Development of a hat style recognition system based on image processing and machine learning

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ABSTRACT – REZUMAT

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The purpose of this paper is to investigate the recognition mechanism of hat styles and develop a corresponding hat style recognition system (HSRS). An image processing and machine learning integrated method (IPML) is proposed and validated for automatic hat style recognition. First, 4 kinds of hat styles (borderless knitted hats, berets, top hats and peaked hats) with 800 pictures are employed as research objects and divided into two categories: the first 400 serve as the training set and the rest 400 as the test set. Then, IPML is proposed to obtain a hat silhouette. Curvature feature points are extracted from hat silhouette and further used as parameters for the automatic hat style recognition. In the real recognition process, a new case is compared with the pre-set 400 samples in the training set regarding these characteristic parameters. A Hausforff distance-based similarity measurement tool is used in the comparison process. The experimental results show that when the curvature feature points are 70 and the output results are 3, the average recognition accuracy rate can reach 90.5%, of which the value of borderless knitted hats is the highest with 98% and followed by the top hats with 95%. This work can be used for hat recommendation systems. It can also be extended to support the area of personalized industrial product design such as fashion design, furniture design and advertisement design.

Keywords: *image processing, hat style, Hausdorff distance, curvature characteristic, automatic recognition*

Dezvoltarea unui sistem de recunoaștere a stilului de pălărie bazat pe procesarea imaginilor și învățarea automată

Scopul acestei lucrări este de a investiga mecanismul de recunoaștere a stilurilor de pălărie și de a dezvolta un sistem de recunoaștere a stilului de pălărie (HSRS). Este propusă și validată o metodă integrată de procesare a imaginii și învățare automată (IPML) pentru recunoașterea automată a stilului de pălărie. În primul rând, 4 tipuri de stiluri de pălării (tricotate fără bor, berete, jobene și chipie) cu 800 de imagini sunt folosite ca obiecte de cercetare și împărțite în două categorii: primele 400 servesc ca set de instruire, iar restul de 400 ca set de testare. Apoi, se propune IPML pentru a obține o siluetă de pălărie. Punctele caracteristice de curbură sunt extrase din silueta pălăriei și utilizate în continuare ca parametri pentru recunoașterea automată a stilului. În procesul de recunoaștere reală, un nou caz este comparat cu cele 400 de eșantioane prestabilite din setul de instruire, în ceea ce privește acești parametri caracteristici. În procesul de comparare este utilizat un instrument de măsurare a similitudinii bazat pe distanța Hausforff. Rezultatele experimentale arată că, atunci când punctele caracteristice de curbură sunt 70 și rezultatele de ieșire sunt 3, rata medie de acuratețe a recunoașterii poate ajunge la 90,5%, dintre care valoarea căciulilor tricotate fără bor este cea mai mare, cu 98% și urmată de jobene cu 95%. Această lucrare poate fi folosită pentru sistemele de recomandare a pălăriilor. De asemenea, poate fi extinsă pentru a sprijini zona de design personalizat a produselor industriale, cum ar fi designul vestimentar, designul mobilierului și designul publicitar.

Cuvinte-cheie*: procesarea imaginii, stil de pălărie, distanță Hausdorff, caracteristică de curbură, recunoaștere automată*

INTRODUCTION

In recent years, with the rapid development of e-commerce, the transaction scale and penetration rate of online clothing shopping have been continuously improved [1]. The sales of online clothing mainly depend on the quality of product images to show and transmit product information [2–4]. Consumers choose their favourite styles and products according to the pictures provided by the merchants [5]. However, the current search on the online shopping platform is still based on text, which has wasted a lot of time and labour on the text labelling of products. Besides, the ability of text to describe products is limited and the text does not have a uniform standard, especially for non-standard consumer products such as clothing [6]. These reasons not only decrease the efficiency of online shopping but also make consumers more bored and even give up shopping during an online search. Therefore, it is necessary to realize the image retrieval of products to identify the clothing styles that the consumers want, which greatly improves the convenience of online shopping and enhances the consumers' desire to purchase [7].

Nowadays, the development of digital image technology has made this demand possible. There are many studies focusing on how to use image technology to realize the automatic recognition of clothing styles. For example, Juan and her co-workers combined the clothing local histogram of oriented gradients (HOG) features with key dimensions to realize the style classification [8]. An et al. proposed a fast and reliable method by adopting wavelet Fourier descriptor, liner discriminant analysis and extreme learning machine to handle multi-class fashion flat sketches classification problems [9]. Hou et al. used the combination of Hu invariant moments and Fourier descriptors to describe the contour features of the garment [10]. However, these shape feature descriptors cannot visually correspond to the contour of the garment. To solve this problem, Li et al. detected the peak value of each point curvature of the garment contour and selected the point with the largest peak to form a feature point set to describe the garment, which achieved the recognition of the clothing style [11]. On the other hand, there have been some studies on image recognition of clothing styles, but few methods have involved computer automatic identification of clothing accessories [12, 13]. Accessories play an indispensable role in clothing. Among them, the hat is one of the most popular clothing items for women. Therefore, the research on automatic recognition technology of hat style not only promotes the efficiency and practical values of image recognition technology in e-commerce but also contributes to the development of clothing intelligent matching recommendation system.

METHODOLOGY

In this paper, an image processing (IP) and machine learning (ML) integrated method (IPML) is developed to support the recognition process. In the recognition process, an IP method will be first used to obtain the contour curve of the pending hat image. After this procedure, a clean and smooth curvature of the involved hat can be obtained. Then, an extraction method will be applied to obtain the feature points of the pending sample. Then these feature points will be processed through a ML method and compared with the feature points of the pre-processed samples in a pre-defined Learning Sample Library (LSL). The style information of the learning sample in the LSL that has the most similar feature points will be utilized as the result of the pending sample.

Working principle of the proposed system

The working principle of the proposed hat style recognition system (HSRS) is based on IPML. The general working process of the proposed system is presented in figure 1.

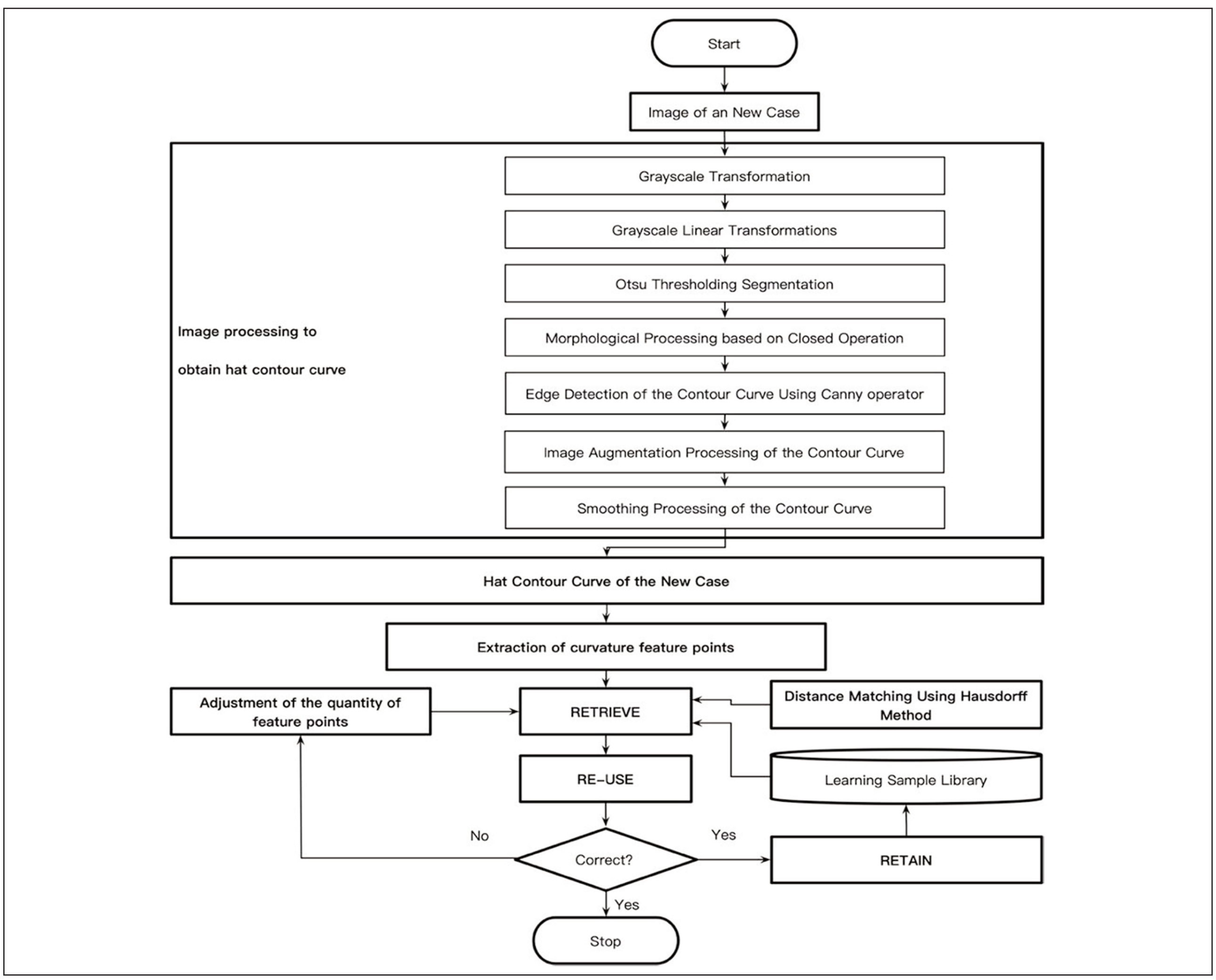


Fig. 1. Flow chart of automatic recognition process of hat style

The IP method includes Greyscale Transformation, Greyscale Linear Transformations, Otsu Thresholding Segmentation, Morphological Processing Based on Closed Operation, Edge Detection Using Canny operator, Image Augmentation Processing, Smoothing Processing of the Contour Curve, and Feature Points Extraction Method. Through these operations, we can first obtain a clean and smooth contour curve of the pending images of any hat, and then the feature points of the contour curves of these hats can also be obtained. There are two functions of the IP method: (1) processing the learning samples in the LSL, and (2) processing the new pending case.

In the recognition process, the IP method will be used to obtain the contour curve of the pending hat image. After this procedure, the feature points of the pending sample can be obtained. Then ML method will be used. There is a pre-defined LSL and the pre-processed hat samples together with their corresponding feature points will be stored inside the LSL. In the real recognition process, the Hausdorff distance method will be used. The pending sample will be compared with those samples which are stored in the LSL. The sample with the highest similarity will be utilized as the learning sample, whose style will be used as the result of the pending sample. When the similarity is below the threshold of 80%, the number of extracted feature points and output results will be adjusted until it is higher than 80%.

Related concepts, processing methods and their principles

The principles, detailed steps and corresponding results of IP used in the HSRS are shown in figure 2. The greyscale transformation process is performed at the beginning stage of the image processing procedure. It is carried out in order to highlight the hat part in the hat image, and also fade the extra background part [14]. Through the greyscale transformation procedure, the image to be processed will be only with black and white pixels, which is easier to facilitate the image segmentation between the hat part and the background, as shown in figure 2, (A). The greyscale transformation is realized in MATLAB R2014a. The greyscale transformation classifies the pixels of the image through the threshold setting. The selection of different threshold settings will affect the effect of greyscale transformation. Let $f(x, y)$ be the image to be processed, and we need to find a threshold A to divid this image. Using the pre-defined threshold A, the image to be processed can be divided into two parts:

$$g(x, y) = \begin{cases} a_0 & f(x, y) \leq A \\ a_1 & f(x, y) \geq A \end{cases} \quad (1)$$

If we let a_0 = 0 (black) and a_1 = 1 (white), the image to be processed will be converted into an image with only black and white pixels. The greyscale liner transformation process is carried out after the greyscale

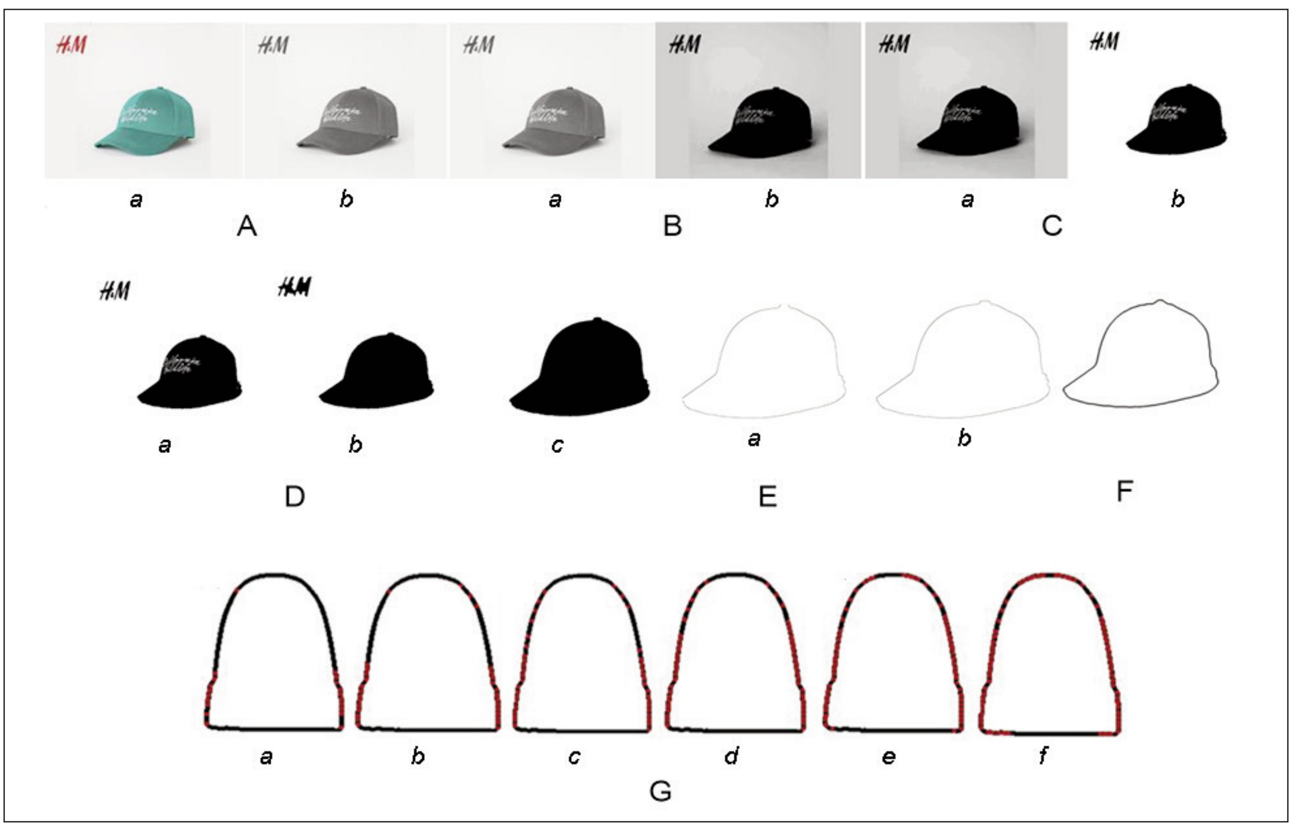


Fig. 2. (A) Greyscale transformation of hat image: *a* – original image; *b* – greyscale; (B) Greyscale liner transformation of hat image: *a* – before; *b* – after; (C) Otsu thresholding segmentation of hat image: *a* – greyscale linear image; *b* – binary image; (D) Morphological process based on closed operation of hat image: *a* – binary image; *b* – morphological closure image; *c* – maximum area image; (E) Image augmentation processing: *a* – before; *b* – after; (F) Contour after curve smoothing process; (G) Extracted feature points of borderless knitted hat: *a* – 20; *b* – 30; *c* – 40; *d* – 50; *e* – 60; *f* – 70

transformation process. The grey value of the image obtained by the greyscale transformation process is sometimes concentrated in a small range due to underexposure or overexposure, resulting in the situation where the grey level of the image is not obvious, and the image clarity is not high [15]. This procedure aims to use linear functions to extend the pixels of the image to improve the blurry situation of the image and make the greyscale of the image clear, as shown in figure 2, (B). The greyscale liner transformation is performed in MATLAB R2014a. If the greyscale range of $f(x, y)$ is $[a, b]$, the greyscale range of the transformed image of $g(x, y)$ will be extended to [c, d], then the linear transformation can be expressed as:

$$g(x, y) = \frac{d-c}{b-a}[f(x, y) - a] + c \tag{2}$$

Where a and b are the minimum and maximum values of the image brightness, respectively; c and d respectively correspond to the maximum value after the transformation. Set the maximum grey level of the image as L. In order to enhance the display effect of the image, the grey value in the $[a, b]$ can be converted to the $[c, d]$ as follows:

$$g(x, y) = \begin{cases} c & 0 \le f(x, y) < a \\ \frac{d-c}{b-a}[f(x, y) - a] + c & a \le f(x, y) \le b \\ d & b < f(x, y) < L \end{cases} \tag{3}$$

After the greyscale liner transformation of the hat image, the hat and the image background occupy different greyscale ranges. In order to realize the division of hat and background, thresholding segmentation technology can classify the greyscale value of the hat image by dividing the pixels with the same greyscale range into the same area. This process is achieved using the maximum inter-class method (also known as Otsu method) to obtain the image threshold, which is a widely used, easy to calculate, stable and effective method [16]. The main principle is to divide the image histogram into two groups at a certain threshold. When the variance of these two groups is the largest, the threshold of segmentation is obtained. This process can separate the hat from the background, by converting the background with a lower greyscale to white, while the hat with a higher greyscale value is retained, as shown in figure 2, (C). Closed operation is one of the basic operations of morphology, which can eliminate the narrow discontinuities and gaps and fill the small holes in the image. Meanwhile, the maximum area of the hat image needs to be extracted based on closed operation in order to filter unnecessary information, such as logo pattern and facilitate the next contour extraction, shown in figure 2, (D). The morphological processing based on the closed operation is also realized in MATLAB R2014a. The edge is one of the most basic features of the image. It exists at the junction of one area of the image and another attribute area. It is the most concentrated place of image information, and often contains most of the information of an image [17]. The edge detection process is performed at the middle stage of the image processing procedure. It is a necessary and important step to identify the hat style in this study because the edge can outline the shape of the hat, which is convenient for subsequent processing. The Canny operator has been widely used due to its excellent performance [18]. It uses a Gaussian filter to reduce noise on the image, which makes the position error of the actual edge and the detected edge very small and then performs non-maximum suppression, which can exclude some non-edge interference, and finally uses a double threshold to determine whether to keep the edges, which can ensure that false edges are not detected. The edge detection using Canny operator is carried out in MATLAB R2014a. The image augmentation process is performed after the edge detection of hat image using Canny operator. When extracting contour lines of the hat image, it is easy to produce discontinuous edges of the image. Therefore, it is necessary to augment the surroundings of the image to ensure the integrity of the extracted curve, as shown in figure 2, (E). The image augmentation process is performed in MATLAB R2014a.

Due to the influence of noise and image digitization errors, the extracted contour lines will appear to be not smooth. In order to prevent these impacts on subsequent experiments, the extracted contour curve obtained after the augmentation processing needs further to be smoothed. The smoothing of the curve can be obtained by spatial domain filtering and frequency domain filtering, but the latter is widely used because it is not affected by the image size. Here, the two-dimensional discrete Fourier transform in the frequency domain is used to smooth the curve, since it can convert the image from the spatial domain to the frequency domain, and has been widely used in image enhancement, image edge detection, and image denoising [19]. The hat outline image of $f(x, y)$ with the size $M \cdot N$ is defined by its two-dimensional discrete Fourier transform $F(u, v)$ as follows:

$$F(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\, e^{-j2\pi(ux/M + vy/N)} \tag{4}$$

Where $u = 0,1,2,\ldots, M-1$ and $v = 0,1,2,\ldots, N-1$ determine the size of the frequency region $M = N$, $F(u, v)$ represents the value of each frequency point (u, v). The definition of inverse Fourier transform is as follows:

$$f(x, y) = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v)\, e^{j2\pi(ux/M + vy/N)} \tag{5}$$

The smooth process is performed in MATLAB R2014a. As can be seen in figure 2, (F), the contour image after the frequency domain filtering process keeps the original details and becomes smooth without small fluctuations and noise, which is conducive to the extraction of characteristic points of the curve later. The contour feature points are the most basic elements representing the shape of the object. The shape can be accurately described by the contour line, and the curvature is an important feature for determining the shape of the curve [20]. Therefore, the extracted curvature of hat image is selected as the feature vector for hat style recognition. The number of curvature feature points is marked as n. After a series of processing of hat images, the obtained contour curves are stored in the form of pixel coordinates in the computer. The coordinates of the contour point is shown as $d(k) = (x_k, y_k)$, where x_k represents the abscissa of pixel point, and y_k represents the ordinate of the pixel point. The curvature value of feature points can be obtained by calculation. The curvature K of the curve $y = f(x)$ at point M is:

$$K = \frac{|y''|}{(1 + y'^2)^{3/2}} \tag{6}$$

Where y' and y'' represent the first and second derivatives of the curve at point M, respectively. The calculated formula is as follows:

$$Y' = \frac{(y_{k+1} - y_k)}{(x_{k+1} - x_k)} \tag{7}$$

$$Y'' = \frac{(y'_{k+1} - y'_k)}{(x'_{k+1} - x'_k)} \tag{8}$$

The extraction process of the curvature feature points is as follows:

1) Perform the first and second order derivation of the hat outline according to equations 7 and 8, and obtain the curvature value of each point on the contour line by equation 6;

2) Detect the peak curvature values and arrange the results in descending order;

3) Select the largest curvature peaks with 20, 30, 40, 50, 60, 70, 80, 90 points as n to test the recognition accuracy of system, respectively. The highest correctness rate is selected as the extracted feature point. Take the borderless knitted hat as an example, figure 2, (G) shows the result of extracting 20 to 70 feature points (red dots). The extraction of curvature feature points is obtained in MATLAB R2014a.

Hausdorff distance has been widely used as a similarity measure function, since it has strong anti-interference ability and fault tolerance [21]. It can describe the distance between sets. The smaller its value, the similarity between point sets [22]. The Hausdorff distance between two sets A and B can be described as follows:

$$H(A, B) = max\ (h(A, B), h(B, A)) \tag{9}$$

$$\begin{cases} h(A,B) = max\ (a \in A)\ min\ (b \in B)\ \|a - b\| \\ h(B,A) = max\ (b \in B)\ min\ (a \in A)\ \|b - a\| \end{cases} \tag{10}$$

Equation 9 is the basic form of the Hausdorff distance, $H(A,B)$ represents the larger value between $h(A,B)$ and $h(B,A)$; $h(A,B)$ and $h(B,A)$ are the one-way Hausdorff distances between the two sets A and B in formula (10). $h(B,A)$ represents the distance between each point a_n in the A set and the point b_m in the set B closest to the a_n, then sort the closest distances $\|a_n - b_m\|$. The maximum value of $\|a_n - b_m\|$ is the value of $h(A,B)$. Take a hat as an example. A hat image first needs to be pro-treated by a series of IP method on the computer. Then, the feature point set B is obtained and matched with the feature point set A of known samples in the training set by calculating the Hausdorff distance. According to the distance from small to large, the first hat style judgment results with the smallest distance from the point set B are sequentially output. The number of hat style output results is expressed by P. Assume that the P is 5. If there are 4 peaked hats and 1 top hat, the output result of the hat style is peaked cap, which means that the highest proportion of the category is the final recognition result. Besides, considering the fact that the output results are easy to appear with 1:1 at $P = 2$, 3 is chosen as the minimum value of output result to avoid this.

Hats can be divided into many categories according to different criteria, such as seasons and materials, etc. The most common classification of hat is determined by the style. Therefore, we firstly build a hat image sample of four common styles including peaked hats, berets, top hats and borderless knitted hats. 800 pictures as samples are obtained from the internet resource (www.taobao.com). There are 200 pictures in each type of hat. 100 of them are randomly selected as the training set, and the remaining 100 sheets are used as test sets. In order to facilitate the research, a solid color background and a flat single-piece hat is selected.

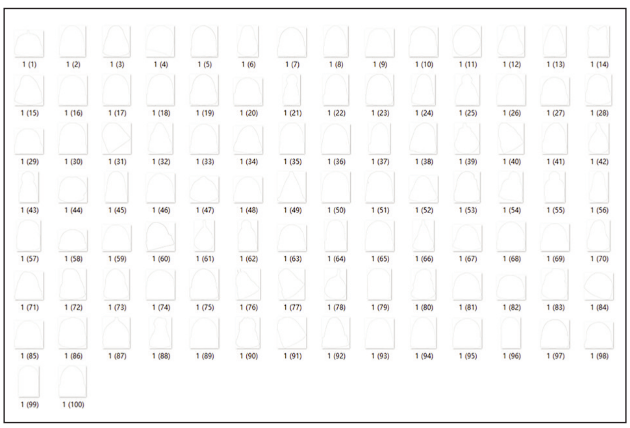
EXPERIMENTS

The purpose of the proposed HSRS is the automatic definition of any hat with four hat styles. In order to realize the proposed system, two experiments are performed. The first one is designed to establish the Learning Sample Library (LSL). The second is intended to evaluate the recognition accuracy of HSRS by testing the stored samples in LSL.

Experiment I: establishment of the Learning Sample Library

There are four common styles of hats, including peaked hats, berets, top hats and borderless knitted hats. In this study, we define the proposed LSL with four sub-libraries: peaked hat library (PL), beret library (BL), top hat library (TL) and borderless knitted hat library (BKL). For each sub-library, we stored 200 samples. 100 of them are randomly selected as the training set, and the remaining 100 sheets are used as test sets. The first 100 training samples first are processed by IP method. Through these operations, the clean and smooth contour curves and corresponding feature points of these hats are obtained. The BKL as an example are shown in figure 3, *a* and *b*. Then, the rest 100 samples are processed and used to validate the learning process. The results show that the overall accuracy of the validation samples for PL, BL, TL and BKL were 83%, 78%, 86% and 91%, respectively. It indicates that the overall accuracy of the learning process is in a generally high level. Next, the unqualified samples for each sub-library are removed from the different libraries

a



b

Fig. 3. Graphical representation of: *a* – original sample images of 100 borderless knitted hats as training set; *b* – extracted contour curves of 100 borderless knitted hats as training set

because they are not representative and it will affect the accuracy of the system for future learning processes. Finally, 100 training samples and the qualified learning samples are all stored in the LSL.

Experiment II: Determination of the quantity of feature points and hat style output

In order to optimize the efficiency of the proposed system, we must determine the quantity of the feature points in the retrieve process. There are two key variables, the curvature feature points (*n*) and hat style output (*P*), that will affect the recognition accuracy of the proposed system. Therefore, we use 200 new cases (50 samples for each style) to investigate the ideal quantity of feature points and hat style output. The result is the average accuracy value of the four types of hats, as shown in figure 4. When n is fixed and used to calculate the Hausdorff distance, the first 3, 5, 8 and 10 judgment results with the smallest distance are selected as the final recognition results. As shown in figure 4, the recognition accuracy gradually decreases with the increase of *P*. The highest recognition accuracy (each value is above 84%) is achieved at $P=3$, while when $P=10$, the recognition accuracy is the most unsatisfactory. This is because the farther the distance is, the smaller the similarity is. Meanwhile, if the output number is too much, it will cause interference on the judgment result, thus affecting the recognition accuracy. When *P* remains unchanged, the influence of *n* on the recognition accuracy is investigated by selecting 20, 30, 40, 50, 60, 70, 80 and 90, respectively. In addition, the recognition accuracy for different *P* fluctuates obviously as the curvature feature points increase. It can be clearly seen that the highest recognition accuracy is achieved with 90.5% at $P=3$ and $n=70$. It may be explained that if there are too few feature points, the extracted image contour is incomplete and the recognition accuracy will be reduced; If there are too many selected feature points, the recognition accuracy will be disturbed by the unimportant points. Therefore, $P=3$ and $n=70$ are used as the final parameter of the identification system.

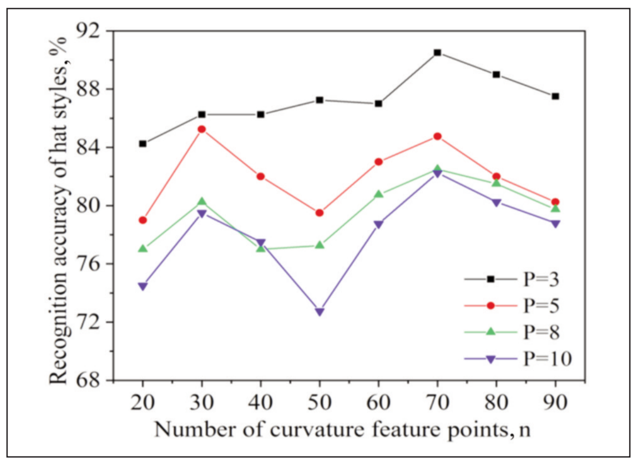


Fig. 4. Recognition results of different parameters

CASE STUDIES

In order to validate the effectiveness of the proposed HSRS, two different cases are discussed. The first case is discussed to show the general working process of an unknown case. The second case study is presented to show how the system will work when the system encounters a recognition result with low accuracy.

Case study I: the presentation of the working process of the recognition of an unknown case

In this case, the proposed system enables to realize a correct recognition of the specific hat style for an unknown hat by IPML. The whole process is as follows: the unknown hat is first processed through the series of operation of the IP method. Then the contour curve and its feature points ($n=70$) of the hat are obtained. Next, these feature points are matched with samples stored in the LSL using the Hausdorff distance method. After the comparisons of all 186 cases in the BKL, BKL93 (figure 5) has the highest similarity with the tested hat with the similarity of 92%, which is higher than the pre-defined threshold of 80%. At the same time, this case will be stored in the BKL as the sample of BKL187. When a new case is similar to BKL187, the BKL186 will be called.

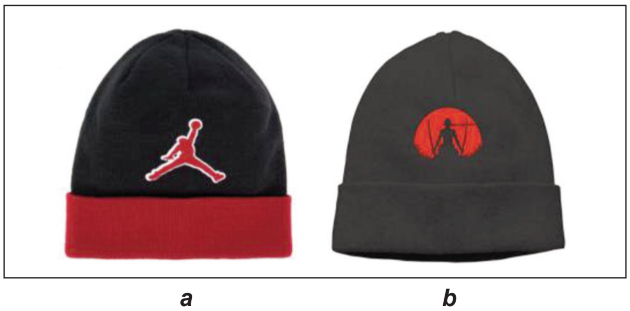


Fig. 5. Sample images of: *a* – BKL93; *b* – tested hat

Case study II: the working principle of the system when the system encounters a recognition result with low accuracy

This case is presented to explain the working principle of HSRS when it encounters a recognition result with low accuracy. There are two new samples to be tested and evaluated (named as C1 and C2). The whole process is similar to Case study I. Then, their feature points are obtained and matched with samples stored in the LSL using the Hausdorff distance method. $P=3$ and $n=70$ are used as the discriminant parameters of the proposed system. However, the recognition accuracy of C1 and C2 is 74% and 78%, respectively, which is below the pre-defined threshold of 80%. In order to improve the recognition accuracy, the number of hat style output remains unchanged ($P=3$) and the number of feature points (n) is adjusted by first increasing the number of feature points, such as 75, 80, 85, etc., and then reducing the number of feature points, such as 65, 60, 55, etc. When its recognition accuracy is higher than 80%, stop adjusting and make a judgment. The results show that the recognition accuracy of C1 with 80 feature points and C2 with 65 feature points is 85% and 86%, respectively. Besides, the two samples will be stored in the corresponding library for the next judgment.

Evaluation of the proposed Hat Style Recognition System

In order to evaluate the accuracy of the proposed system, 400 new samples (100 for each style) are carried out and analysed. When $P=3$ and $n=70$, the recognition results of the four hat types are shown in figure 6, (A). It can be seen that the recognition accuracy of the borderless knitted hat is the highest with 98%, followed by the top hat with 95%, while the recognition accuracy of the peaked hat and beret is relatively low, 88% and 81%, respectively. This is due to the fact that the contour curve of the beret is round and simple with fewer inflexion points, and its overall shape is similar to that of the top hat, resulting in recognition errors, as shown in figure 6, (B) [23, 24]. In addition, the peaked cap is easily misidentified as a beret or top hat, because it has more shape and style, compared with those of the other three caps. At the same time, the contour curve of the peaked hat is variable, which leads to great uncertainty in the identification process, thus affecting the final recognition result.

CONCLUSIONS

To achieve the automatic recognition of hat styles, an image processing and machine learning (IPML) integrated method is proposed. 4 kinds of hat styles with 800 pictures (borderless knitted hats, berets, top hats and peaked hats) are created as research samples, including 400 training sets and 400 test sets. After obtaining a smooth and complete contour curve by a series of pre-processing, the curvature feature points of the hat profile are extracted as the feature values

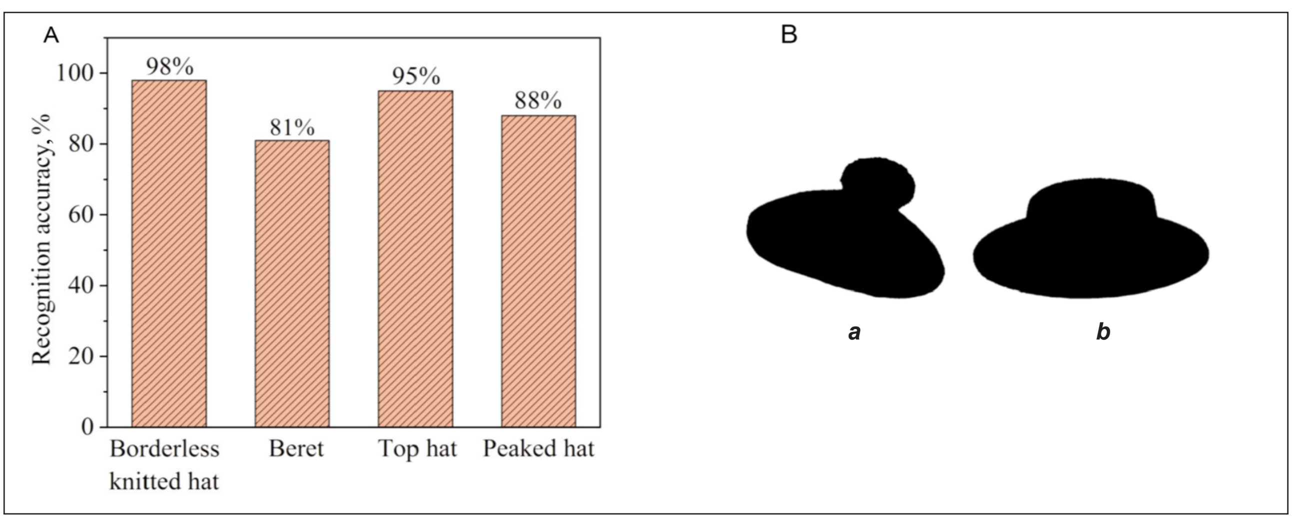


Fig. 6. Graphical representation: *A* – Recognition accuracy of four types at $P=3$ and $n=70$; *B* – The contour curve of: *a* – beret; *b* – top hat

of the style recognition. Then, the Hausdorff distance is calculated and used to match the similarity between the samples and the training set. The identifying results are output by similarity from high to low and the highest output proportion is taken as the final recognition result. The experimental results are as follows:

- When $P=3$ and $n=70$, the average recognition accuracy of the four types of hats is the highest, reaching 90.5%.
- Different types of hats have different recognition accuracy. When $P=3$ and $n=70$, the highest recognition accuracy is 98% for the borderless knitted hat, followed by the top hat with 95%, while the low recognition accuracy of the peaked hat and beret is 88% and 81%, respectively.
- The automatic recognition system is suitable for the simple outline hat like the borderless knitted hat and top hat. However, for hats with complex contours and large differences in shape, a single curvature feature point cannot fully characterize the hat image shape. The recognition accuracy of this method needs further study.

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