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A Non-parametric RDP Algorithm Based on Leap Motion

Xue-Jian Zhang[1], Hong-Zhe Liu[1*], Jia-Zheng Yuan[1] and Xian-Kai Huang[2]

[1] Beijing Key Laboratory of Information Service Engineering, Beijing Union University,
Beijing 100101, China
{zhangxuejian, liuhongzhe, yuanjiazheng}@buu.edu.cn

[2] Beijing Open University,
Beijing 100081, Taiwan, ROC
huangxiankai@buu.edu.cn

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Abstract. With the popularization of computer hardware and software technology, human-machine interaction technology plays an increasingly important role within the Museum field, and it received prominent attention from academia and industry. Particularly, the appearance of Leap Motion controller, man-machine interaction application is more extensive and mature. The operator by contacting fewer devices is ready for operation, without the use of external devices such as touch screen, mouse, keyboard. It makes computer interaction more responsive and convenient. In order to increase the accuracy and practicability of gesture recognition, this paper proposes a non-parametric RDP (Ramer-Douglas-Peucker) detection algorithm based on Leap Motion and the RDP algorithms are compared. Tests show that non-parametric RDP detection methods can effectively identify signs and have good adaptability.

Keywords: gesture recognition, human-computer interaction, leap motion, non-parametric RDP detection algorithm

1 Introduction

With the application of new technologies in the field of innovation and development of museums, virtual reality technology has greatly enhanced the museum forms and interactivity, which are widely used in the Leap motion. Leap Motion [1-2] is a somatosensory controller for PC (personal computer) and Mac (Macintosh) released by Leap in 2013. The Leap Motion Controller tracks hands and fingers and reports position, velocity, and orientation with low latency and good accuracy [3]. The Leap Motion controller system consists of a hardware device and a software component which runs as a service or daemon on the host computer [4]. The Leap Motion controller uses optical sensors and infrared light. The sensors have a field of view of about 150 degrees. The effective range of the Leap Motion Controller extends from approximately .03 to .6 meters above the device (1 inch to 2 feet) [5-6]. The software component analyses images produced by the hardware and sends tracking information to applications. The Leap Motion Unity plugin connects to this service to get data. Scripts included with the plugin translate Leap Motion coordinates to the Unity coordinate system. And Kinect [8-9] different, Leap Motion can only recognize hand movements, such as the palm, finger position, direction, angle and other information. However, precision can reach 0.01mm. It appears to solve the problem of visual recognition provides a new way.

Leap Motion using frame technology achieves video stream and records hands coordinate points of each frame in real time. Connecting adjacent dots draw a gesture model, the developer gesture library to match the model performed Gesture Recognition. Leap Motion provides four gesture model, utilizing the four hand gestures can be developed design. To obtain developer frame by hand motion gestures matching list database corresponding to the gesture subject, as indicated in Fig. 1. But as the museum

* Corresponding Author

tour in increasing demand for human-computer interaction, using only four gestures, it has been impossible to meet the needs of developers. Therefore, in order to be able to identify species more gestures, this paper proposes a non-parametric RDP detection algorithm based Leap Motion and applied in the museum's virtual guide. We also acknowledge more complex gestures - vertical fold, horizontal poly line and square gesture using the algorithm we proposed and compared with RDP algorithm for recognition. Experimental results demonstrate that using the non-parametric RDP detection algorithm to identify gesture is better. Moreover, the algorithm for different scales of gestures have better adaptability.

Leap Motion can provide a good hand tracking algorithm, but for the recognition of complex gesture is not sufficient. Many scholars to be able to identify gestures better, expanding research into various areas. Based on Leap Motion gesture recognition method mainly divided into two categories. One is based on gesture recognition method of machine learning. Chen, Ding, Chen and Wu [4] based on SVM (Support Vector Machine) algorithm proposed a fast gesture recognition method, which uses dynamic gestures. It expanded the library of recognition of 0-9 Arabic numerals and A-Z alphabet. However, this method can only identify each of these gestures, there is a significant distance away from practical application. Elons, Ahmed, Shedid and Tolba [5] uses of neural network algorithms supervised can be 50 kinds of Arabic sign language recognition. Similarly, although the algorithm has a good recognition, but the gestures cannot recognize randomly in the database. The other is a gesture detection method based vantage points. Trindade Danilo uses the RDP algorithm to carry on the very good recognition to three kinds of complex dynamic gestures. The RDP algorithm can fit the polygon with more points, but the adaptive ability is poor. Trindade Danilo [10] uses the RDP algorithm to carry on the very good recognition to three kinds of complex dynamic gestures. The RDP algorithm can fit the polygon with more points, but the adaptive ability is poor. And there are some other methods of gesture recognition based on multi sensors, Penelle and Debeir [6] using multiple sensors developed an augmented reality system, set the Kinect and leap motion two somatosensory controllers of their respective advantages to track hand motion (Fig. 1), make the tracking more extensive and accurate, but the equipment is more complicated. Although this method has very good accuracy, but the use of equipment is more complex.

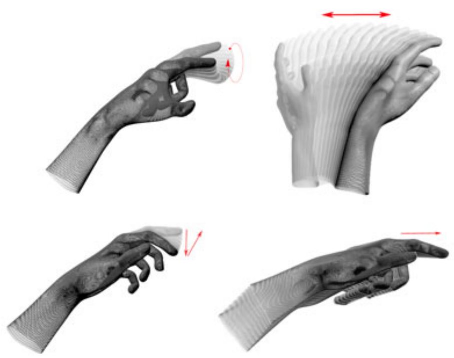


Fig. 1. From left to right, from top to bottom in order of circle, wave, key tap and screen tap

According to the existing problems above, we based on RDP algorithm proposed a non-parametric RDP algorithm based on Leap Motion. The algorithm can recognize the complex dynamic gestures, and has a good robustness when a slight jitter noise happened. It can be applied to human-computer interaction in the museum and for different gesture's sizes. The adaptabilities are great. It can reduce the computational complexity and improve the computational efficiency. We applying the algorithm on the guide of virtual cultural relic in museum. We design three dynamic gestures and use two parameters RDP detection and the algorithm we proposed to test the identification. Through experiments, we find that the non-parametric RDP detection algorithm based on Leap Motion has the better effect of recognition than the RDP detection algorithm. And it has a better robustness for the noise generated by the equipment. Moreover, the operator's gesture operation doesn't need to be standard, so it applied in museum compatibly.

The following sections of the article are as follows: The Section 2 introduces the researches of gesture recognition based on leap motion; Section 3 elaborates the non-parametric RDP detection algorithm based on leap motion; In Section 4, comparing this algorithm with RDP algorithm through two experiments, and analyze the superiority of the non-parametric RDP detection algorithm.

2 Related Work

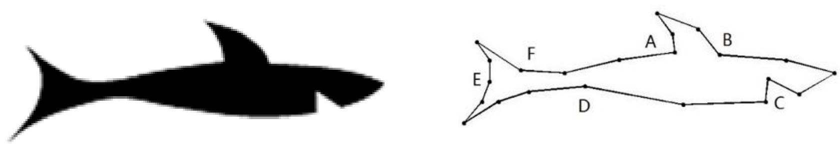
The core technology of the interaction concept that is proposed in this paper is a robust multi-technology gesture recognition algorithm. We following review the different strategies that may be found in literature to address this issue.

It is important to note that “gestures” in our work refer to hand motions without consideration of hand postures. The gesture motions are sensed and tracked by different tracking systems such as video-based or inertial-based systems, and the captured signal contains the spatial and temporal data of the movement so that the gesture recognition can be generalized as spatial-temporal pattern recognition problem. In this article, we assume the gesture signal is pre-isolated, i.e. the gesture signal to be recognized contains only one gesture and the start and end point of the gesture is already known. Gesture spotting which tries to segment meaningful patterns from a continuous stream of motion, is out of the scope of discussion.

2.1 Ramer-Douglas-Peucker detection algorithm

Trindade Danilo [10] using the Ramer-Douglas-Peucker (RDP) detection algorithm [11] developed several simple dynamic gestures. RDP detection algorithm is a dominant point detection algorithm based on parameter control. Through this method, we can detect the edge of the image, which can represent the concave and convex nature of the image edge, and connect these points to form a polygon to approximate the edge of the image. RDP detection algorithm has the following properties and function: composed of detected two adjacent line segments to approximate the corresponding contour image; Detected by multiple points can show the outline of the image features of curvature of curve; Because the images edge can use a small amount of approximate point out, so in image processing, using edge detection algorithm can significantly improve the efficiency of the time.

An example is presented in Fig. 2, a digital shape of a shake is illustrated. The boundary of the shape is composed of 346 pixels. Using dominant point detection algorithm get points down to 22 points, as showed in (b) in A-F. The polygon that is connected to the points of the outline approximates the original image. At the same time, drawing the outline of the characteristic curve of the bending in the original image can be properly represented.



a. original image b. polygonal approximation

Fig. 2. An example of a digital shape and its polygonal approximation

RDP algorithm can effectively reduce the points on the line which is comprised of a series of points, and the results approximate the original. RDP is the original form by the Urs Ramer in 1972, and proposed by David Douglas and Thomas Peucker in 1973, then, improved by other scholars [11-14]. The Ramer–Douglas–Peucker algorithm is an algorithm for reducing the amount of points in a curve that is approximated by a series of points. The purpose of the algorithm is, given a curve composed of line segments, to find a similar curve with fewer points. The algorithm defines ‘dissimilar’ based on the maximum distance between the original curve and the simplified curve (i.e. the Hausdorff distance [15] between the curves). The simplified curve consists of a subset of the points that defined the original curve.

The starting curve is an ordered set of points or lines and the distance dimension $\varepsilon > 0$. The algorithm recursively divides the line. Initially it is given all the points between the first and last point. It automatically marks the first and last point to keep. It then searches for the point that is furthest from the line segment with the first and last points as end points; this point is obviously furthest on the curve from the approximating line segment between the end points. If the point is closer than ε to the line segment then any points not currently marked to keep can be discarded without the simplified curve being worse than ε. If the point furthest from the line segment is greater than ε from the approximation, then that point must be retained. The algorithm recursively calls itself with the first point and the worst point and then at the worst point and the last point, which include marking the worst point being marked as kept. When the recursion is completed a new output curve can be generated consisting of all and only those points that have been characterized as kept. The expected complexity of this algorithm can be described by the linear recurrence $T(n) = 2T(n/2) + \Theta(n)$, which has the well-known solution (via the master theorem) of $T(n) \in \Theta(n \log n)$. However, the worst-case complexity is $\Theta(n2)$.

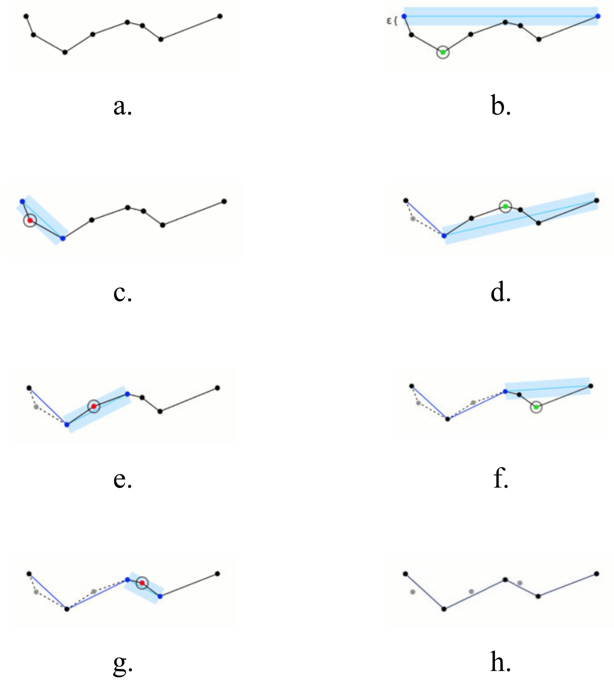


Fig. 3. The procedure of RDP algorithm

RDP algorithm has a good gesture recognition effect. However, at a large crowd scene, such as museum, as the operator's habits are different, the size of the gesture is also unlike. RDP algorithm is a fixed parameter detection method, which does not have the multi scale of gesture recognition, so it is not suitable for the museum of such a huge crowd scene.

2.2 Detection Method Based on Machine Learning

HMM (Hidden Markov Model) [16] is widely used in a variety of pattern recognition systems, including daily conversation, handwriting and recognition system. HMM using k-means as well as the forward and backward algorithms for training and recognition. Fok, Ganganath, Cheng and Tse [7] applied HMM into the application of the American Sign Language recognition. In the system, in order to make a fine gesture recognition, the gesture modeling is required. HMM is a recursive method that uses the forward and backward variables of the altered state of the adjacent time to continuously update the value of the state matrix. Utilizing two variables and expectation to estimate the parameters of HMM (i.e. π, A and B). Define the current HMM model is $\lambda = (A, B, \pi)$, and use the backward algorithm to re estimate the HMM model is $\overline{\lambda} = (\overline{A}, \overline{B}, \overline{\pi})$. The next assessment process is the process of hand gesture recognition. The method uses forward algorithm to calculate the probability of the observation sequence and the HMM model to obtain the maximum probability model. Using the forward algorithm can well improve the computational efficiency. The time complexity is $\Theta(n2)$.

Next is the classifier's training, each HMM classifier is represented by a gesture, through the Leap Motion controller to collect enough data to train the classifier. However, this method needs to cost more time on recognizing and modeling, and the operator's action is more standardized, which is not easy to do in the real experience.

3 A Non-parametric RDP Algorithm Based on Leap Motion

Depending on the problems existing in the above two methods, we propose a non-parametric RDP algorithm based on Leap Motion. In every iteration of the RDP detection algorithm, it can change the parameter adaptively, in order to reach the multi scale of gesture recognition. And the algorithm has good robustness to the noise generated by the Motion Leap controller.

3.1 Get Point

The Leap Motion controller can get the image of the hand of each frame. It can determine the orientation and the normal vector of the hand precisely, and make every detail perfectly. We select the average position of the tip in each frame at the point of the gesture.

3.2 Handle Point

The dynamic gestures point processing firstly, due to record by Leap Motion is not all gestures points. Such as the points produced in the moving before making gestures must be removed. According to the experience we need to remove the first 2 points. So, the calculation of the parameters will be more efficient after removing. The points are labeled as $\{P_1, P_2, \cdots P_k\}(k \in K+)$.

3.3 Calculation Parameters

The key problem of non-parametric RDP detection algorithm based on Leap Motion to be solved is selecting the best parameter ε automatically. Connecting the P_1 and P_k to get the segments l, calculating the distance $s=|P_1 P_k|$, slope m and the value of ε. The detailed methods as follows.

According to the length and slope of each line and the included angle between the line segments, we can control the variation of the parameters adaptively. A general point $P(x, y)$ can be approximated by a pixel $P'(x', y')$ according to digitization [17-18] in the case of digital images. The value of x' denotes the rounding of the real number x to its nearest integer. $P'(x', y')$ satisfies the following:

$$x' = round(x); \quad y' = round(y),, \tag{1}$$

$$x' = x + \Delta x; \quad y' = y + \Delta y,, \tag{2}$$

Suppose m and m' were slopes of the line P_1P_k and digital line $P_1'P_k'$ respectively. So,

$$m = \tan\phi = \frac{y_k - y_1}{x_k - x_1},, \tag{3}$$

$$m' = \frac{y'_k - y'_1}{x'_k - x'_1} = (m + \frac{\Delta y_k - \Delta y_1}{x_k - x_1}) \Big/ (1 + \frac{\Delta x_k - \Delta x_1}{x_k - x_1}). \tag{4}$$

We also estimate the error, that is the angular difference between the numeric tangent and the digital one. Now, we get:

$$\partial\phi = \left| \tan^{-1} \frac{m(\Delta x_k - \Delta x_1) - (\Delta y_k - \Delta y_1)}{(1+m^2)(x_k - x_1) + (\Delta x_k - \Delta x_2) + m(\Delta y_k - \Delta y_1)} \right|. \tag{5}$$

Substituting Eq. (3) in Eq. (5):

$$s = \sqrt{(x_k - x_1)^2 + (y_k - y_1)^2},, \tag{6}$$

$$t = \frac{(\Delta x_k - \Delta x_1)(x_k - x_1)}{s^2} + \frac{(\Delta y_k - \Delta y_1)(y_k - y_1)}{s^2}, \tag{7}$$

Then, we get the following:

$$\begin{aligned}\partial\phi &= \left|\tan^{-1}\left(\left(\frac{x_k - x_1}{s^2}\right)(1+t)^{-1}(m(\Delta x_k - \Delta x_1) - (\Delta y_k - \Delta y_1))\right)\right|. \\ &= \left|\tan^{-1}\left(\left(\frac{x_k - x_1}{s^2}\right)(m(\Delta x_k - \Delta x_1) - (\Delta y_k - \Delta y_1))(\sum_{n=0}^{\infty}(-t)^n)\right)\right|.\end{aligned} \tag{8}$$

Moreover, while $|\Delta x_k\text{-}\Delta x_1|=|\Delta y_k\text{-}\Delta y_1|=1$ we note the maximum value of t and the maximum value of $\partial\phi$ is given as:

$$\partial\phi_{\max} = \max\left(\tan^{-1}\left\{\frac{1}{s}(|\sin\phi \pm \cos\phi|)(1 - t_{\max} + t_{\max}^2)\right\}\right) + \Theta(t_{\max}^3). \tag{9}$$

$O(t_{max}{}^3)$ represents the upper limit of growth rate is $t_{max}{}^3$. In each iteration of the RDP detection algorithm, by using Eq. (8), we can get the parameter $\varepsilon=s\partial\phi_{max}$.

3.4 Handle Parameters

To improve the robustness of the non-parametric RDP detection algorithm to the noise generated by Leap Motion, we need to round the value of a parameter in every iteration of the algorithm. According to the experience, we will remove the parameter which is less than 1/3 of the previous parameter. After the process, we find that the algorithm has a good robustness to the noise generated by Leap Motion. As shown in Fig. 4 in the red circle which is needed to be removed in the detection process, because it does not belong to the gesture.

Fig. 4. The points achieved

3.5 Calculate the Maximum Distance between Points

After derive the ε, we calculate the distance between P_1 to P_k for all points to the line *l*. It then finds the point p_{max} that is furthest from the line segment *l* with the first and last points as end points; this point is obviously furthest on the curve from the approximating line segment *l* between the end points. If the point is closer than *ε* to the line segment *l*, then any points not currently marked to be kept can be discarded without the simplified curve being worse than *ε*. If the point furthest from the line segment is greater than *ε* from the approximation, then that point must be kept. The algorithm recursively calls itself with the first point and the worst point and then at the worst point and the last point, which include marking the worst point being marked as kept. When the recursion is completed a new output curve can be generated consisting of all and only those points that have been marked as kept.

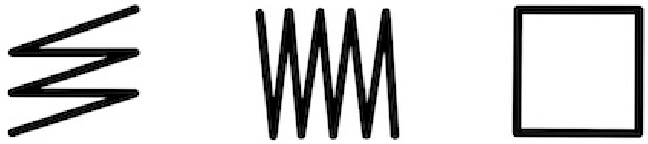
3.6 Match the Library of Gesture

Connecting the vertices in order to generate the graph of gesture, and matching the gesture in the database. Experiments show that the use of non-parameter RDP detection algorithm based on Leap Motion has better robustness than the RDP algorithm.

4 Experimental Results and Analysis

In order to verify the superiority of the non-parametric RDP detection algorithm, two sets of experiments were set up. Compared it with the RDP detection algorithm from the accuracy, recall, multi-scale. We equipped a computer which has 21.5 inches LED (Light Emitting Diode) screen, 4 core Intel core i5

4570R processor, Intel GMA (Graphics Media Accelerator) Iris Pro 5200 graphics card, 8G memory and Mac OS X Yosemite operating system. It can display of virtual artifacts in the museum in real time. Moreover, we use Leap Motion controller to track the movements of the hand. The system is in C # language in Unity3d environment. The experiment selects non-parametric RDP detection algorithm, ε=15 RDP detection algorithm and ε=20 RDP detection algorithm. Three simple dynamic gesture specifications (Fig. 5), vertical zig zag, horizontal zig zag and square are operated by 100 operators, and the two algorithms are compared in hand gesture recognition.



a. vertical zig zag b. horizontal zig zag c. square

Fig. 5. Three simple dynamic gesture

In order to evaluate the two algorithms, we use F-Measure (also F-score) [19] which is a measure of a test's accuracy. It considers both the precision P and the recall R of the test to compute the score: P is the number of correct positive results divided by the number of all positive results, and R is the number of correct positive results divided by the number of positive results that should have been returned. The F-Measure can be interpreted as a weighted average of the precision and recall, where an F-Measure reaches its best value at 1 and worst at 0. The formula is as follows:

$$F = \frac{(\alpha^2 + 1)P \times R}{\alpha^2 (P + R)}. \quad \textbf{(10)}$$

In the real scene, ensure good experience of the tourists in the process of human-computer interaction, gesture recognition precision P and recall R is equally important, so we use F (α =1) as the evaluation index. In the first set of experiments, the 100 operators in turn tested the gestures at the top of the Motion Leap and recorded the results (Table 1). Due to the differences of the operators, the sizes of the gestures are different, which is random in the test process. Therefore, through the difference sizes of the gestures drawn by the operators to compare the precision, recall and F-Measure.

Table 1. Test results of the three gestures

	classification	true positives	false positives	false negatives	precision rate	recall rate	F-Measure
vertical zig zag	non-parameter RDP	87	6	7	93.55%	92.55%	93.05%
	RDP(ε =15)	70	8	22	89.74%	76.09%	82.35%
	RDP(ε =20)	66	11	23	85.71%	74.15%	79.52%
horizontal zig zag	non-parameter RDP	83	6	11	93.26%	88.30%	90.71%
	RDP(ε =15)	69	7	24	90.79%	74.19%	81.66%
	RDP(ε =20)	65	9	26	87.84%	71.43%	78.79%
square	non-parameter RDP	81	10	9	89.01%	90.00%	89.50%
	RDP(ε =15)	58	14	28	80.56%	67.44%	73.42%
	RDP(ε =20)	61	14	25	81.33%	70.93%	75.78%

The data in the table 1 can be used to obtain the precision rate, recall rate and F-Measure of the three gestures' test. And it is found that the F-Measure of the non-parameter RDP detection algorithm was the highest, which was 93.05%, 90.71% and 89.05%, respectively. However, the F-Measure of the RDP detection algorithm using two parameters was significantly lower than that of the former. This result is explained by the two RDP detection algorithm which is controlled by the constant parameters. They have a great ability to identify the sizes of the parameters of the respective parameters. However, in the trial of 100 different operators, their gestures are completely different in size.

In order to further verify the non-parametric RDP detection algorithm with multi scales, we designed a different set of experiments. Let 100 operators use only gesture of vertical zig zag, respectively, with the length of 5cm, 10cm, 15cm, 20cm, 25cm and 30cm amplitude value to test gestures, to compare the two kinds of detection algorithm. Although the amplitude of the operator's hand movements is not particularly accurate, but the error range can be guaranteed within 3cm, so the error caused by the amplitude action is not considered in the experimental process. The experimental results are shown in Fig. 6.

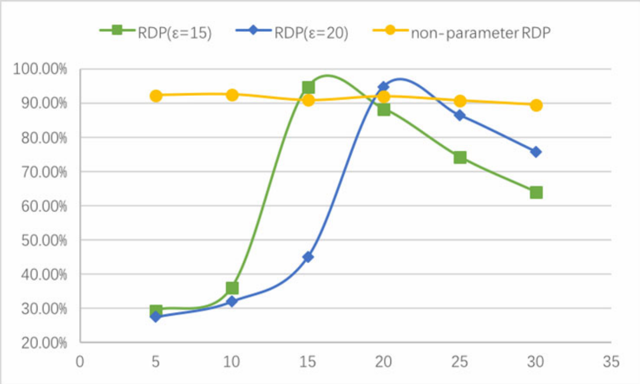


Fig. 6. F-Measure of the three algorithms

We can see that the RDP detection algorithm in their respective small range of values (ε-3, ε+3) has higher F-Measure. However, the F-Measure of the non-parametric RDP detection algorithm is stable basically, and maintained at about 90%. Through the analysis of the ε for 15 and 20 of the RDP detection algorithm and non-parametric RPD detection algorithm of the graph of false positives (Fig. 7), and the graph of false negatives (Fig. 8), we can see that the false positives and false negatives of non-parametric RDP detection algorithm will not be with gesture size growth and dramatic changes, and the numerical maintained at a very low level.

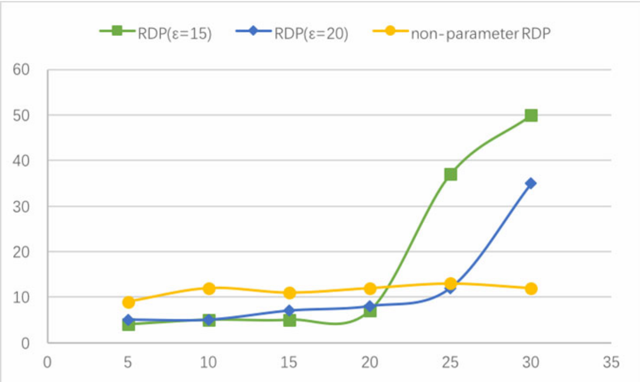


Fig. 7. False positives of the three algorithms

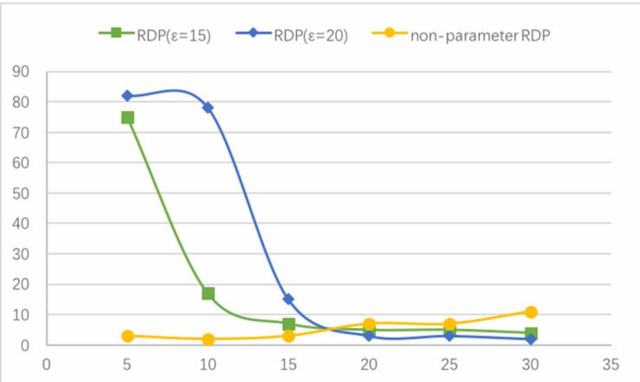


Fig. 8. False negatives of the three algorithms

It can be seen from the false positives of the three algorithms (Fig. 7), when the parameters of the two RDP detection algorithms are smaller than their respective parameters, their variation trends are relatively stable and the number of false positives are relatively low. This is because the two parameter RDP detection algorithms can only maintain a very good detection results in a small range of their parameters. When their parameters were lower than the scope of their respective parameters, most of the gestures were missing. It gave rise to a small number of false positives, the change trend is relatively gentle. As the parameters in the range, the two RDP algorithms can be normal for the gesture recognition, and the number of false positives return to the normal levels. However, parameters of the two RDP algorithm are beyond a certain range, the number of false positives is gradually improved, and the recognition effect is poor. But the non-parametric RDP detection algorithm does not vary with the parameters. This is due to the multi scale of the algorithm, which has a superior adaptability in different gesture scales.

Through the observation of the false negatives of the three algorithms (Fig. 8), when the parameters of the two RDP detection algorithms are less than their respective parameter range, they have no way to detection and recognition of gesture, so the higher the false negatives. As they are in the range of parameters, the two RDP detection algorithms can detect the gesture. However, the parameters of the two RDP detection algorithms were greater than their respective range, most gestures can be recognized, but each segment and offset are larger than the parameters, gesture recognitions will generate errors. So when the parameters of the two RDP detection algorithms are greater than the respective parameters in a certain range, false negatives do not increase, because most of the gesture would pick up mistakenly. However, the false negatives of non-parameter RDP detection algorithm is maintained at a low level.

Analyzing the two groups of experimental data, we found that the non-parametric RDP detection algorithm is better than the RDP detection algorithm for the noise generated by operator's hand shake, as shown in Fig. 9.

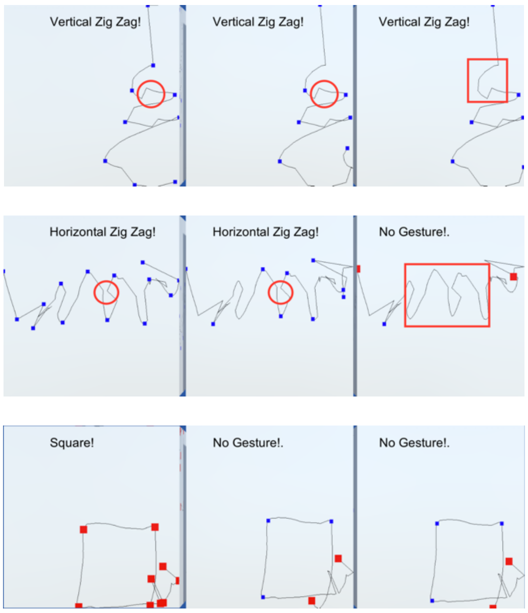


Fig. 9. From top to bottom are vertical zig zag, horizontal zig zag and square, from left to right are non-parameter RDP detection algorithm, ε=15 and ε=20 RDP detection algorithms

As the size of gesture becomes smaller, two parameter RDP detection algorithms for gesture recognition robustness are also reduced, but the non-parameter RDP detection algorithm has great gesture recognition. The red box in the graph is generated by the algorithms. The reason why the non-parameter RDP detection algorithm for noise generated by shaking has a better robustness is due to the algorithm removed some useless vertices and reduces the interference of the parameter. After the parameters are calculated, the parameters are accepted. At the same time, the non-parametric RDP detection algorithm has the characteristics of multi scale, which can eliminate the interference of noise generated by the shake of different hand gestures.

Therefore, through the comparison of two groups of gesture recognition, a non-parametric RDP detection algorithm based on Motion Leap is proposed in this paper, which has a better recognition for more complex gestures. Moreover, compared to the RDP detection algorithms, it has a multi scale, for different gestures of operators have a better adaptability. The non-parametric RDP detection algorithm has a good robustness to the noise generated by the operator's shake. The operator's gesture action specification is not high, and the operation is more friendly.

The method needs to be improved: the operator's gestures need to be completed coherently, if the interruption happened, the identification will fail; Due to the limitation of the range of Leap Motion, the controllable range of the operator is small, which limits the operator's behavior; And the data extracted by the Leap Motion includes a lot of frames which is not useful probably, so the data can be obtained through key frame technology to reduce redundant information, thereby reducing the amount of computation greatly.

5 Conclusions

Gesture recognition technology plays a major role in the field of human-computer interaction. The recognition algorithms based on Leap Motion are emerging in endlessly. Two common methods which based on the machine learning and dominant points are used primarily. The gesture detection method based on machine learning needs too much recognition and costs more modeling time, which cannot be applied to the museum's human computer interaction. The detection method based on dominant points does not have the characteristics of multi scale, and it is difficult to meet the gesture operation of different operators in the Museum where has a lot of people.

Therefore, this paper proposes a non-parameter RDP detection algorithm based on Leap Motion, and we applying the algorithm on the guide of virtual cultural relic in museum. We design three dynamic gestures and use two parameters RDP detection and the algorithm we proposed to test the identification. Through experiments, we found that the non-parameter RDP detection algorithm based on Leap Motion has the better effect of recognition than the RDP detection algorithm. And it has better robustness for the noise generated by the equipment. Moreover, the operator's gesture operation doesn't need to be standard, so it applied in museum compatibly.

In the future, aiming at the gesture must be continuous, we add interrupt feature to judge the gesture, so as to improve the stability of gesture recognition. And using the key frame technology to simplify the gestures for reducing the computation and improving the rate of recognition.

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