Exploring Circular Hough Transforms for Detecting Hand Feature Points in Noisy Images from Ghost-Circle Patterns

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Abstract. Several applications involve the automatic analysis of hand images such as biometry, digit-ratio measurements, and gesture recognition. A key problem common to these applications is the separation of hands from the background. Color based approaches struggle to detect the boundaries of the hand and the background if these have similar colors. This paper thus describes work-in-progress with a spatial approach for finger feature point detection based on the circular Hough transforms. The main challenge is to interpret finger feature points in the patterns of circles amidst noise. The approach was implemented in java and tested on a set of images. The results were assessed using manual visual inspection. Such spatial approaches hold potential for more robust and flexible hand related image analysis application. Moreover, these approaches could also give faster algorithms as there is no need for image binarization and threshold optimization.

Keywords: Finger feature points, Hand analysis, Image analysis, Hough transform.

1 Introduction

Hands are used in a variety of applications including detecting gestures [1], biometry [2] and digit ratio measurements [3]. Certain gesture applications employ cameras to capture the movements of an individual and thereby interpret the actual motions of the person and hence his or her gestures. The person can therefore use gestures to control computers. The approaches often involve sophisticated image analysis algorithms for detecting arms, hands and fingers for the orientation and location of the individual fingers [4, 5, 6]. Similarly, several biometric applications, that is, the detection of an individual's identify based on his or her unique human features, rely on hand information such as fingerprint [7], the shape and texture of the hands [8] or palmprints [9, 10, 11]. Common for these is that overall hand features must be detected before the detailed information can be analyzed, that is, the fingerprint location, or the palm location and orientation, etc.

Automatic digit ratio measurement [12, 13, 14] is another area that requires the accurate detection of hand feature points. The purpose of digit ratio measurements is to find the length ratio between the index finger and the ring finger of a person as this is an estimate of exposure to certain hormones early in life. To measure finger lengths, it is necessary to identify the feature points of such fingertips and the joining of two fingers.

Applications requiring hand feature points typically attempt to first separate the hand from the background. Several general binarizing techniques have been proposed [15]. However, the problem is challenging, and the problem is often solved for a specific domain. The detection of skin versus non-skin is no exception [16, 17]. A problem with the pixel-based approaches that use the pixel color to classify a pixel as skin or not skin is that they often fail if the background has a similar color as the skin. The proposed method thus does not rely on a binarization step. Instead, the spatial characteristics of features are analyzed. For this purpose, the classic circular Hough transform is employed [18].

2　Related work

There is a vast body of work on finger tracking, especially in context of gesture-based interaction where the hands are moving. Several studies have used RGB-depth cameras, usually the widely available Kinnect device. Liang, Yuan, and Thalmann [19] used a Kinnect depth camera to track fingers and palms using a Kalman filter and particle filter. Maisto et al. [20] also used a Kinnect depth camera and identified fingertips by extracting the hand contour which were transformed to piecewise linear contours to compute the center of mass. Next, the fingertips were detected using the convex contour. A similar approach using a Kinnect camera and convex hull was reported by Alamsyah and Fanany [21]. Lin et al. [22] used a Kinnect with kernelized correlation filters, principle component analysis and extended inscribed circles to detect the fingertip locations. Other fingertip tracking approaches utilizing Kinnect include Silanon and Suvonvorn [23].

Wu and Kang [24] extracted fingertip locations based on the curve of the hand silhouette by using a combination of temporal and spatial features, using optical flows to combine tracking and detection. Higuchi and Komuro [25] detected the location and orientation of a single finger with complex backgrounds. Li et al. [26, 27] proposed a two-stage tracking process using discriminative correlation filters that first tracked at a course grained level followed by tracking at a fine-grained level. A discriminative correlation filter was also applied by Liu, Li, and Tang [28]. Grzejszczak, Molle, and Roth [29] focused on tracking hidden fingers folded inside the hand by recognizing hand landmarks through distinctive gestures. Wu and Kang [30] detected the hands using optical flow and a skin color model and then detected the fingers based on the resulting region using distances to the centroid. A similar approach was reported in [31]. Bhuyan, Neog, and Kar [32] proposed a hand pose recognition method based on a probabilistic model of the geometric features of the hand.

Several approaches have also applied circular Hough transform for fingertip tracking. Do, Asfour and Dillmann [33] used a Hough transform to extract fingertip locations for moving hands. The movements were tracked using a particle-based filter. Hasan and Mishra [34] employed circle templates. Although similar to circular Hough transforms, circular templates are not strictly speaking a circular Hough transform per se. The circular templates are fitted within the area of the and their positions were used to detect fingertip positions. Alam and Chowdhury [35] used a circular Hough transform to detect potential fingertip locations and then selected the most probable candidates using color features. Boswas [36] used a combination of the line Hough transform and the circle Hough transform to find fingertip locations. The circular Hough transform indicated the fingertip contenders while the Hough lines were used to select the most probable alternatives.

3   Method

3.1   Assumptions

A manual inspection of numerous images confirms that the silhouette of hands has rounded features. The roundedness is caused by the equal forces that act on all areas of the human skin filled with soft tissue. Both fingertips and finger-hand joints occur as arcs (see Fig. 1). Given a method for detecting circles, such as the one offered by the circular Hough transform, it should be possible to detect such features. In reality, the circular shapes are inexact, aliased and fuzzy, and one is likely to observe additional ghost circles, that is, smaller circles inside the larger circles (see Fig. 2). Moreover, one is likely to see ghost circles between fingers, across fingers and across hands when enough pixels across the silhouette points appear in circular shapes. The method explored herein is thus based on exploiting not only the main circles, but also the patterns of the ghost circles. R_{max} denotes the maximum radius of the Hough transform circles. As shown by Figs. 1 and 2 it is important to select the radius R_{max} such that it is sufficiently large to capture fingertips, yet sufficiently small not to trigger ghost circles across fingers assuming that the widths of the fingers are wider than the gap between the crevice fingers.
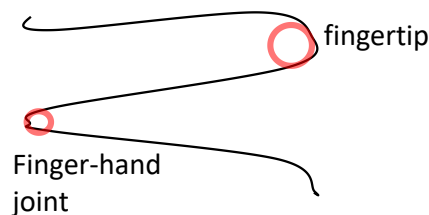

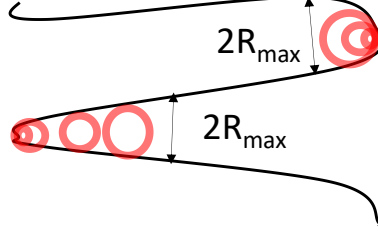**Fig. 1.** Optimal situation with one circle per fingertip and finger-hand joint

Fig. 2. Realistic situation with ghost circles.

3.2 Preprocessing

Hand images captured by flatbed scanners are input to the system. Current image capturing hardware usually have a high resolution. It is assumed that the hand is occupying most of the image view. Next, the images are down-sampled such that the new width is 100 pixels. The down-sampling is effectively a low-pass filter that removes irrelevant high-frequency image noise while maintaining the low-frequency hand features. Moreover, the smaller down-sampled images are faster to process in subsequent steps. The system then applies edge detection to the resulting images. In this study, a simple convolutional edge detector was used with a 5×5 Laplacian kernel given by:

$$\begin{bmatrix} -4 & -1 & 0 & -1 & -4 \\ -1 & 2 & 3 & 2 & -1 \\ 0 & 3 & 4 & 3 & 0 \\ -1 & 2 & 3 & 2 & -1 \\ -4 & -1 & 0 & -1 & -4 \end{bmatrix} \tag{1}$$

3.3 Circle Detection

The fingertips and finger-hand joints have the visual appearance of half circles. The idea is therefore to detect areas of interest using a Hough transform [18]. The Hough transform is a general method that has been used for identifying basic geometric shapes such as lines, circles, and ellipses. The Hough transform represent circles using three parameters the coordinate (p, q) of the circle center and the circle radius r, namely

$$x = p + r\cos(\theta) \tag{2}$$

$$x = q + r\sin(\theta) \tag{3}$$

The transform works by searching the image for pixels that matches the two equations for different values of p, q and r. Matches are stored in a three-dimensional accumulator array. Circles are detected as accumulator array entries with the most hits. The circular Hough transform is applied to the edge-detected image and the result is a list of circle candidates. The Hough transform is limited to circles with maximum radii related to the maximum expected finger width.
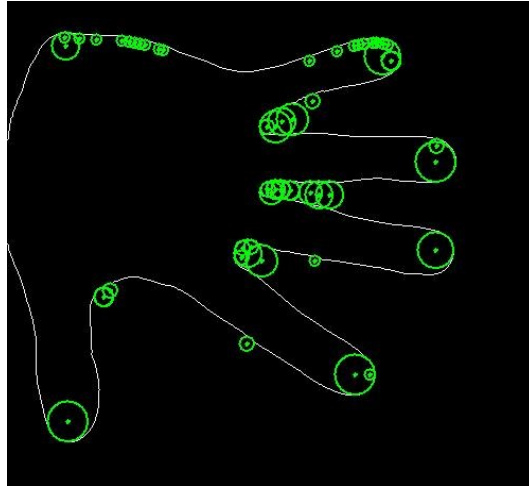
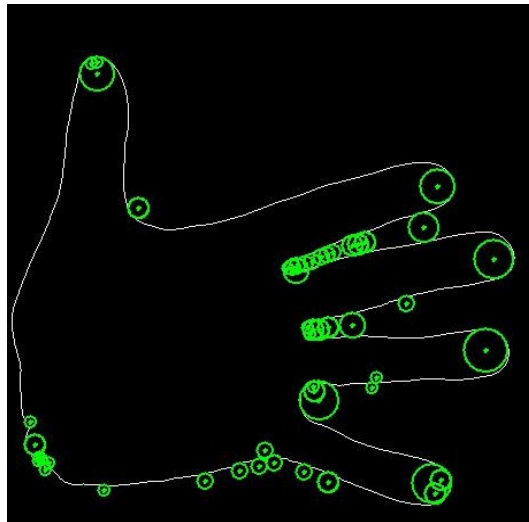**Fig. 3.** Example Hough circles for the left hand.

Fig. 4. Example Hough circles for the right hand.

Figs. 3 and 4 show examples of Hough circles based on a very basic hand contour. As can be seen circles occur at the fingertips. Some fingertips also have multiple circles, where smaller circles occur inside the larger circles. Similarly, the finger-hand joints are also clearly characterized by circles. Figs. 3 and 4 show that these fall into one of two categories, the ones where the fingers are close and the ones where the fingers are more spread. If the fingers are spread the finger-hand joint appears as a clear circular shape with larger radius. These are observed as larger circles with

smaller circles inside. The cases where the fingers are closer together are characterized by circles with smaller radii.

There are circles also circles extending out along the gap between the fingers. These circles to not actually touch the finger-hand joint. However, the radii increase with the distance to the finger-hand joint.

Note that the contours in Figs. 3 and 4 are the result of hand binarization and tracing the edge of the hand. Next, color fill was used to separate the two hands, that is, a filling algorithm was used till in the areas of the two hands with green and blue to separate the two hands. The resulting edges are thus free from noise such as scanning artefacts and uneven backgrounds.
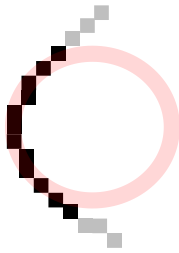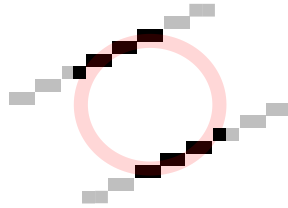
Fig. 5. Circle classification: arc circle.

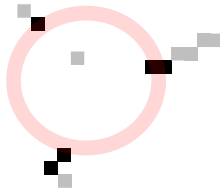**Fig. 6.** Circle classification: ghost circles.

Fig. 7. Circle classification: noise.

An edge detected image based on a convolutional edge detector will thus contain many additional edges and the hands will not be separated. The Hough transform will thus report many more circles not related to the hand outline, as well as circles occurring across hands if the hands are separated by a distance related to the Hough transform radius range. This example was generated with the author's own java image processing library.

3.4   Overlapping Circle Detection

To detect fingertips and finger-hand joint contenders, sets of overlapping circles need to be detected. Two circles a and b are overlapping if

$$(p_a - p_b)^2 + (q_a - q_b)^2 < (r_a + r_b)^2 \qquad (4)$$

That is, the circles are overlapping if the distance between the two circle centers are smaller than the sum of the two radii. If the circles are overlapping, the smallest circle is kept and the largest is discarded.

3.5   Circle Classification

To make an overall decision of whether it is a fingertip or finger-hand joint the proposed method depends on defining the image as a half arc (see Fig. 5), a ghost circle occurring between two fingers (see Fig. 6) or simply noise to be discarded (see Fig. 7). The classification is simply performed by exploring the pixels lying along the lines of the circle in the edge detected image. To detect whether a pixel x, y is on the circle given by center p, q with radius r, the distance d between x, y and p, q must satisfy $r - \delta r \leq d \leq r + \delta r$. That is, instead of considering the exact circle, a flat donut shape with width $2\delta r$ is used.

Once the pixels on the circle are detected, the angular distribution is used for classification. That is, if most of the pixels are grouped in one area the circle is classified as an arc, if the majority of pixels are located in two groups it is classified as a ghost circle, otherwise the circle is classified as noise.

4   Results and discussions

The proposed approach was implemented in Java and tested on a selection of hand scans and the results were visually inspected. A visual inspection approach was chosen due to a lack of a reference dataset with ground truths. Moreover, the manual visual inspection method was practical, quick, and informative. Clearly, the quality of the results varied with the quality of the images analyzed. For some images, a clear set of hand feature points could be detected, while with other images many ghost circles remained leading to ambiguity in what constitutes the actual hand feature points (see for instance Figs. 3 and 4). It was easy to decipher this through the manual inspections, but quite hard to do automatically by machine. On a few occasions the approach detected too few feature points, while in most other situations too many feature points were detected. Therefore, it seems unrealistic to end up with exactly 9 feature points for each hand (5 fingertips and 4 finger cervices). Moreover, the approach does not determine the mapping from a specific Hough circle to a specific finger feature. Therefore, a second step is needed to perform such mappings and filter the remaining ghost circles. Obviously, Hough circle post-processing cannot compensate for missing circles.

One weakness of the Hough circle approach is that features are extracted at micro level, that is, all identified circles trigger a potential feature point. This approach thus introduces the second challenge of assessing the relevance of the contenders. It is possible that a global approach may be a more fruitful direction, such as the methods based on hand silhouettes. Instead of using all detected circles as feature point contenders, the contour of the hands can be traced, and its overall features used to detect the finger points. Although this approach may seem straightforward, there are challenges with identifying the actual tip of the fingers and the crevices as detecting a point slightly offset to the middle of the finger will render inaccurate measurements. Moreover, with high resolution images it is necessary to focus on the global turns and ignore the small but frequent perturbations on the finger contours. However, a global contour-based approach relies on successfully binarized images. On the other hand, the Hough transform does not require the input image to be perfectly binarized. Note that the test performed herein where all using binarized images. It would have been relevant to also have tested the approach by bypassing the binarization step. One would expect that noisy backgrounds also would yield many additional ghost circles that could be challenging to separate from the actual hand feature points.

The hand feature detection approach described herein is quite different to most of the approaches to finger tracking described in the literature. First, most of the finger detection approaches described in the literature were intended for tracking moving hands, for instance for the purpose of gesture detection. However, the approach described herein was intended for still images (hand scans). Second, the approaches in the literature were mostly intended for detecting the approximate locations of the fingers and hands such that the overall hand shape or gestures could be detected. The goal of the problem domain explored herein was to obtain an accurate measurement of the hand features. Hence, the literature focused on the overall hand shape classification and location, while the presented approach focused on the accurate measurements of hand dimensions. Third, general three-dimensional hand tracking involves also tracking obstructed fingers and fingers inside grasped hands. However, for the hand feature point measurements one can assume that all the fingers are visible, flat and spread out.

5   Conclusions

A spatial method for detecting hand finger points of interest was proposed based on circular Hough transform. The Hough transform over-detect circles in the image and the characteristics of the circles are used to classify a region as simply noise, a finger-tip, or finger-hand joints. The method is promising in terms of being robust to background and image noise such as scanning artefacts, lighting interference, etc. However, the method reports both false negatives and false positives. Future work will focus on improving the algorithm further and systematically record its performance of the algorithm.

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