Touch Sensing by Image Analysis of Fingernail

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Abstract: In this paper, we propose a new method to recognize finger contact by image analysis, which does not disturb user's tactile feeling. When a finger touches a desktop surface, the color pattern of its nail changes from pink to white. The appearance change of the nail can be used to distinguish the finger contact onto a desktop surface by image matching between a camera image and a fingertip image database. Due to high dimensionality of the database, we apply EigenNail method based on principal component analysis (PCA) to realize the quick image matching.

Keywords: Nail image, touch sensing

1. INTRODUCTION

In recent years, interactive display has been in widespread use such as *iPhone*[1] and *Microsoft Surface*[2], where intuitive interactions as well as direct operations of a video image are realized. Currently, the contact recognition of the fingertip is implemented on a touch panel. However, the range where a contact recognition is possible is limited onto the surface of the panel. Therefore touch panels cannot be applied to projection-based interactive systems where any surface in a real world can be used as a touch sensitive interactive surface.

In this paper, we propose a method to recognize finger contact based on image analysis, which can be applied to any kind of real surfaces. In this method, the fingertip contact is recognized by using the property that the color pattern of its nail changes from pink to white when it touches a surface. This method does not disturb user's tactile feeling and not limit the range where a contact recognition is possible.

2. RELATED WORK

Many studies which focus on the fingertip contact recognition technique used in projection-based interactive systems have been reported so far.

Rekimoto proposed *SmartSkin*[3] which is based on capacitive sensing. It tracks the position of the user's hands and also calculates the distance from the hands to the surface. It is constructed by laying a mesh of transmitter / receiver electrodes on the surface. However, since it cannot easily cope with the online change of the projection position, the range where the contact can be recognized is limited on the sensed plane.

Cotting et al. proposed a contact position recognition technique[4] where a thin layer of infrared light using infrared laser plane modules covers the projection surface. Whenever a fingertip comes close to the surface and penetrates the laser layer, light is reflected to the camera set behind the surface. From a position of borrowed light in the captured image, contact position is calculated. However, in this system, it is hard to cope with the change of the projection position as well since infrared modules have to be set on the projected surface. In addition, it can be used only in a dark place since the overall accuracy of the recognition process adversely affected by the environment light.

On the contrary to a lot of studies on sensing of a fingertip's pressure on a touch sensor (see references [5, 6] for a state-of-the-art overview of such techniques), Mascaro et al. proposed the technique to detect the change of the nail color pattern with a high definition camera[7]. The force direction of the fingertip in a three directional orthogonal coordinate system is estimated by matching a captured nail image with a database which is a learning set of nail images. When acquiring the nail images, a lighting dome[8] is installed to keep a particular illumination condition. Due to high dimensionality of the database, EigenNail method based on principal component analysis (PCA) is proposed to realize the quick image matching. Since the method can be used without any equipment on the surface but needs only a camera over it, we propose to modify the method to realize a touch sensing on any surface in a real world for a projection-based interactive system where the special light dome cannot be installed.

3. SYSTEM OVERVIEW

The proposed system extracts a fingertip region in an input image where a whole hand is captured, then recognizes its touch on a surface by analyzing the color image of the fingertip (Fig. 1).

The process flow is shown in Fig. 2. At first, flesh colored pixels are detected from the input image, and the mask image is made. Next, fingertip position and direction are calculated from the mask image, and fingertip images are clipped from the input image. The following process is divided into the database construction and the contact recognition. Fingertip images acquired in advance are used to calculate the low dimensional image vectors by PCA, and consequently the database is constructed. The contact recognition is performed through matching of the input fingertip image with the database.

3.1 Acquisition of normalized fingertip image

The hand region is extracted as follows. First, we define the ideal flesh color vector $\boldsymbol{C_I} = (R_I, G_I, B_I)$. Sec-

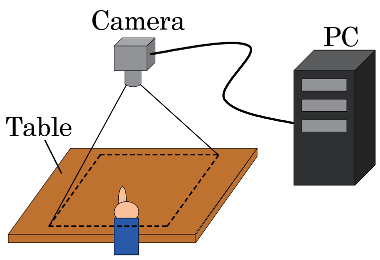


Fig. 1 System overview

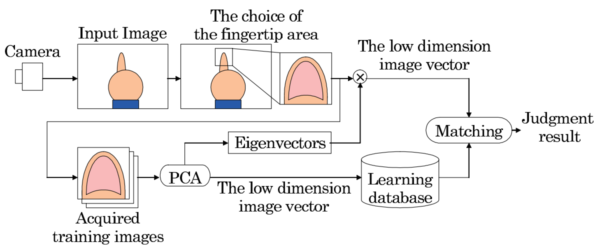


Fig. 2 The flow of the processing

ond, the input RGB color image is raster scanned and the cosine of angle θ between the color vector of a pixel $\boldsymbol{C_x} = (R_x, G_x, B_x)$ and $\boldsymbol{C_I}$ is calculated. And if calculated $\cos\theta$ satisfies the following condition, the pixel is extracted as an flesh colored pixel.

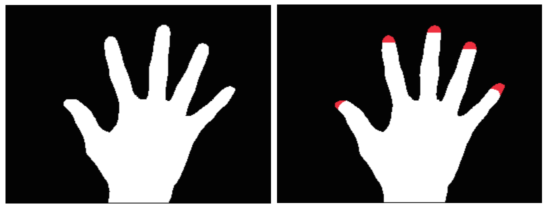
$$\cos\theta = \frac{\boldsymbol{C_I}\boldsymbol{C_x}}{|\boldsymbol{C_I}||\boldsymbol{C_x}|} > \mathrm{T} \tag{1}$$

where T is the threshold and $|\cdot|$ represents Euclid norm. This process is applied to all the pixels in the image to derive the hand mask image (left side of Fig. 3).

The detection of the fingertip position is performed as follows. The mask image is raster scanned. If a pixel (called the focused pixel below) has the flesh color, the number of pixels which have the flesh color in $n \times n$ rectangular region whose center is the focused pixel is counted. If the number is within a particular range defined in advance, the focused pixel is decided as a fingertip (right side of Fig. 3). In this process, it takes huge computation time if the rectangular region is moved pixel by pixel simply. Therefore, by a high-speed calculation method to count the number of the flesh colored pixels in the rectangular region with Integral Image[9], real-time processing is achieved. Finally, the detected fingertip region is labeled and the barycenter of each label is calculated as a fingertip barycenter $BC1_i$. The calculated barycenters are recorded as the fingertip barycenter position.

The fingertip direction is detected as follows (Fig. 4). First, pixels on the arc with radius r around each fingertip barycenter $BC1_i$ are searched for and the barycenter of the flesh colored pixels on the arc is calculated $(BC2_i)$. Second, the intersection points of the arc and the half line which connects both barycenters $BC1_i$ and $BC2_i$ in each fingertip is calculated. Third, if the pixel on this intersecting point has the flesh color, the arc is traced in both directions (clockwise and counterclockwise) from the intersection and two endpoints on the arc which are defined as intersection points of the edges of the flesh colored region and the arc are detected. Fourth, the fingertip direction is defined by the fingertip barycenter $BC1_i$ and the middle point of the endpoints. Even if some flesh colored noise pixels coexist on the arc, the proposed technique robustly detect the right fingertip direction.

Finally, the normalized fingertip images are clipped through these processing, and they are resized into 20×20 pixels.



Hand mask Fingertip position

Fig. 3 Hand mask and fingertip position

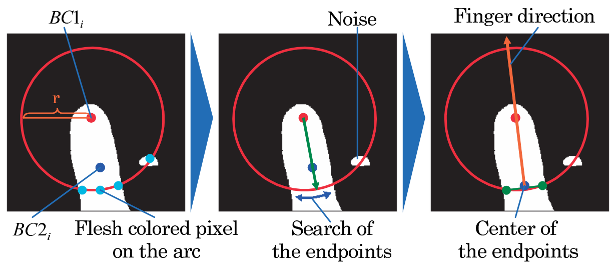


Fig. 4 Acquisition of the fingertip direction

3.2 EigenNail method

The proposed finger contact recognition is performed with EigenNail method[7] which applied Eigenface method[10] in the face image recognition to a nail image. In matching between images, it takes huge computational time when the matching of an input fingertip image and the hundreds of stored images in the database is conducted since the dimension of the database is enormous. Therefore, in EigenNail method, deficit of the information is kept to the minimum by PCA and the pattern matching in the low dimension is performed.

Nail images of $N \times N$ pixels are converted into N^2-dimensional image vectors. M frames of learning sample images are prepared, and the i-th N^2-dimensional image vector is expressed with $\boldsymbol{I_i}$. The difference between each image vector and the mean vector $\bar{\boldsymbol{I}} = \frac{1}{M}\sum_{i=1}^{M} I_i$ is introduced to simplify the following processing. That is $\tilde{\boldsymbol{I}}_{\boldsymbol{i}} = \boldsymbol{I_i} - \bar{\boldsymbol{I}}$. The image database is expressed as matrix $A = [\tilde{\boldsymbol{I}}_{\boldsymbol{1}}, \tilde{\boldsymbol{I}}_{\boldsymbol{2}}, \cdots, \tilde{\boldsymbol{I}}_{\boldsymbol{M}}]$.

M pieces of orthonormal base vectors $\boldsymbol{u_n}$ which are derived from the optimum transformation of the original image data set in terms of mean least square by PCA. The k-th vector $\boldsymbol{u_k}$ is chosen so that

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}({\boldsymbol{u_k}}^T\tilde{\boldsymbol{I}}_{\boldsymbol{n}})^2 \tag{2}$$

is maximized. Here, the orthonormal base vectors satisfy the following formula.

$$\boldsymbol{u_l}^T \boldsymbol{u_k} = \delta_{kl} = \begin{cases} 1 & if\ l = k \\ 0 & otherwise \end{cases} \tag{3}$$

Vector $\boldsymbol{u_k}$ and scalar λ_k are eigenvector and eigenvalue of covariance matrix

$$\Sigma = \frac{1}{M} \sum_{n=1}^{M} \tilde{\boldsymbol{I}}_{\boldsymbol{n}} \tilde{\boldsymbol{I}}_{\boldsymbol{n}}{}^{T} = AA^T \tag{4}$$

of A respectively. $\Sigma = AA^T$ is $N^2 \times N^2$ matrix. Therefore, real-time process becomes impossible if N is large. Because the number of the eigenvectors is $M - 1$ when the number of the learning sample images is smaller than the dimension of the image vector (in other words $M < N^2$), the real-time process is enabled by the following method.

Each eigenvector of $A^T A$ is defined as $\boldsymbol{v_i}$ and its eigenvalue is defined as μ_i.

$$A^T A \boldsymbol{v_i} = \mu_i \boldsymbol{v_i} \tag{5}$$

Then,

$$AA^T A \boldsymbol{v_i} = A \mu_i \boldsymbol{v_i} \tag{6}$$

results in eigenvector of Σ is provided as $\boldsymbol{u_i} = A\boldsymbol{v_i}$. Therefore the calculation of the $N^2 \times N^2$ dimension is reduced to the $M \times M$ dimension.

The eigenvectors and eigenvalues are sorted in order of decreasing eigenvalue and the top L eigenvectors are selected as basis vectors $U = [\boldsymbol{u_1}, \boldsymbol{u_2}, \cdots, \boldsymbol{u_L}]$. Then the image vector $\hat{\boldsymbol{I}}$ in the eigenspace is expressed in

$$\hat{\boldsymbol{I}}_{\boldsymbol{n}} = U^T \tilde{\boldsymbol{I}}_{\boldsymbol{n}} \tag{7}$$

and the image vector of N^2 dimension can be approximated with L dimension. It is empirically decided to adopt the eigenvectors till cumulative proportion exceed 90%, and L is derived.

In the contact recognition processing, Nearest Neighbor matching method (NN matching method) is applied to captured fingertip image and the learning database, and the recognition result is output. In calculation of the distance in NN matching method, Euclid norm is adopted.

4. EXPERIMENTS

4.1 Experimental setup

In this section, we present the system described in Section 3 and clarify the effectiveness of our technique through the experiments. The devices used in the experiments are as follows.

PC: DELL PRECISION 530 (OS: Microsoft Windows 2000, CPU: Intel XEON 2.20GHz), **Camera**: SONY EVI-G20 (Effective pixels: 38 million pixels, RGB 8bit), **Capacitance type pressure sensor**: NITTA PD3-32, **AD converter**: TURTLE TUSB-1612ADSM.

The camera is installed in the position that can capture a finger pushing the pressure sensor without occlusion (Fig. 5). The flat aluminum board of 2.0 [cm] square is fixed in the upper part of the pressure sensor. Therefore fingertip images pushing the plane surface can be captured.

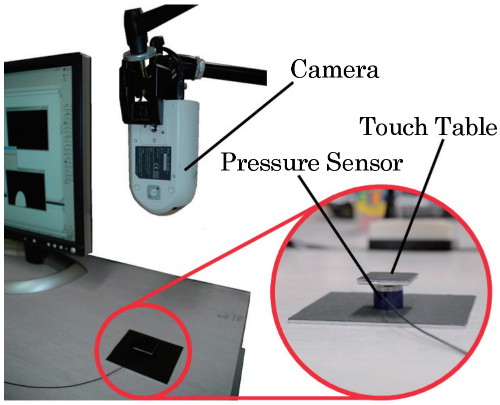


Fig. 5 Outlook of experimental system

4.2 Experiments of contact and force direction recognition

The experiments include not only the simple contact recognition but also the force direction recognition where the color pattern change of the fingertip caused by the direction of the force added at a fingertip. In addition, the experiments analyze the difference of the individual color pattern of the fingertip of the right hand forefinger image of 5 subjects.

The data used in the experiments include six state of noncontact / fore / back / right / left / down. The finger force direction and the examples of the difference of the fingertip color patterns are shown in Fig. 6 and Fig. 7 respectively.

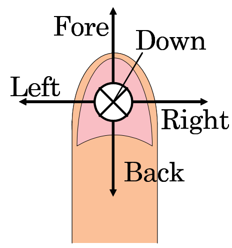


Fig. 6 Setting of the finger force direction

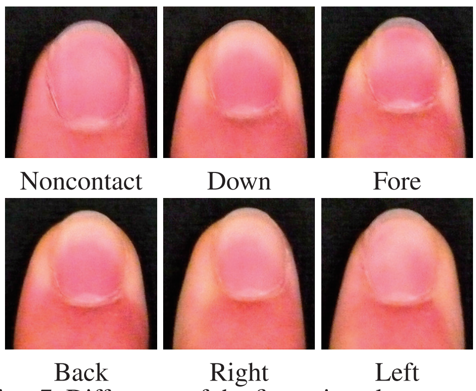


Fig. 7 Difference of the fingertip color patterns

Each 100 fingertip images of six states of each subject are sampled for the learning database. All the images are normalized and resized into 20×20 pixels. In Eigen-

Nail method and analysis of the recognition rate, only R-channel is used from the RGB color image.

First, we apply EigenNail method to the sampled images of each subject to build each learning databases. The result of each subject in EigenNail method is shown in Table 1. Top four eigenimages of each subject are shown in Fig. 8, where the eigenimages of the first principal component of all the subjects look similar but the ones of over the second principal component look different each other. Therefore by comparing these eigenimages, the existence of the interindividual difference of the fingertip color pattern is confirmed.

Table 1 Dimension and cumulative proportion of each subject

Subject	Dimension	Cumulative proportion
1	6	90.5%
2	7	90.6%
3	5	91.8%
4	6	92.2%
5	9	90.7%

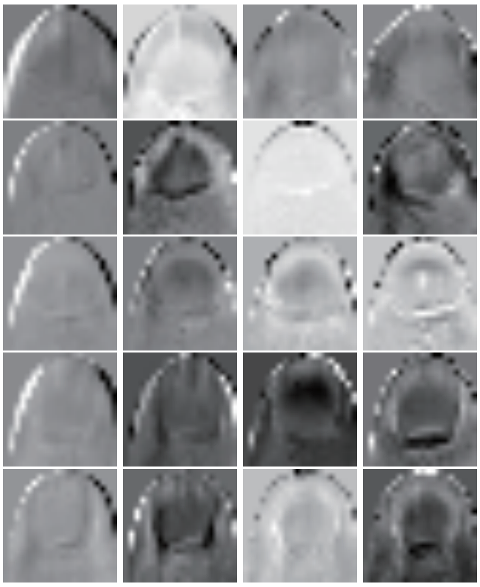


Fig. 8 Eigenimage of each subject

With the learning databases of each subject, the recognition rates are examined. The test images which consist of 100 fingertip images of six states of 5 subjects are acquired under the same environment of the image acquisition for the learning database. NN matching method is applied to the test images and the learning database in the eigenspace, and the recognition rate is measured. The result is shown in Table 2. Because the recognition rate of 100% is observed in all subjects in the case of "Noncontact", contact / noncontact recognition is possible. In addition, the recognition rate of the force direction recognition that the force adds at a fingertip is more than 80%. From the result, it can be said that a high recognition rate is achieved when the matching was conducted between a test fingertip image of a subject and the learning database which consists of the fingertip images of the same subject.

Table 2 Recognition rate of matching with personal DB

Subject	1	2	3	4	5
Noncontact	100%	100%	100%	100%	100%
Down	99%	99%	86%	90%	94%
Fore	100%	93%	92%	100%	100%
Back	98%	92%	91%	97%	92%
Right	100%	97%	100%	100%	99%
Left	100%	100%	100%	98%	100%

Second, we apply EigenNail method to the images of all the subjects to build one learning database. Thereby, the cumulative proportion reached 90.6% with top 15 eigenvectors. The eigenimages corresponding to these eigenvectors are shown in Fig. 9.

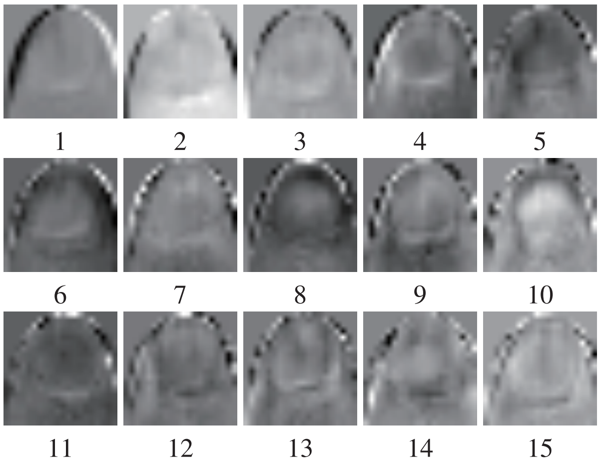


Fig. 9 Eigenimages of all subjects

With the learning databases of all the subjects, the recognition rates are examined. Through the matching of the test images and the learning database, the recognition rate is measured. The result is shown in Table 3. In Table 3, the recognition rate of data of "Fore" of the subject5 is 24%. In comparison with Table 2 (results of the experiment with the learning database including only the data of subject oneself), it shows an extremely low value. In others, there is not the large fall of the recognition rate. In addition, some recognition rates are increased in comparison with Table 2.

Third, we constitute the database with data of 4 subjects except one test subject and examine the recognition rate with the test images of the test subject. The aim of this experiment is to make it clear whether contact / direction recognition is possible when the test data was matched with the learning database which consists of the data of the other people. And we examined the personal difference of the fingertip color pattern.

Table 3 Recognition rate of matching with DB of all

Subject	1	2	3	4	5
Noncontact	100%	100%	100%	100%	100%
Down	99%	100%	72%	98%	94%
Fore	100%	90%	89%	100%	24%
Back	99%	98%	95%	97%	75%
Right	100%	100%	100%	100%	100%
Left	100%	89%	100%	100%	99%

For each subject, EigenNail method is applied to construct each learning database which consists of the fingertip images of the other 4 subjects. Results of EigenNail method for each data are shown in Table 4. Cumulative proportions surpass 90% by adopting 13 dimensions in all cases. In terms of the dimension and the cumulative proportions, the big difference is not seen between each case.

The recognition rate is examined for all the 5 cases. Results are shown in Table 5. In Table 5, there is big unevenness between recognition rates, and they fall remarkably by comparison with Table 3 (results of the experiment with the database including the data of all the subjects).

Table 4 Dimension and cumulative proportion of another subject

Subject	Dimension	Cumulative proportion
2,3,4,5	13	90.6%
1,3,4,5	13	90.3%
1,2,4,5	13	90.1%
1,2,3,5	13	90.3%
1,2,3,4	13	91.0%

Table 5 Recognition rate of matching with DB of another subject

Subject	1	2	3	4	5
Noncontact	100%	3%	100%	0%	1%
Down	35%	0%	0%	0%	70%
Fore	13%	100%	0%	0%	11%
Back	83%	72%	0%	0%	20%
Right	56%	13%	100%	100%	25%
Left	26%	0%	100%	100%	1%

5. DISCUSSION

In Section 4.2, three kinds of experiments of the recognition rate with the learning database of the each subject, of all the subjects and of the combinations of 4 subjects were conducted. The recognition rate of the case where the fingertip images of the same subject are both used as the test input and used in the construction of the learning database was comparatively high. On the other hand, the recognition rates of the other cases ware remarkably low. We consider the cause why such results ware provided by projecting the learning data on the eigenspace.

First, the data of “Down” of 5 subjects are shown in Fig. 10. In Fig. 10, the data are plotted in the graph adopting top two eigenvectors in each axis. The distribution of data of “Down” on the eigenspace varies among subjects greatly. However, the plots of the each subject are gathered and make an obvious cluster respectively.

Second, the data of “Noncontact” of 5 subjects are shown in Fig. 11. In Fig. 11, the projected positions of the data make different clusters according to the subjects. However, a data set of a subject is divided into two clusters. In addition, some data are plotted away from the clusters.

From these results, the existence of the interindividual difference of the fingertip color pattern became clear. Therefore, in the case of the contact recognition with NN matching method, it is thought that it is necessary to incorporate the user’s own data in the learning database. Because NN matching method outputs the nearest data, it is met with the data of another person unless the user’s own data are included in the learning database, and it is very likely that a wrong result is output.

When the user’s own data are included in a learning database, a higher recognition rate is achieved even if the learning database includes the data of another person. In addition, the recognition rate will be improved more if k-Nearest Neighbor matching method (k-NN matching method) is used instead of NN matching method which was used in this experiment.

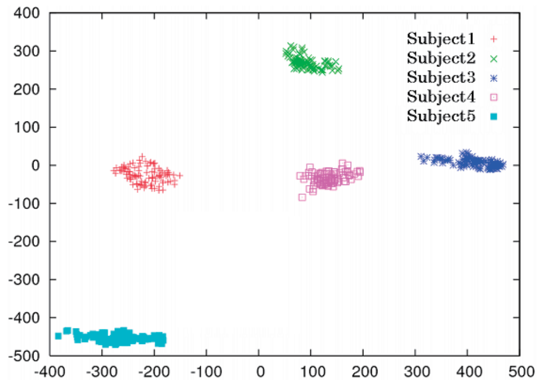


Fig. 10 Clusters representing the data of “Down” in the eigenspace

6. CONCLUSION

In this paper, we proposed the fingertip contact recognition technique which did not disturb user’s tactile feeling by analyzing the color pattern of a fingertip image acquired with a camera. Through the experiments, we measured recognition precision of contact and directional force that a fingertip push horizontally, and confirmed the effectiveness of the proposed technique. At the same

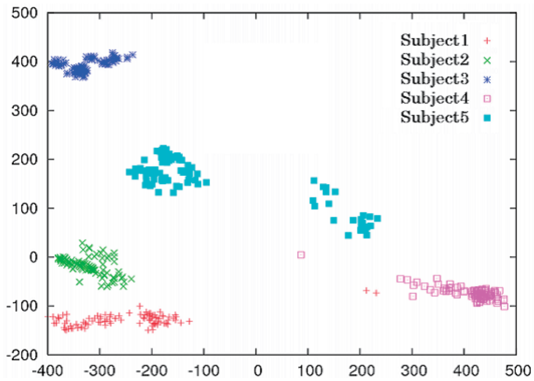


Fig. 11 Clusters representing the data of “Nontouch” in the eigenspace

time, we found that there was the interindividual difference of the fingertip color pattern.

The construction of the system which is not influenced by projected video image, illumination and the interindividual difference of the fingertip color pattern would be our future work. As long as an RGB color image is used for the process, it is very likely that the contact recognition of the fingertip is failed since RGB values of the fingertip greatly change. As a solution of the issue, it is thought that other information is used for matching process instead of RGB color information. The spectral information of hemoglobin of blood flowing a fingertip can replace it. It is confirmed that the hemoglobin has a characteristic absorption spectrum[11]. Therefore quantity of hemoglobin of the fingertip, in other words change of the blood volume, is detected by extracting the specific spectral component from a fingertip, and it is thought that the fingertip contact recognition that does not depend on color information is enabled.

By using the proposed system, it is thought that not only the interaction to the projection type displays but also the interaction to the liquid crystal displays which are not equipped with touch panel is enabled. And from the viewpoint of user interface, application to the mixed reality technology is expected.

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