy for all subjects. Considering the fact that there are big force level variations in each force direction, the accuracy is reasonably good for use in applications.

4.4. Differences between Fingernails

According to Section 4.2, the common features obtained from the EigenNails can successfully represent the color patterns due to directional forces. The centroids of the clusters vary with individuals due to the differences between fingnails. Figure 6 shows the EigenNail features representing the differences between subjects. They were trained from the zero force images of all 7 subjects. Here the force direction is no longer a variable. The differences are from subjects. We can see that the top EigenNail capturing the difference between subjects is very close to the top EigenNail in Figure 3.

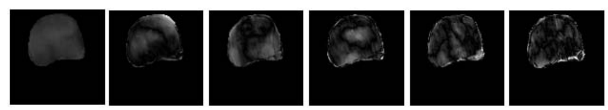

Figure 6. The top 6 EigenNails for 7 subjects at zero force.

Figure 7 shows the clusters of each subjects in a 2D plane spanned by the top 2 EigenNails. We can see that they are very much different.

The differences between subjects are not coming from the environment since the lighting was welled controlled to be exactly the same for all subjects. The auto adjustment functions of the camera were turned off, so that the internal condition of the camera does not change over subjects either. A reasonable explanation is that the differences are from the property of fingernails. The differences can not be simply eliminate with image normalization that is widely used in lighting compensation, since the distributions of the color are more complicated than Gaussian. A simple normalization will not only change the color feature of the fingernails but also disturb the color pattern due to directional force. After we normalized all nail images to a pre-defined mean and deviation, the recognition of the common EigenNail and the common centroids goes down to 52%.

5. Discussion

This paper presented a detailed analysis of recognition of 6 discrete force directions based on EigenNails. The results show that based on a simple classifier, with common

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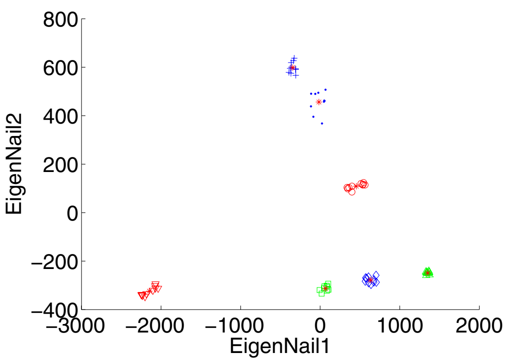

Figure 7. 7 subjects are in o, $\triangle$, ., $\triangledown$, $\square$, $+$ and $\diamondsuit$ respectively. '*'s are the centroids.

EigenNails trained from all 7 subjects and individual feature centroids trained from each individual subject, the EigenNail method is fairly accurate and repeatable even when the force levels are not restricted. With individually trained EigenNails and feature centroids, the average accuracy is even higher. In conjunction with [12] which showed that the dynamic responding is pretty fast, this provides a new HCI technique.

The comparison of the recognition accuracies of 3 scenarios indicates that the spatial features of the color patterns responding to different directions of force are common to all people, but each individual fingernail has its own feature centroids. To have a good recognition rate, the centroids need to be individually trained. The *individual centroids* can be learned for each individuals during use with K-mean [3] with the *common centroids* as initial points.

The study in this paper does not include surrounding skin. [13, 12] have reported that the surrounding skin transduce fingertip force as well as or even better for large force than the fingernail. Including the surrounding skin may increase the recognition accuracy.

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. Further, we will investigate the possibility of integrating this technique with the force estimation in isolation in [13] to predict 3D force continuously.

The lighting in the experiments was fully controllable to be uniform and consistent. For more general usage, the lighting environment is not controllable. The Eigenfaces 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.

Acknowledgments

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