Journal of Computers Vol. 29 No. 5, 2018, pp. 29-40
doi:10.3966/199115992018102905003

Convex Defect Detection and Density Distribution Based Hand Gesture Recognition

Yanan Xu[1], Yunhai Dai[2*]

[1] Department of Game and Multimedia Engineering, PaiChai University, Daejeon, 35345, South Korea
qustxyn@gmail.com

[2] Department of General education and International Trade, Namseoul University, Chungcheongnam-do, 31020, South Korea
professordai520@nsu.ac.kr

Received 22 May 2017; Revised 07 October 2017; Accepted 30 October 2017

Abstract. Vision based hand gesture recognition takes use of camera to capture image sequence, through image preprocessing and feature analysis to recognize and classify hand gestures, the extraction of features has direct relationship with the purpose and method of recognition. The commonly used hand gesture feature extraction techniques such as HOG (Histogram of Gradient) and image subspace projection, they are not only liable to fail when the background is cluttered but also need the training of a large number of samples, on the basis of former experiences, a new method based on density convex defect detection and density distribution is proposed in this paper, convex defect features and gesture distribution features are integrated to describe the characteristics of hand gesture including fingertips, contour length and area, density distribution and relative distance between fingers. The feasibility of the features proposed are proved by choosing 5 kinds of number gestures with total 500 images as test images for hand gesture recognition experiences, results shows that proposed approach is invariant to rotation, scale and translation, and it is more simple and precise than other similar methods.

Keywords: convex defect detection, density distribution, hand gesture recognition, human-computer interaction

1 Introduction

Hand gesture recognition provides a direct way for the interaction and communication between human and machines. Compared with traditional human-computer interactive mode, such as keyboard, mouse, joystick and wireless input devices [1], vision based static hand gesture recognition does not need any intermediate hardware mediums. And compared with other biological characteristics of human beings that can be used as natural interaction technologies, such as facial expression recognition, face recognition, lip reading recognition, limb movement tracking, eye gaze tracking and pose recognition [2], hand is the most flexible part of human body, it is natural, direct and can express rich and various meaning.

The development of hand gesture recognition is original from hardware based hand gesture recognition to vision based one, hardware based technologies such special data gloves, have the advantages of high accuracy, simple data and fast processing speed, but the equipment is always expensive, inconvenient to operate and not suitable for long-distance control, vision based hand gesture recognition has simple input mode with lower dependence on equipment, it is in line with the daily interaction habit of people and bound to be the pursuit of new human-computer interaction.

For the research on vision based hand gesture recognition, researchers have obtained a lot of achievements [3], such as the Fujitsu laboratory completed the identification of 46 sign languages

* Corresponding Author

symbols in 1991. Davis and Shah [4] used gestures captured from visual gloves with bright marks on the part of fingertips as the input of system, this system can recognize 7 kind of hand gestures. Starner et al. achieved a recognition rate of 99.2% on the recognition of short sentences composed of 40 words with part of speech in American Sign Language. Grobel and Assam extracted features from video, and used HMM to recognize 262 isolated words, the recognition rate reached to 91.3% [5-6]. Also, Vogler and Metaxas [7] applied these two methods to the recognition of American Sign Language, by using a position tracker and three mutually perpendicular cameras as the gesture input device they completed the recognition of 53 isolated words with recognition rate of 89.9%.

Although the research on vision based hand gesture recognition method has made great progress and achieved high recognition rate in different regions it still faces many challenges, there are mainly difficulties in target detection due to the various background and unforeseen environmental factors and difficulties in recognition because hand is an elastic object contains redundant information, the project direction of hand gesture is diverse which can confuse the recognition accuracy, in additional, the non-smooth surface of hand is easy to product shadows. Since these problems have not solved well yet, it always necessary to add some restrictions when doing hand gesture recognition. In order to maximize the reduction of these limitation, this paper proposed a series of new features from both overall and local attitude, that is, to describe the hand gesture shape and detect fingertips from global space, to calculate the relationships between fingers from local space.

2 Vision Based Feature Extraction

Hand gesture is the movements of hands made by people consciously, including the bending and stretching of fingers and rotation of wrist, it is a way to express a signer’s intention. From the view point of hand gesture recognition, hand gesture can be defined as a variety of gestures or movements by hands or arms combined. Vision based hand gesture recognition takes use of the camera to capture image sequence, through image processing and analysis to get further recognition. It aims to explain the high-level implications contained according to the posture and changing process of hand.

The flowchart of vision based hand gesture recognition mainly includes sample capture, image processing, feature extraction and classification four parts [8] as shown in Fig. 1.

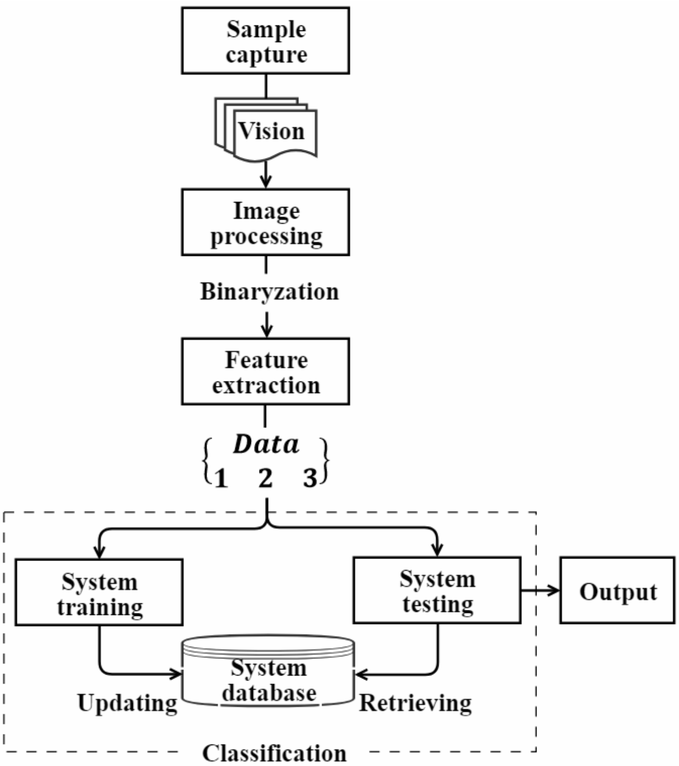


Fig. 1. Convex defects of hand gesture

Sample capture is a process to capture an image such as static gesture or a sequence of images such as dynamic gesture that can be used for processing next, this process is mostly done using a single camera with a frontal view of human hand performing some gestures. The basic aim of image processing is to optimally process the sample image, extract its binary image and prepare for feature extraction. Feature extraction aims to find and extract features that can be used to determine the meaning of a given gesture, features are the most useful information that has close relationship with the accuracy of classification, a feature or a set of features should have the abilities of describing the gesture uniquely and be robust to the shift and rotation of hand gesture in order to achieve the reliable recognition. Classification is the task of assigning the extracted features to some preprocessing images and recognize the definition of the hand gestures contained, it is a process to find the best matching reference features between the test and standard images. Each step has great correction with others, the quality of each step has direct relationship with the final recognition result. This paper mainly focuses on the study of extraction of recognition features.

According to the requirement of hand gesture recognition, the features extracted from the hand image should not only be able to maintain a good non deformation in the same type of gesture, but also can distinguish different types. Various methods can be applied for representing the features that can be extracted, the commonly used features of static hand gestures include: HOG (Histogram of Gradient), image subspace projection, shape features, etc. [9]. Techniques on HOG like have been proposed in the past which employ edge and gradient based descriptors for hand gesture recognition, but they are only able to detect hand gestures in a simple background and are liable to fail when the background is cluttered. Image subspace projection (e.g. PCA, ICA) is a kind of statistical signal processing technique, this method is able to removing the correlation of higher-order statistics and making relatively comprehensive representation of the local features of training sample images. However, the feature invariance of this method is acquired in the training of a large number of samples, that is to say, once the training samples are not able to cover all the position, scale and rotation angle, such method cannot achieve the extraction of invariant features. Shape such as contour, silhouette, fingertips based method has fully considered the invariance of translation, size and rotation in the process of features extraction, so it is the most commonly used feature extraction algorithm for static gestures currently.

3 Convex Defect Feature Extraction

In issues involving human hands such as sign language recognition and gesture recognition, fingertip is one of the most popular characteristics, because the number of fingertips can be considered to be the number of fingers and the direction of fingertips can effectively express the stretch information of fingers. The most commonly used fingertip detection method is contour analysis, such as the edge curvature method [10] and least square ellipse fitting method [11], these methods are much rely on high accuracy of hand gesture segmentation and large amount of computation.

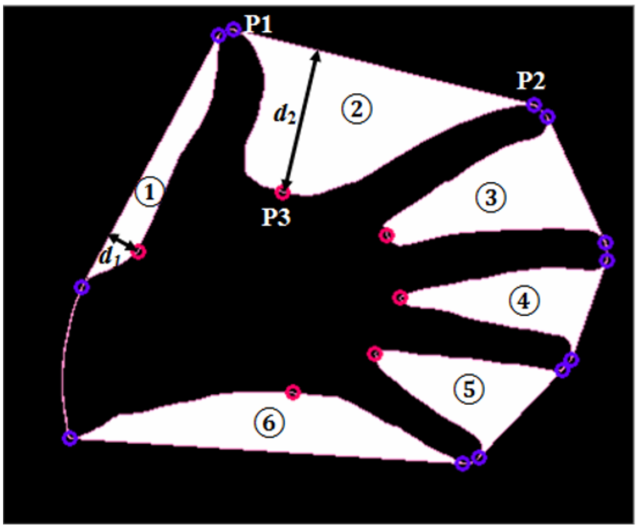


Fig. 2. Convex defects of hand gesture

Convex defect detection is a contour based method for the detection of fingertips, as shown in Fig. 2, the convex defect such as the circle number from one to six gives the set of values in the form of vector: start point P1, end point P2 and concave point P3 with furthest distance named as depth d from convex hull, where, the convex hull refers to the convex polygon surrounded by all convex vertices, Fig. 3 is the extracted convex hull of Fig. 2. It shows that the fingertip is closely related to the convex defect, which is close to the start and end contour points of convex defect.

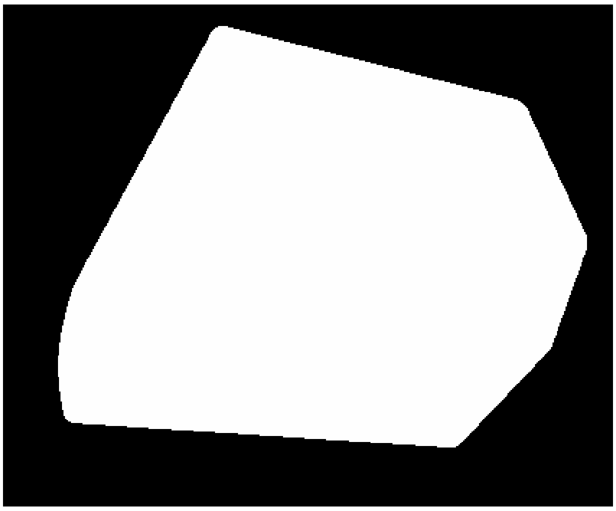


Fig. 3. Convex hull of hand gesture

The count and position of fingertips can be determined as following:

(1) Remove convex defects that cannot meet the requirement using fixed threshold, the normalized depth d cannot be too small and too bigger, according to the biological structure of human hand, it is appropriate to set its range as:

$$d \in [1/5, 1/2] \times contour\ Height. \qquad \textbf{(1)}$$

The height of gesture contour is defined as the length of rectangle formed by points composed of the minimum and maximum x, y coordinate values as shown in Fig. 4, so for Fig. 2, d_2 is the depth meets the requirement while d_1 is not.

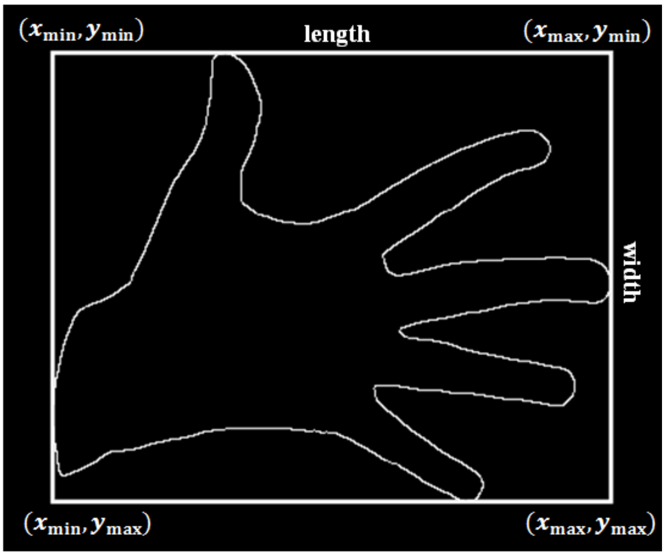


Fig. 4. Definition of gesture contour height

(2) Take the start point of the first convex defect as the first fingertip, and the end point of the last convex defect as the last fingertip respectively.

(3) The position of fingertips except the first and last fingertip can be calculated by the average of end point of current and start point of next convex defect as:

$$(end\ Point_{current} + start\ Poing_{next})/2. \quad \textbf{(2)}$$

In this paper, we will extract the gesture convex feature as one of the hand gesture recognition features, which is defined as the combination of gesture convexity δ and relative position α, β of fingertips.

The gesture convexity is defined as the tightness of hand gesture contour to its convex hull, its value is defined as the ratio of gesture contour area and convex hull area, that is

$$\delta = contour\ Area / hull\ Area. \quad \textbf{(3)}$$

As shown in Fig. 5, We can get that hullArea > contourArea, so $\delta \in (0,1)$, and the bigger the value, the tighter the gesture contour to convex hull.

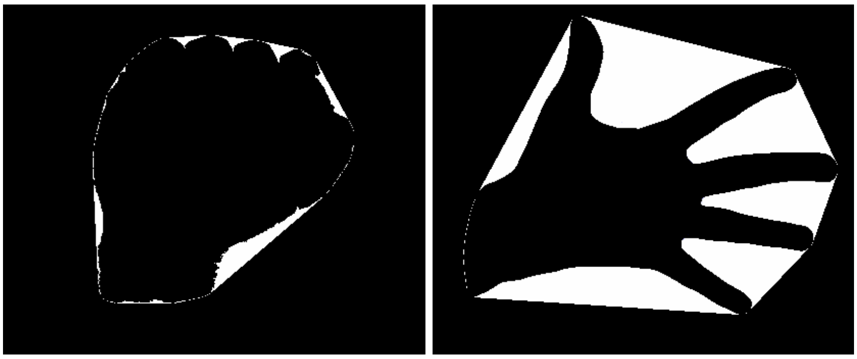


Fig. 5. Tightness of contour to convex hull

The relative position of fingers is composed of two values of α and β, for N fingertips, suppose using θ to describe the angle composed of the first fingertip and other fingertips with hand centroid as vertex, then define

$$\begin{cases} \alpha = \theta_1 + \theta_2 + \cdots + \theta_{N-1} \\ \beta = \theta_{N-1} \end{cases}. \quad \textbf{(4)}$$

Fig. 6 shows that different gestures have different hand gesture convex features.

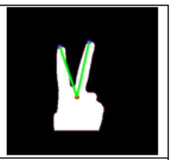
Hand Gesture			
δ	**0.9388**	**0.7707**	**0.7048**
α(°)	**0**	**0**	**31**
β(°)	**0**	**0**	**31**
Hand Gesture			
δ	**0.6968**	**0.6915**	**0.6776**
α(°)	**131**	**159**	**351**
β(°)	**79**	**84**	**128**

Fig. 6. Different relative position of fingertips

The hand gesture recognition method based on the convex defect detection can greatly reduce the count of contour scanning and the amount of computation, since this kind of analysis method is based on the overall image of the hand gesture, so it has a certain degree of robustness, the gesture differences occurred by the changes of light will not lead to the inconstant of convex defects, but the weakness of hand gesture recognition method based on convexity and relative position of fingertips is that convex defect detection is limited to recognize hand gestures that not completed opened, because when the hand gesture is not completely open, the convex defect depth between the adjacent fingers maybe too much small and be filtered out as noise referring to formula (1), which could lead to large errors in the gesture recognition, so that the number of the fingertips cannot be correctly detected, so this kind of method always needs the assistant of other features when doing vision based hand gesture recognition.

4 Distribution Feature Extraction

For the binary image obtained by hand gesture segmentation, spatial distribution information is very helpful for the description of hand gesture shape, because the alternative distribution of white pixels (target) and black pixels (background) can constitute different target shapes. We will extract the gesture distribution feature (GDF) as another series of features to describe the hand gestures.

GDF is a derivation of density distribution feature (DDF). The basic idea of DDF [12] is to get the statistic of distribution situation of target pixels in different regions to reflect their spatial distribution, it is defined as:

$$DDF = (r_1, r_M; dr_1, \ldots, dr_M).. \quad \textbf{(5)}$$

Where, M is the sub image count, r represents the density of target pixels within each sub region, dr is the first order difference of r in the direction of radial coordinate.

The division process of the M sub image regions includes:

(1) Calculate the maximum distance $D_{\max}$ from target pixels to the centroid of the binary image $F(x, y)$, namely center of gravity (x_c, y_c).

(2) With (x_c, y_c) as center, $D_{\max}$ as radius to draw the circumscribed circle of target region, and then divide the image to M sub image regions using the region division method of equidistant or equal areas [13].

(a) Equidistance division method

That is, the interval length covered by each sub image region is equal, which means:

$$R_i = \{(x, y) \mid (i-1) \times D_{\max} / M < \sqrt{(x - x_c)^2 + (y - y_c)^2} \le i \times D_{\max} / M\}. \quad \textbf{(6)}$$

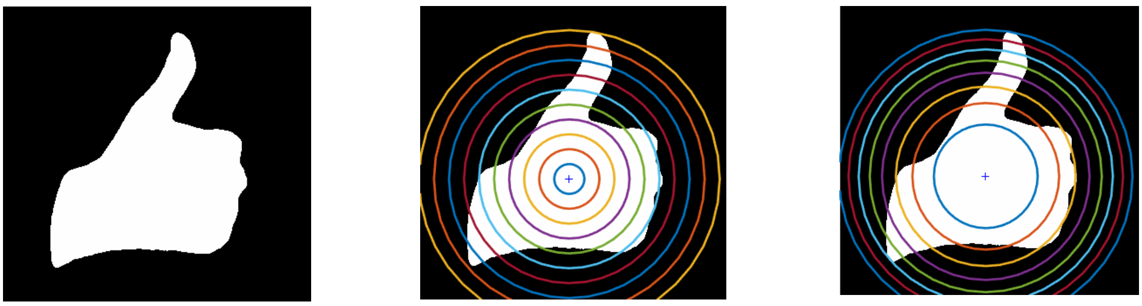
(b) Equal area division method

That is, the area of each sub image region is equal, which means:

$$R_i = \{(x, y) \mid (i-1) \times D_{\max}^2 / M < [(x - x_c)^2 + (y - y_c)^2] \le i \times D_{\max}^2 / M\}. \quad \textbf{(7)}$$

Where, $(x, y) \in F(x, y), 1 \le i \le M$.

Fig. 7 is an example of region division of binary image, Fig. 7(a) is the original image, Fig. 7(b) is the division result using method of equidistant, the internal length (the width of annulus or the radius of circle) of each sub image region (annulus or center circle) is equal, Fig. 7(c) is the division result using method of equal area, and the area of each sub image area is equal.



(a) Original image (b) Equidistant region division (c) Equal area division

Fig. 7. An instance of image region division

As shown in Fig. 8, different images Fig. 8(a) and Fig. 8(c) with similar gestures usually have similar density distribution information Fig. 8(b) and Fig. 8(d).

DDF can be regarded as a kind of effective shape feature that can well reflect the general shape information of a binary image, it has following virtues:

(1) DDF can grasp the overall shape info of image.

(2) DDF has the property of shift invariant. It benefits from the choice of gravity as centroid and taking care of target area only for the partition of sub image regions, the position of target in the image does not affect the value of DDF.

(3) DDF is not sensitive to scale deformation. Since the target area of all images are divided into same number of sub image regions, so the DDF of the new image obtained after the enlargement or reduction is basically same as the original one.

(4) DDF is invariant to rotation. Because of the adopting of circular division method, the change of rotation has little effect on DDF.

Human hand is articulated complex deformable object consisting of one palm and 5 adjacent fingers, each finger is composed with several segments and joints. From a whole point of view, the gesture is a joint structure, with the movement of joints, the shape of the hand is constantly changing, and the different attitude of gesture can be described by means of the changing of spatial state of segments and joints. On the one hand, the different shape of gestures can be described by the distribution of pixels in the space, on the other hand, the different shape of hand gesture is derived from local attitude of gesture, that is, connecting relationship of fingers such as joint angles, the selection of joint angles in different regions can well describe the changes in the joints of human hand.

DDF can be regarded as a kind of effective shape feature that can well reflect the overall shape information of a binary image, but different images can also have similar density distribution information. The concept of GDF is a way to avoid this weakness from the view point of both overall and local attitudes, it is derived from DDF with a new part of normalized arc length to describe the connecting relationship of fingers. Fig. 9 shows the sketch map of GDF.

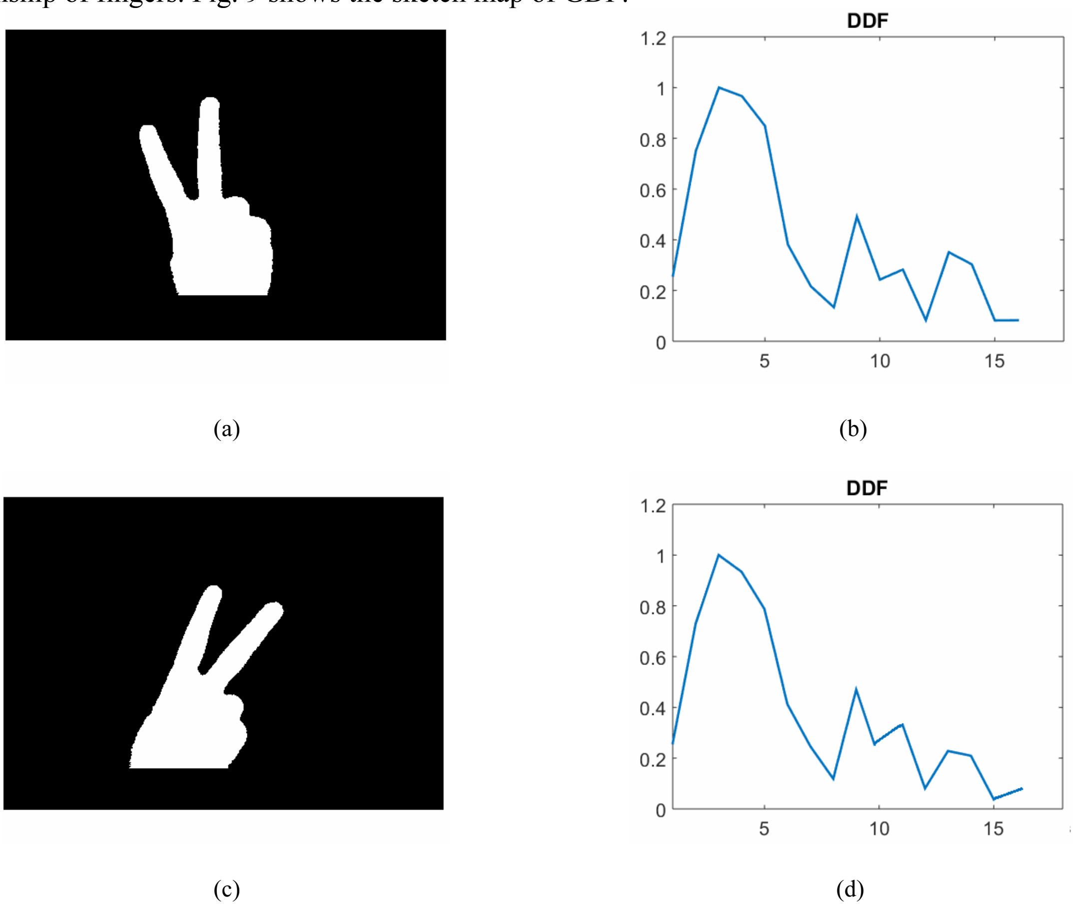


Fig. 8. Density distribution of different images with similar gestures

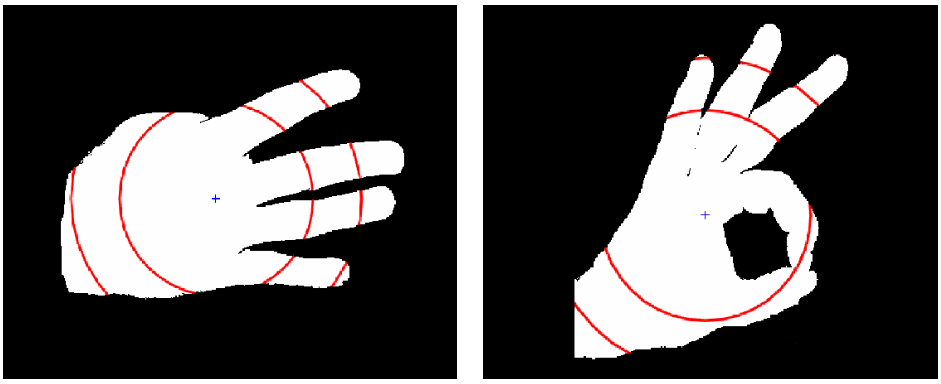


Fig. 9. Sketch map of arc component of GDF

Overall, the structure of GDF is defined as:

$$GDF = \begin{pmatrix} r_1, & \cdots, & r_M; \\ dr_1, & \cdots, & dr_M; \\ arc_1, & \cdots, & arc_M \end{pmatrix}. \quad \textbf{(8)}$$

Where, the first vector r refers to the relative density of target pixels in each region after diving the image into M sub image regions, the second vector dr is the first order difference of r in the direction of radial coordinates, and the third vector arc represents the arc length of skin region in each sub region outer edge.

As the third component of GDF, arc is mainly relies on the distribution feature of fingers, so when certain constraints are satisfied, only sub image regions that contain fingers can be sampled to reduce the computational complexity and improve the gesture recognition speed. According to the physiological structure of human hand, the sub image regions in which the distance from target pixels to the centroid of the binary image is bigger than but not equal to the half of maximum distance $D_{\max}$ are sub regions that meet requirement, as shown in formula (9).

$$dis\tan ce(pixel_{sub}, centroid) \in (\frac{1}{2}, 1) \times D_{\max}.. \quad \textbf{(9)}$$

So, the improved GDF is expressed as:

$$GDF = \begin{pmatrix} r_1, & \cdots, & r_M; \\ dr_1, & \cdots, & dr_M; \\ arc_{M/2}, & \cdots, & arc_{M-1} \end{pmatrix}. \quad \textbf{(10)}$$

The calculation steps of GDF are as follows:

(1) Segment the binary image into M sub image regions using the region division method of equidistant.

(2) Conduct the statistics for each sub image region, that is, count the amount of target pixels in each sub region $S_i (i = 1, \ldots, M)$, and find out the max value:

$$S_{\max} = \max_{i=1,\cdots,M} S_i. \quad \textbf{(11)}$$

(3) Calculate each component of the first feature vector r of GDF:

$$r_1 = \frac{S_i}{S_{\max}} (i = 1, \ldots, M). \quad \textbf{(12)}$$

(4) Calculate each component of the second feature vector d_r:

$$dr_1 = \begin{cases} |r_1 - r_2|, & i = 1 \\ |2r_i - r_{i-1} - r_{i+1}|, & 1 < i < M \\ |r_M - r_{M-1}|, & i = M \end{cases} . \quad \textbf{(13)}$$

(5) Conduct the statistics on the length of skin outer edge of each sub image region that contains fingers $arc_i (i = M/2, \cdots, M-1)$, and find out the max value:

$$arc_{\max} = \max_{i=M/2,\cdots,M-1} arc_i . \quad \textbf{(14)}$$

(6) Calculate each component of the third vector arc of GDF:

$$arc_i = \frac{arc_i}{arc_{\max}}, i = \frac{M}{2}, \cdots, M-1 . \quad \textbf{(15)}$$

5 Similarity Measurement

Until now, the final feature vector based on convex defect detection and density distribution was obtained, it includes gesture convexity, relative position of fingertips and gesture distribution feature, that is:

$$(\delta; \alpha; \beta; r_1, \ldots, r_M; \ldots dr_1, \ldots dr_M; arc_{M/2}, \ldots, arc_{M-1}) . \quad \textbf{(16)}$$

In order to classify different hand gestures to be recognized, we proposed the classification method based on Euclidean distance and Gaussian model. Euclidean distance [14] is proposed to measure the similarity distance between test and standard images and the Gaussian model [15] is adopted to the normalization of similarity distance, since each sub feature has different feature space, it is necessary to normalize the corresponding distance before merging them, different from the normalization of each internal component of the feature, it is the normalization of the similarity distance of each sub feature.

The steps of similarity measurement include:

(1) Calculate the corresponding Euclidean distance of each sub feature between the query image and each standard image in the image database as $d_\delta, d_\alpha, d_\beta, d_r, d_{d_r}, d_{arc}$.

$$d = \sqrt{(v_{query_1} - v_{standard_1})^2 + \cdots + (v_{query_n} - v_{standard_1})^2} . \quad \textbf{(17)}$$

$v_{query} - v_{standard}$ are the corresponding sub features of the query image and standard image, and n is the dimension of the sub feature, such as for δ, n=1, and for r, n=M.

(2) Normalize each Euclidean distance using the mean value μ, standard deviation σ based on Gaussian model.

$$\overline{d} = \begin{cases} [(d-\mu)/3\sigma + 1]/2, d \in [\mu - 3\sigma, \mu + 3\sigma] \\ 1, \quad otherwise \end{cases} . \quad \textbf{(18)}$$

The normalized distance of each sub feature is expressed as $\overline{d}_\delta, \overline{d}_\alpha, \overline{d}_\beta, \overline{d}_r, \overline{d}_{dr}, \overline{d}_{arc}$ respectively with range belongs to [0, 1].

(3) Calculate the similarity distance of the similarity measurement.

$$d_f = \alpha_1 \times \overline{d}_\delta + \alpha_2 \times \overline{d}_\alpha + \alpha_3 \times \overline{d}_\beta + \alpha_4 \times \overline{d}_r + \alpha_5 \times \overline{d}_{dr} + \alpha_6 \times \overline{d}_{arc} . \quad \textbf{(19)}$$

Where, $\alpha_1, \ldots, \alpha_6$ are weights of each sub feature, and $\alpha_1 + \cdots + \alpha_6 = 1, d_f$ is the final similarity distance between features of two hand gesture images.

The smaller the similarity distance, the similar between the test and standard images.

6 Result and Conclusion

We implemented experiments of 5 different kinds of number gestures (one to five) under simple background to show the recognition result of the hand gesture recognition algorithm proposed in this paper. Table 1 lists features adopted of some standard number gestures, it shows that these features have a certain ability to distinguish the number gesture templates used in this paper.

In order to verify the desirability of recognition features proposed in this paper, we selected 20 representative images for each kind of number gesture as query images for hand gesture recognition experiment, for each image, first remake it by translating, rotating and scaling in the experiment, thus, there would be total 100 images for each gesture in the query image database. For the segmentation of hand gesture and extraction of the corresponding binary image, we adopted the hand gesture region location method based on Color balance, YCgCr color space conversation and fixed threshold, because it has simple calculation process and be robust to the illumination of both while and colored light source [16].

Table 2 shows the recognition result, it shows that in the case of the ideal segmentation of the hand gesture region, the recognition accuracy of the static number gesture based on simple background can basically reach the expected standard. By analyzing the misidentified gestures in the experiment, we found that the cause of some false recognition is the difference in the length of the wrist compared with the corresponding standard gesture, for example, the nine misidentified hand gestures in series of gestures of number 1, the whist length contained in these gestures is longer than their responding standard gesture, while series of number 5 is shorter. And this is one of the limitations of the hand gesture recognition algorithm used in this paper, which is another problem needs to be solved in our next work.

Table 1. Recognition features proposed in this paper

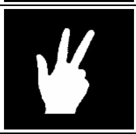
Gesture	δ	α (°)	β (°)	GDF(r, d_r, arc)
	0.7707	0	0	[0.3232, 0.9280, 1, 0.2471, 0.1017, 0.0823] [0.6047, 0.5327, 0.8249, 0.6075, 0.1260, 0.0194] [1, 0.1523, 0.1391]
	0.7048	31	31	[0.3663, 0.9353, 1, 0.8769, 0.2817, 0.1545] [0.5690, 0.5043, 0.1878, 0.4721, 0.4680, 0.1272] [1, 0.4646, 0.2323]
	0.6968	131	79	[0.2841, 0.7703, 1, 0.5607, 0.1659, 0.0867] [0.4862, 0.2565, 0.6690, 0.0445, 0.3156, 0.0792] [1, 0.3160, 0.1745]
	0.6915	159	84	[0.2736, 0.7434, 1, 0.8360, 0.6161, 0.1731] [0.4698, 0.2133, 0.4206, 0.0558, 0.2232, 0.4430] [1, 0.8383, 0.3277]
	0.6776	351	128	[0.2648, 0.7586, 0.9976, 1, 0.5451, 0.1497] [0.4938, 0.2548, 0.2366, 0.4573, 0.0594, 0.3954] [1, 0.6913, 0.2450]

Table 2. Recognition result of 5 kinds of number gesture under simple background

Gesture	Total	Right	Wrong
1	100	91	9
2	100	100	0
3	100	100	0
4	100	100	0
5	100	89	11

This paper focuses on the features extraction of static hand gesture recognition.

(1) Extract features of gesture convexity and relative position of fingertips based on convex defect detection.

(2) Extract gesture distribution feature composed of density distribution feature and normalized arc length of fingers.

(3) Classify the test hand gesture using similarity measurement.

Experiments show that the proposed features is feasible, convex defect detection aims to extract the hand gesture area size and relative position of fingertips, it is not influenced by the direction and position of the gestures compared with HOG, hand distribution feature uses the center of gravity as centroid and performs the circular division based on the axial symmetry and central symmetry, compared with DDF, HDF not only can collect the feature information from overall attitude but also local attitude, with which, the drawback of DDF with different gestures can generation similar distribution information can be solved, so the proposed hand gesture recognition algorithm has good robustness to the rotation, translation, scaling of hand gesture image.

Our future works include: improve the accuracy of hand gesture region location method by achieving the segment of hand gestures from hand-like noises contained images; improve recognition rate with consideration of wrist, achieve recognition of gestures with small discrepancies or large areas of pixel loss while hand gesture segmentation.

Acknowledgements

Funding for this paper was provided by Namseoul University.

References

[1] L. Gupta, S. Ma, Gesture-based interaction and communication: automated xlassification of hand gesture contours, IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews 31(1)(2009) 114-120.

[2] N.D. Binh, T. Ejima, Real-time hand gesture recognition using pseudo 3-D hidden Markov model, in: Proc. 5th IEEE International Conference on Cognitive Informatics, 2006.

[3] Y. Xu, Y. Dai, Review of hand gesture recognition study and application, Contemporary Engineering Sciences 10(8)(2017) 375-384.

[4] J. Davis, M. Shah, Visual gesture recognition, IEEE Proceedings on Vision, Image and Signal Processing 141(2)(1994) 101-106.

[5] T. Starner, A. Pentland, Real-time American sign language recognition from video using hidden Markov models, in: Proc. International Symposium on Computer Vision Proceedings, 1995.

[6] K. Grobel, M. Assam, Isolated sign language recognition using hidden Markov models, in: Proc. the IEEE International Conference on Systems, Man and Cybernetics, 1997.

[7] C. Vogler, D. Meraxas, Adapting hidden Markov models for ASL recognition by using three-dimensional computer vision methods, in: Proc. the IEEE International Conference on Systems, Man and Cybernetics, 1997.

[8] B. Tusor, A.R. Varkonyi-Koczy, Circular fuzzy neural network based hand gesture and posture modeling, in: Proc. IEEE Conference on Instrumentation and Measurement Technology, I2MTC, 2010.

[9] T.R. Trigo, S.R.M. Pellergrino, An analysis of features for hand-gesture classification, in: Proc. the 17th International Conference on Systems, Signals and Image Processing, 2010.

[10] A.A. Argyros, M.I.A. Lourakis, Vision-based interpretation of hand gestures for remote control of a computer mouse, in: Proc. the International Conference on Computer Vision in Human-computer Interaction, 2006.

[11] T. Lee, T. Hollerer, Handy AR: markerless inspection of augmented reality objects using fingertip tracking, in: Proc. 11th IEEE International Symposium on Wearable Computers, 2007.

[12] H. Liu, S.Q. Feng, Document image retrieval based on density distribution feature and key block feature, in: Proc. the 2005 Eight International Conference on Document Analysis and Recognition, 2005.

[13] L. Guo, X.H. Sun, Distance distribution histogram and its application in trademark image retrieval, Journal of Image and Graphic 7(10)(2007) 1027-1031.

[14] N. Krislock, H. Wolkowicz, Euclidean distance matrices and applications, International Series in Operations Research & Management Science 166(2011) 879-914.

[15] N.Z. Liu, J.Y. Yang, Color image retrieval using both color and texture features in object region, Computer Engineering and Applications 39(32)(2003) 187-203.

[16] Y. Xu, G. Pok, Identification of hand region based on YCgCr color representation, International Journal of Applied Engineering Research 12(6)(2017) 1031-1034.