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# A NOVEL VISION-BASED FINGER-WRITING CHARACTER RECOGNITION SYSTEM

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A novel video-based finger writing virtual character recognition system (FVCRS) is described in this paper. With this FVCR system, one can enter characters into a computer by just using the movement of fingertip, without any additional device such as a keyboard or a digital pen. This provides a new wireless character-inputting method. A simple but effective background model is built for segmenting human-finger movements from cluttered background. A robust fingertip detection algorithm based on feature matching is given, and recognition of the finger-writing character is by a DTW-based classifier. Experiments show that the FVCRS can successfully recognize finger-writing uppercase and lowercase English alphabet with the accuracy of 95.3% and 98.7%, respectively.

*Keywords*: Finger-writing; character recognition; fingertip detection; background model.

## 1. Introduction

Vision-based HCI (Human–Computer Interaction) is an important technology in making machines more intelligent.[1,2] One type of vision-based HCI application is the tracking and detection of finger or fingertip movement. There have been significant researches in this field: Gesture recognition,[2] sign-language recognition,[3] finger mouse,[4,5] augmented desk interface systems,[6–9] window system control (such WWW navigator, menu control),[10] finger-painting system,[5] and so on. Fingertip movement could also be used to write characters, virtually in air, and through computer vision and pattern recognition technologies, it is possible for the computer to recover and recognize the finger-writing characters. Nevertheless, in the literature, there has few reports on using fingertips to write characters for human–computer interaction.

Character-input HCI is being increasingly important because of the popularity of many portable devices, such as PDA, pocket PC, smart mobile phone, etc. Conventionally, character-input usually achieved by keyboard, or pen-based computing technology (such as handwritten character recognition based on touch screen or digital tablet). For mobile application, the human–machine interface based on keyboards and screens is not effective since the dimensions of the fingers limit the minimum size of keyboards. Although handwriting has been recognized as one main character-inputting modality for many mobile devices,[11] it is not convenient for mobile application when the size of screen is limited. Moreover, special hardware (touch screen, pen, or digital tablet, etc.) is needed. Therefore, there is a need for alternative method for human–machine communications that involve smaller hardware for portable application. Rather than using the traditional tablets and touch-sensitive screens, handwriting can also be captured using a video camera. As camera is becoming more and more popular in many portable device (e.g., mobile phone), the camera-based human–machine interface have a significant role to play in the development of the interfaces in future,[12] because cameras can be miniaturized, thus making the interface much smaller.

In this paper, we propose a novel vision-based finger-writing virtual character recognition system (FVCRS). The basic idea of FVCRS is that one can write characters virtually by just using the movement of fingertip. We call this "finger-writing". In this system, the trajectories of the fingertip are detected and tracked in real-time, which provides a kind of inkless character pattern. Since there is no ink when we use the fingertip to "write", we call the reconstructed character as "virtual character". The virtual character is finally recognized by a classifier. In this way, a human can enter character into a computer by just using the movement of his/her fingertip, providing an interesting wireless character-inputting modality for HCI application. The diagram of our fingertip-based virtual character-inputting HCI system is given in Fig. 1.

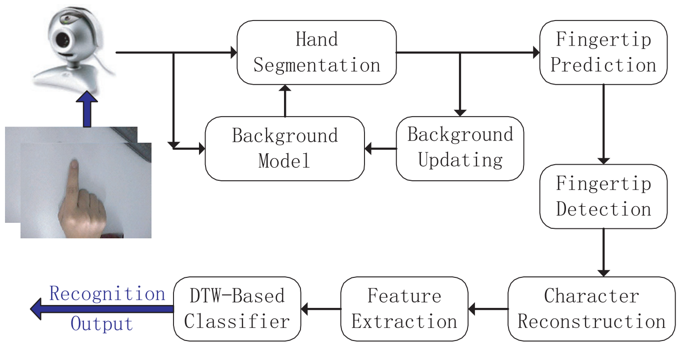


Fig. 1. Diagram of our FVCR system.

## 2. Fingertip Segmentation from Cluttered Background

Background modeling is one important computer vision problem. Although many methods have been proposed to address the problem,[13–17] a universal model for foreground detection from arbitrary background has not been developed. Pixel intensity is one of the most commonly used features in background modeling. The pixel intensity is often modeled with some statistical distribution, whose parameters are obtained after a process of training and recursive updating. A Gaussian distribution-based model (mixed Gaussian model is often used, since single Gaussian model is not good enough) is one popular background model for many applications.[14] Nevertheless, models based on mixed Gaussian are computational intensive and not fit for real-time application without special hardware support. Besides the Gaussian-based model, there are many other models have been proposed, such as the temporal deviation model in W4,[16] nonparametric model,[15] and so on. But from experiments, we found most of these background modeling methods are not very suitable for real-time indoor application such as our system.

In our FVCR system, an ordinary USB PC camera is used in indoor sites for video capture. Although the background of indoor scene is not as complex as that of an outdoor scene, there are still many issues that should be taken into consideration, which include shadows, flash light, etc. In order to solve the problem of indoor background modeling, we proposed a simple but effective background model to segment the human hand from a cluttered background. Our background model $M_t(x)$ is given by:

$$M_t(x) = \begin{bmatrix} m_t(x) \\ d^t_{\mathrm{median}} \\ d^t_{\max} \end{bmatrix} = \begin{bmatrix} m_t(x) \\ \mathrm{median}_z\{|I^t(z) - I^{t-1}(z)|\} \\ \max_z\{|I^t(z) - I^{t-1}(z)|\} \end{bmatrix}, \tag{1}$$

where $z$ is pixel index over the current frame. Here, parameters $d^t_{\mathrm{median}}$ and $d^t_{\max}$ are the median and max values of intensity change over the current frame, and are updated frame by frame. $I^t(x)$ denotes the intensity value of pixel $x$ at frame $t$. $m_t(x)$ is the mean of intensity value of background model of pixel $x$ at time $t$, and it is updated by Eq. (2):

$$m_t(x) = \begin{cases} I^t(x) & \text{if } (\mathrm{pixel}(x) \in \mathrm{update} - \mathrm{region}), \\ m_{t-1}(x) & \text{if } (\mathrm{pixel}(x) \in \mathrm{hand} - \mathrm{region}), \end{cases} \tag{2}$$

where

$$m_0(x) = \frac{1}{N} \sum_{i=1}^{N} |I^i(x)|.$$

$N$ is the number of initial frames (typically 20–40) without foreground. In Eq. (2), the hand-region is automatically determined by a connection-region detection algorithm, starting from the detected fingertip pixel. The update-region is then defined as the region excluding the hand region (see Fig. 2).

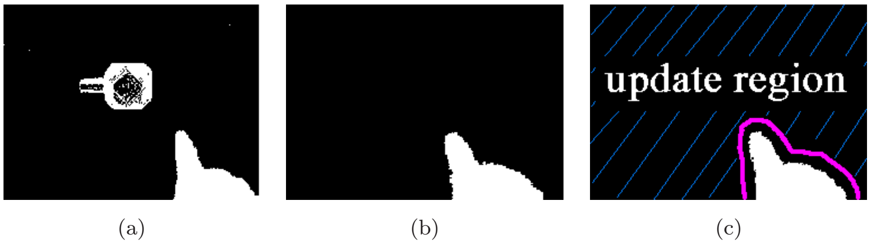


Fig. 2. Definition of update region: (a) Original image, (b) hand connect-region detection, and (c) update region.

After $M_t(x)$ is determined, the following equation is used to judge whether a pixel $x$ belongs to foreground or not:

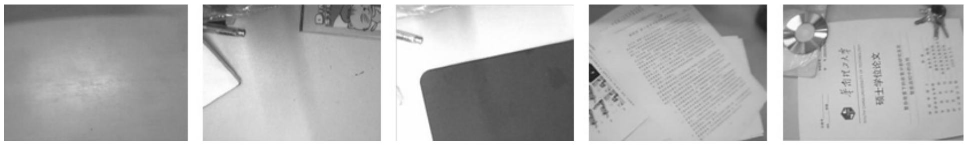
$$B(x) = \begin{cases} 0 \quad \text{background} & \text{if} \quad \begin{array}{l} I^t(x) - m(x) < k_{\text{median}} \cdot d^t_{\text{median}}\,, \\ \vee I^t(x) - m(x) < T \quad \vee I^t(x) - m(x) < k_{\max} \cdot d^t_{\max}\,, \end{array} \\ 1 \quad \text{foreground} & \text{otherwise}\,. \end{cases} \tag{3}$$

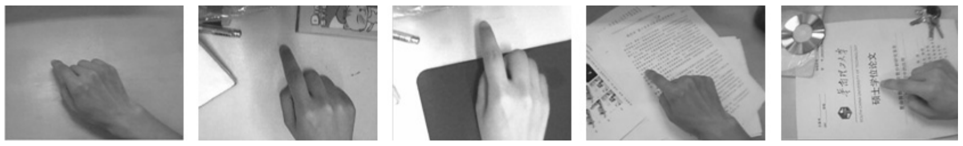
In Eq. (3), $d^t_{\text{median}}$ is median value of $I^t(x) - m(x)$, $d^t_{\max}$ is max value of $I^t(x) - m(x)$, $k_{\text{median}}$ (typically 1.5–1.8) and $k_{\max}$ (typically 0.2–0.3) are the constant weights of $d^t_{\text{median}}$ and $d^t_{\max}$. $T$ is a threshold constant (typically 25–28).

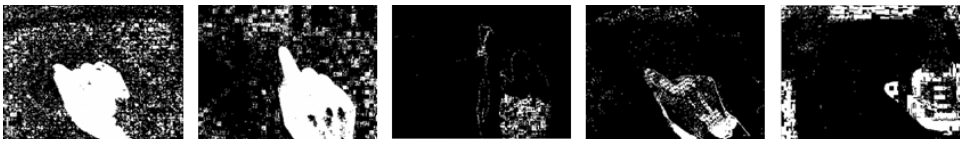
Although our background model based on Eqs. (1)–(3) is just a simple model without high computation, experiments show that it works very well with indoor scenes. Compared with some other similar background models such as W4, nonparametric model,[15] and single Gaussian model, it works even better. Figure 3 shows some experimental results of our model and previous models. In Fig. 3, the 1st column from left shows a normal situation with simple background. The 2nd column from left shows a situation with heavy shadow disturbance. The 3rd column shows a situation when a flash light was shining by. The 4th and 5th columns give some situations where the background is composed of complex texture objects. From Fig. 3, it can be seen that our background model can adapt to intensity changes caused by the flash light, shadows, complex texture background more effectively.

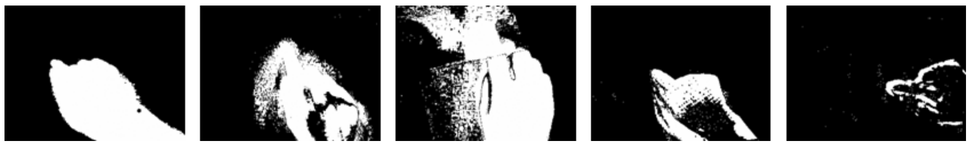
## 3. Fingertip Detection

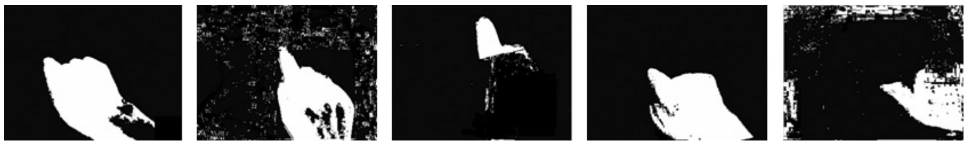
In early finger-based HCI system, the problem of fingertip detection was easily solved by using special marked gloves and color makers,[18] and some basic image-processing technology, such as histogram analysis and template matching. But for more natural HCI interaction, accurate and robust fingertip localization is the key to building a bare-hand interaction system. Many approaches have been proposed to solve this problem, such as the 3D fingertip model or the 2D fingertip model. As the 3D fingertip model needs more than one camera and thus heavy computation will be involved, the 2D appearance-based fingertip model is more suitable than


(a) Original background.


(b) Background + hand foreground.


(c) Foreground segmentation results using single Gaussian model.


(d) Foreground segmentation results using nonparametric model.


(e) Foreground segmentation results using W4 model.

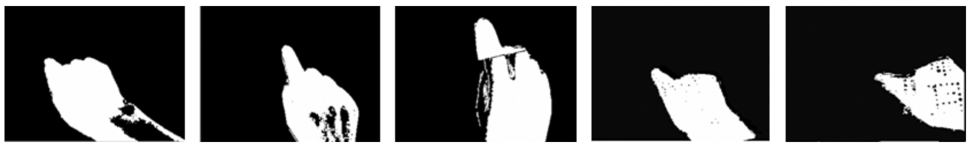

(f) Foreground segmentation results of our model.

Fig. 3. Foreground segmentation results of our model and some previous models.

the 3D fingertip model for real-time application with only a single camera. For 2D fingertip position localization with the bare-hand, previous fingertip localization methods mainly include contour analysis, template match,[5] heuristics method,[19] and so on. Unfortunately, most of these approaches can only work well under some special constraints, such as white background,[19] clear contrast between hand and background,[8] hand motion cannot be very fast[6,8] (usually the speed of hand motion should be less than 10 fps), the direction of fingertip must be upward,[7] etc. To overcome these constraints, we propose a new approach for robust fingertip detection, which consists of two stages. In the first stage, re-sampling process is used to solve the problem of blur and the rough location of the fingertip is detected. In the second stage, a circle cross feature vector is extracted from the fingertip image for accurate fingertip position location. The diagram of our fingertip detection approach is shown in Fig. 4. Details are described in the following sections.

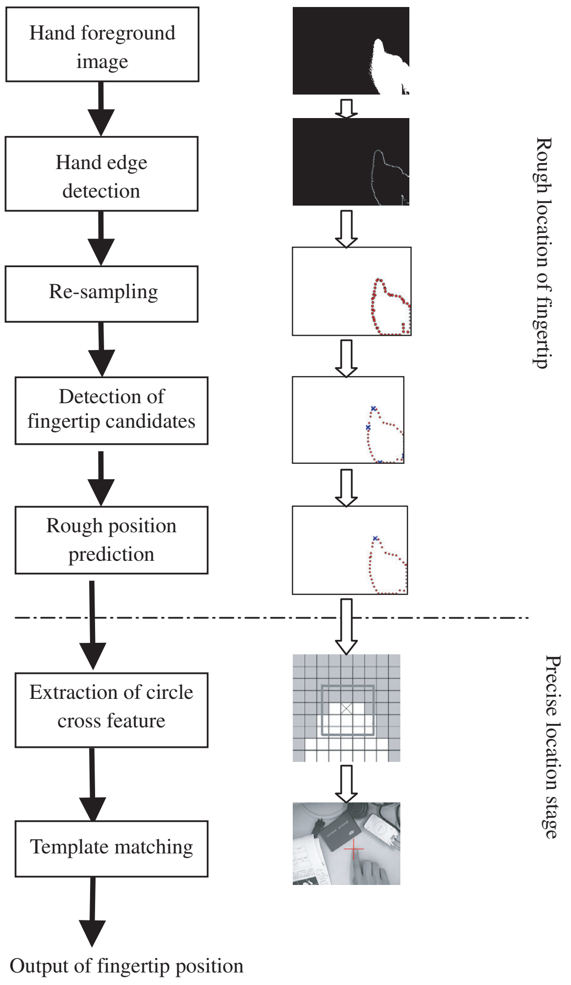

Hand foreground image
Hand edge detection
Re-sampling
Detection of fingertip candidates
Rough position prediction
Extraction of circle cross feature
Template matching
Output of fingertip position
Rough location of fingertip
Precise location stage

Fig. 4. The flowchart of fingertip detection process.

## 3.1. *Rough localization of fingertip*

The contour of the hand is used to determine the fingertip position. However, if we use the contour of the whole "hand" to determine the position of the fingertip directly, too much computation would be required and failure can occur because of sometime the contour of hand can be blurred caused by fast motion. So, we propose a rough fingertip localization method based on re-samples of the edge image (contour) of the hand. As shown in Fig. 5, we first got the hand-edge image (with size of $320 \times 240$ pixles) from the segmented foreground using edge operator (see Fig. 5(c)). Then, grids of size $10 \times 10$ are marked for the edge image (Fig. 5(d)). Each grid of the edge image will be finally mapped to a white or black pixel according to whether there are edge pixels in each grid (Fig. 5(e)). In this way, the original $320 \times 240$ hand contour is mapped to a re-sampled $32 \times 24$ contour. From Fig. 6, it can be seen that after the re-sampling process of the original hand contour, some heavily blurred contour become clear and smooth without loss of useful fingertip information. This is very helpful for further fingertip detection. Obviously, another merit of the re-sampling process is that the size of hand contour is reduced greatly (from $320 \times 240$ to $32 \times 24$), so the amount of computation required is greatly reduced.

In our FVCR system, it is found that the rough position of the tip of the pointing finger must be one of the four directional peaks of the closed curve of the finger contour. So, the four peaks are treated as the candidates for the rough position of the fingertip (see Fig. 5(e)). The overall shape of a human finger can

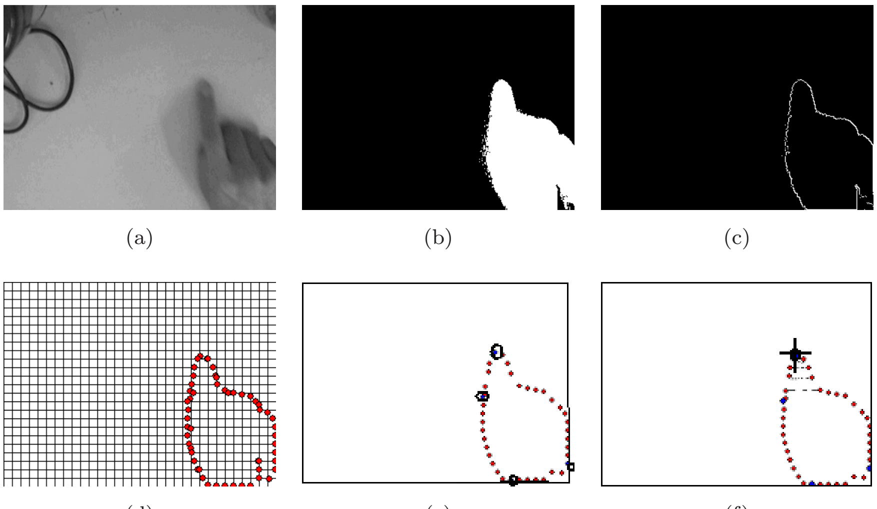


Fig. 5. Processing of rough fingertip detection: (a) Original image, (b) segmented hand foreground, (c) edge of hand, (d) griding re-samping of hand contour, (e) detect four peaks form the re-sampled contour, and (f) rough fingertip detection.

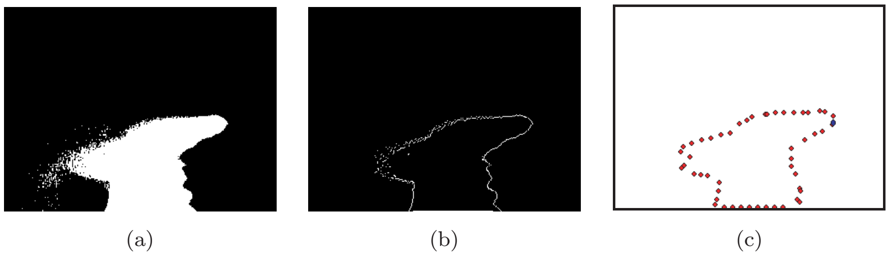


Fig. 6. An example of re-sampling of a blurred image: (a) Foreground, (b) the contour image, and (c) the re-sampling contour image.

be approximated by a cylinder with a hemispherical cap. We then select several sample point-pairs starting from each candidate peak anticlockwise and clockwise. The variance of the distances of these point-pairs around each peak is calculated. The peak corresponding to the minimal variance is regarded as the rough fingertip position (see Fig. 5(f)).

### 3.2. *Precise localization of fingertip*

It should be noticed that the fingertip position detected by the stage mentioned in Sec. 3.1 is not accurate enough, since the hand contour may not be accurate due to disturbance from shadows, or mis-segmentation of the correct hand foreground, according to the complexity background. So, we need to detect the precise fingertip position from the original image. In our FVCR system, the moving fingertip may point to different directions in different frames. Experiments show that when the fingertip is not pointed upward, traditional template matching cannot locate the finger accurately, even with multiple templates. To solve the rotation-invariant problem, we propose a method based on circle cross feature matching. As shown in Fig. 7, a set of rectangles (typically 12–18) are drawn around the fingertip, with the number of white pixels from each rectangle passed as an accumulated feature. All features will finally form a feature vector, which we call a **circle cross feature**

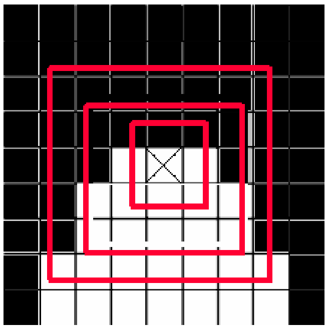


Fig. 7. Extraction of circle cross feature for fingertip.

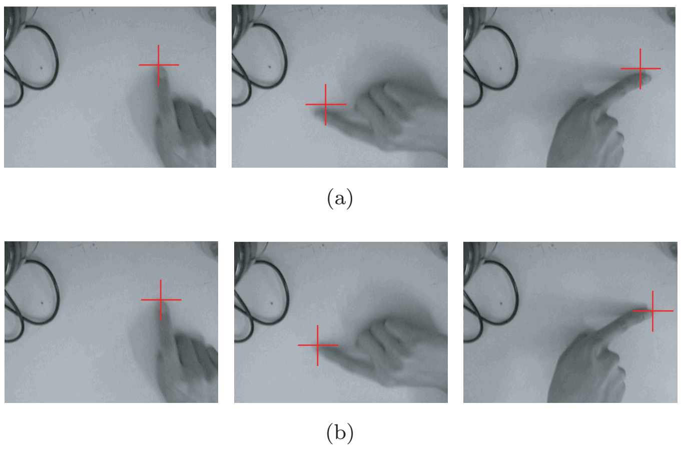


Fig. 8. Comparison of our fingertip detection method and conventional method: (a) Fingertip detection results using conventional template matching method and (b) results using the proposed circle cross feature matching method.

**vector**. For example, the circle cross feature along the three rectangles shown in Fig. 7 is 5, 7 and 7, respectively. To find the precise location of the fingertip, the circle cross feature vector of fingertip template is matched with an unknown image around the region of the rough fingertip position. The position that produces the highest matching score will be regarded as the fingertip location.

Figure 8 shows a comparison of the fingertip detection results using the traditional template matching method and our circle cross feature matching method. It can be seen that when the orientation of fingertip is not upward, the traditional template method is not good enough. The circle cross feature matching method is robust when the fingertip points to different orientations. Figure 9 gives more experimental results.

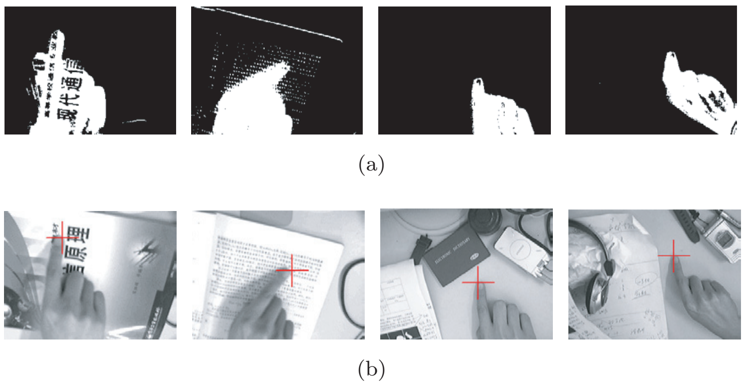


Fig. 9. More fingertip detection results: (a) The segmented foreground and (b) the localization of fingertip in corresponding original images.

## 4. Virtual Character Reconstruction

Since the moving trajectories of the fingertip are inkless, we need to find a way to recover the character written by the finger. To link all trajectories of fingertip can be done in a simple and natural way, but there are three problems that need to be taken into account: First, how to decide the starting point of a virtual character. Second, how to decide the end of writing, and third, how to process some wild points (as shown in Fig. 10) caused by a mis-detected fingertip position. We use the following strategies to solve these problems.

Detection of start writing:

(i) The fingertip position is in the region from the top to the middle line; and
(ii) the vertical or horizon displacement is more than 15 pixels in three consecutive frames; and
(iii) the angle between the two vectors composed by the fingertip position in three consecutive frames is less than a given threshold.

Detection of end writing:

(i) The pixels belonging to the foreground less than 100, or
(ii) the position of fingertip stays in the same place for 15 frames.

Processing of wild points:

(i) A point will be considered as wild and be erased if both of the distances between it and the previous and the next one are more than 1.5 times the average distance.
(ii) For three consecutive points in a video sequence, if the distances from them and the corresponding predicted points (by Kalman filtering[8]) is more than 1.5 times the average distance of the series, the points are considered as wild and erased.

By using the above strategies, the accuracy in detecting of the start of writing is more than 96%, and the accuracy in detecting of the end of writing is more than 99%. Also, most wide points (more than 95%) are successfully removed.

The virtual character reconstruction is implemented by linking all consecutive detected fingertip positions together after applied the above processing. Then, the

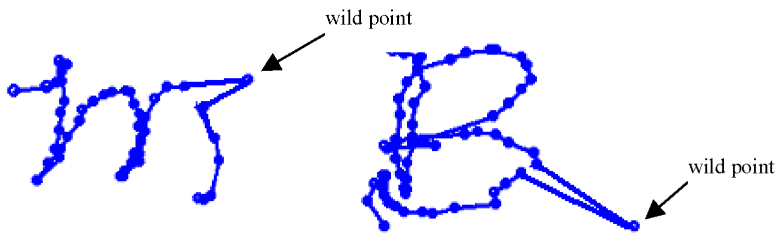


Fig. 10. Example of wild points along the tracked fingertip trajectories.

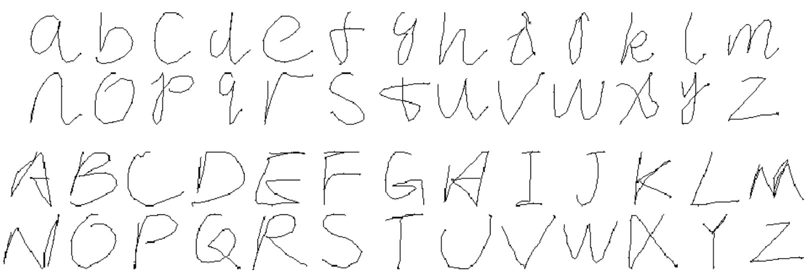


Fig. 11. Reconstructed virtual character samples.

reconstructed character is linearly normalized to an image with the size of 64 × 64 pixels. Examples of some reconstructed characters are given in Fig. 11.

## 5. Character Recognition

One special property of a reconstructed virtual character is that all its strokes are connected (since it is difficult to distinguish between upwards and downwards movements of the finger). So, it is a kind of one-stroke type of character, which is different from conventional online character captured by touch screen of digital pen. To solve the problem of the one-stroke style character recognition in our FVCR system, we proposed an online one-stroke cursive character recognition approach using a combination of directional and positional features, and a DTW (Dynamic Time Warping[20])-based classifier.

### 5.1. *Feature selection and extraction*

#### 5.1.1. *Normalized discrete directional feature* (*NDDF*)

In our recognition system, templates are presented by strings of normalized discrete directional angle values. The angle value are calculated as shown in Fig. 12. An angle represents the direction of writing direction at an extracted feature point in a handwritten character's stroke. The value is an integer between 0 and 255, linearly mapped from 0° to 359° in order to reduce the required storage.

#### 5.1.2. *Sampling positional feature based on NDDF*

There is no positional feature stored in our templates, since we found that the coordinates $(x_i, y_i)$ of a character could be reconstructed from NDDF templates as:

$$x_i = x_i + d \cdot \cos\left(\frac{2\pi\theta_i}{256}\right), \tag{4}$$

$$y_i = y_i + d \cdot \sin\left(\frac{2\pi\theta_i}{256}\right), \tag{5}$$

where $\theta_i$ is the directional angle value of the $i$th feature point, $d$ is the sampling distance (a value between 3 and 5). The starting point's coordinates are initialized

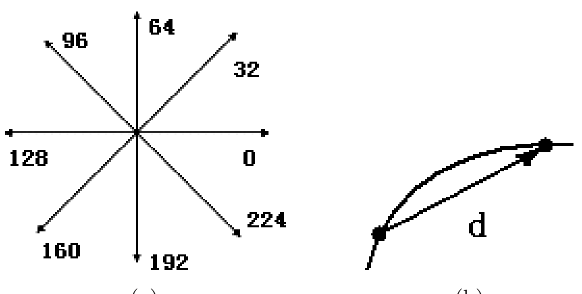


Fig. 12. (a) Normalized discrete directional angle value and (b) two successive feature points extracted along the stroke's curve.

to 0. After calculating every point's coordinates by Eqs. (4) and (5), the starting point's coordinates can then be figured out by Eqs. (6) and (7):

$$x_0 = 0 - MinX\,, \tag{6}$$

$$y_0 = 0 - MinY\,, \tag{7}$$

where $MinX$ and $MinY$ are the minimal values along $x$ and $y$ axis, respectively.

From the reconstructed character, the positional feature points can be sampled along the strokes. By using this technique, the size of template files are reduced without significant loss of recognition accuracy.

### 5.2. *DTW-based classifier design*

The classifier used in our work is based on prototype matching by DTW.[20] The $k$-nearest neighbor ($k$-NN) rule is used as the decision criterion. When performing the directional feature matching by DTW, the local distance is calculated by a quadratic curve equation (8):

$$d(i,j) = \begin{cases} (\Delta\theta)^2, & 0 \le \Delta\theta < 64\,, \\ -(\Delta\theta - 128)^2 + 8192 & 64 \le \Delta\theta < 128\,, \end{cases} \tag{8}$$

where

$$\Delta\theta = \begin{cases} |\theta_i - \theta_j| & 0 \le |\theta_i - \theta_j| < 128\,, \\ 256 - |\theta_i - \theta_j| & 128 \le |\theta_i - \theta_j| < 256\,, \end{cases}$$

$d(i,j)$ is the local distance between the $i$th angle in the template and the $j$th angle in the input sample, $\theta_i$ is the normalized angle at the $i$th feature point. From experiments, we found that the quadratic distance is more robust than traditional Euclidean distance.[21] Comparing with the Euclidean distance, an improvement of about 1% recognition accuracy is obtained when using the quadratic curve distance.

Since directional feature alone cannot present all features of a character, we also include positional feature in our classifier. We use positional features for the final classification. After directional feature matching by DTW is performed, all the characters that can be written in a similar stroke order congregated in front of the candidates queue. Let $C_i$ be the $i$th candidates, $D_k$ be the global distance of the $k$th candidates, $\Delta D_k = D_k + 1 - D_k$. $\beta$ and $\gamma$ are two parameters where $\beta > 1$, and $0 < \gamma < 1$ (We chose $\beta = 1.2$ and $\gamma = 0.5$ in our system). Then a parameter $K$ is computed by Eq. (9) in order to determine a candidate set $G$ given by Eq. (10):

$$K = \arg\min_k \left\{ \text{as long as } \Delta D_k > D_1 \cdot \beta \text{ or } \frac{\Delta D_{k+1}}{\Delta D_k} < \gamma \right\}, \tag{9}$$

$$G = \{C_i | i \leq K\}. \tag{10}$$

Once the set of candidates has been determined by Eq. (10), a combined score is computed for each candidate in this set, as:

$$S_{\text{total}} = S_{\text{dir}} + \alpha \cdot S_{\text{pos}}, \tag{11}$$

where $S_{\text{dir}}$ is the global directional distance of the candidate, $S_{\text{pos}}$ is the global positional distance, and $\alpha$ is a constant value chosen according to experiments (We chose $\alpha = 1$ in our experiments). All the candidates in set $G$ are rearranged in ascendant order by $S_{\text{total}}$. The first candidate is taken as the result of recognition.

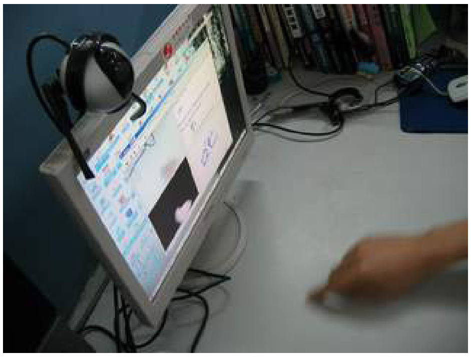
## 5.3. *Recognition experimental results*

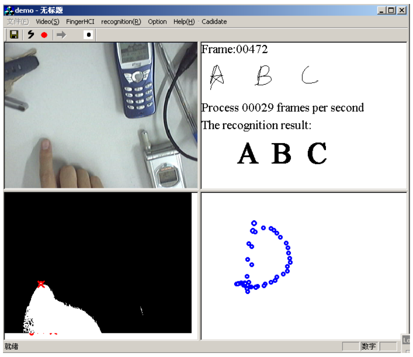
As there is no public finger-writing character database available, we collected 69 sets of uppercase and lowercase English letters written by different people using our camera user interface. We use templates constructed by hand to test the efficiency of character recognition. The size of the template files are 3.86 K and 4.88 K, respectively.

An experiment was conducted to compare different strategies and feature-matching methods. The experimental results are shown in Table 1. It can be seen that directional feature is better than positional feature when recognizing uppercase letters while positional feature is better for lowercase letters. This is because more lowercase letters have similar stroke direction such as "a", "d" and "q" and the directional feature can hardly classify them. The results also show that the combination of these two features is a success. The recognition rate is raised by more than 10% after directional and positional feature are combined for lowercase letters.

Table 1. The recognition results of English letters by different strategy and feature matching (DF = directional feature only; PF = positional feature only; CF = combined both features).

| | Feature | | |
|---|---|---|---|
| Recognition rates | DF | PF | CF |
| Uppercase letters | 95.0 | 93.0 | 98.7 |
| Lowercase letters | 80.9 | 84.8 | **95.3** |


(a)


demo - 无标题
文件(F) Video(S) FingerHCI recognition(R) Option Help(H) Cadidate
就绪
数字

Frame:00472

Process 00029 frames per second

The recognition result:

A B C

(b)

Fig. 13. (a) System setup and (b) user interface of our FVCR system.[a]

## 6. System Implementation

The proposed FVCRS system was implemented on a PC with Pentium IV 3.0 G processor and 512 M memory. We use an ordinary low resolution USB PC camera to capture the fingertip video, where the lens is integrated with the camera. The resolution of image is $320 \times 240$. The user can write with fingertip on a nature desk plane. There may be nothing else on the desk (which forms a simple background), or there may be some other objects on the desk, such as pen, book, phone, etc. (which forms a complex/cluttered background). In both cases, our system works well and can detect the fingertip from background successfully with an average accuracy of 98.5%. There is also no special requirement for the "virtual finger-writing" space, as long as it is convenient for the user to write naturally. Usually an area of $9\,\text{cm} \times 9\,\text{cm}$ is large enough. Figure 13(a) shows the system setup. Figure 13(b) shows the user interface of our FVCRS.

The speed of the system is about 28–30 fps (depending on the complexity of the background), suggesting that it is suitable for real-time application. Our system can attain a recognition rate of above 95% at about 50 letters per minutes writing speed. Although this speed is lower than a PC-based keyboard typing speed, it is comparable with the speed of the system based on online character recognition algorithm.[22]

## 7. Summary

In this paper, we have described a background model for fingertip segmentation from a cluttered background, a new fingertip detection method based on circle cross feature matching, and an approach for one-stroke virtual character recognition. Based on these technologies, a novel vision-based finger-writing virtual character

[a]An AVI demonstration of the FVCRS could be downloaded from http://218.192.171.88/teacher_p/staff/eelwjin/demo_fvcrs.html.

recognition system (FVCRS) has been built. With the FVCRS, one can input character into a computer by just using the movement of a fingertip. The FVCRS only use an ordinary cheap PC USB camera as sensor, without any additional device such as keyboard, touch screen or digital pen.

The proposed FVCR technology can be used to make mobile character-inputting device much smaller, since the camera can be miniaturized and integrated with the portable device. Another potential application of the FVCRS is in the area of electronic learning and entertainment. For example, it can be used to develop novel educational learning machine/system which can help children to learn handwriting in an interesting fashion.

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