Slope Difference Distribution and Its Computer Vision Applications

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Abstract—Slope difference distribution (SDD) is computed from the one-dimensional curve and makes it possible to find derivatives that do not exist in the original curve. It is not only robust to calculate the threshold point to separate the curve logically, but also robust to calculate the center of each part of the separated curve. SDD has been used in image segmentation and it outperforms all classical and state of the art image segmentation methods. SDD is also very useful in calculating the features for pattern recognition and object detection. For the gesture recognition, SDD achieved 100% accuracy for two public datasets: the NUS dataset and the near-infrared dataset. For the object recognition, SDD achieved 100% accuracy for the Kimia 99 dataset. In this memorandum, I will demonstrate the effectiveness of SDD with some typical examples.

Index Terms—Slope difference distribution; threshold selection; pattern recognition; feature detection; image segmentation

I. INTRODUCTION

Slope difference distribution (SDD) has been proposed for image segmentation in recent years and it could calculate the clustering centers of the one-dimensional histogram more robustly than state of the art methods [1]. It could also calculate the threshold point from the one-dimensional histogram more robustly than state of the art methods [2]. SDD based image segmentation method does not require any training datasets and still performs better than state of the art image segmentation methods in segmenting the left ventricles in magnetic resonance images [3]. In this memorandum, I will evaluate the robustness of SDD to calculate the peak features and valley features of the object’s contour. The hand gestures are recognized solely based on the computed features by SDD and 100% accuracy was achieved in two public datasets, NUS subset A and near-infrared dataset. For other public datasets, the proposed method in this memorandum also achieved better accuracy than state of the art methods. The used object recognition datasets include Kimia 99, Kimia 216 and MPEG-7 and SDD also achieved state of the art accuracy.

II. OBJECT RECOGNITION BY SLOPE DIFFERENCE DISTRIBUTION

After the centroid of the object is computed, the 1D curve of the object \( C_{iD}^j \), \( j = 1, \ldots, L \) is computed as the distance distribution from the centroid of the hand to each point on the 2D object’s contour:

\[
C_{ij}^D = \left[ (x_j - x_c)^2 + (y_j - y_c)^2 \right]^{1/2}, \quad j = 1, \ldots, L
\]

where \( L \) is the total number of points on the 1D object curve. The slope difference distribution of the 1D object curve contour \( C_{iD}^j \), \( j = 1, \ldots, L \) is decomposed into different frequency components by discrete Fourier transform (DFT). The low frequency components reflect the global variations of the hand contour and the high frequency components reflect the local variations of the hand contour. Since the different shapes could be differentiated by the global variations of the object’s contour, only the low frequency parts of the object curve is kept. The 1D object curve \( C_{iD}^j \), \( j = 1, \ldots, L \) is transformed into the frequency domain by discrete Fourier transform (DFT).

\[
F(k) = \sum_{j=1}^{L} C_{ij}^D e^{-2\pi jk}; \quad k = 1, \ldots, L
\]

The high frequency components of transformed 1D hand contour are reduced as:

\[
F'(k) = \begin{cases} 
F(k); & k \leq W \\
0; & k > W
\end{cases}
\]

where \( W \) is the cut-off frequency of the low pass DFT filter. After high frequency component elimination, the distance distribution, i.e., the 1D object curve is transformed back into spatial domain as follows.

\[
C_{iD}^{DP} = \frac{1}{L} \sum_{j=1}^{L} F'(k) e^{-\frac{2\pi jk}{L}}; \quad j = 1, \ldots, L
\]

where \( C_{ij}^{DP} \) is the 1D object curve with global components and the slope difference distribution of it is computed as follow.

Firstly, \( N \) points \( (x, C_{i}^{DP}) \); \( x = j, j-1, \ldots, j-N+1 \) on the left side of the point \( (j, C_{j}^{DP}) \) or \( N \) points \( (x, C_{i}^{DP}) \); \( x = j, j+1, \ldots, j+N-1 \) on the right side of the point \( (j, C_{j}^{DP}) \) are selected to fit a line.

\[
y = aj + b
\]

where \( a \) is the slope of the line and \( b \) is a constant coefficient.

\[
[a, b]^T = \left( B^T B \right)^{-1} B^T Y
\]

\[
B = \begin{bmatrix}
    j+1 - N & 1 \\
    j+2 - N & 1 \\
    \vdots & \vdots \\
    j - 1 & 1 \\
    j & 1
\end{bmatrix}
\]

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Two slopes, \( a'_j \) and \( a'_j \) at the \( j \)th point \( (j, C_j^{(DP)}) \); \( j = N + 1, N + 2, ..., L - N \) could be obtained from Eq. 5. The slope difference distribution \( s_j \) is computed as:

\[
s_j = a'_j - a'_j \quad j = 1, N, ..., L - N
\]

Setting the derivative of \( s_j \) to zero and solve it, we get the positions of the valleys \( V_j; i = 1, 2, ..., N_F \) with greatest local variations on the slope difference distribution and their magnitudes \( M_j^{HP}; i = 1, 2, ..., N_F \). we also get the positions of the peaks \( P_j; i = 1, 2, ..., N_F \) and their magnitudes \( M_j^{HP}; i = 1, 2, ..., N_F \). The feature selection rules are then designed to select the detected valleys and peaks for object recognition.

The positions of these 1D features also correspond to the 2D feature points on the 2D object curve. The corresponding 2D peak feature points are computed as:

\[
P_{iF}^{PF} = \{(x, y) \mid x = P_{iF}^{PF}, y = y_{iF}^{PF}, i = 1, 2, ..., N_F\}
\]

The corresponding 2D valley feature points are computed as:

\[
P_{iF}^{VF} = \{(x, y) \mid x = x_{iF}^{VF}, y = y_{iF}^{VF}, i = 1, 2, ..., N_F - 1\}
\]

After the 2D peak features are computed, they are normalized as:

\[
P_{iF}^{PV} = \left( x_{iF}^{PV} - x_{iF}^{PF}, y_{iF}^{PV} - y_{iF}^{PF} \right), i = 1, 2, ..., N_F
\]

\[
P_{iF}^{NV} = P_{iF}^{PV} / \max\left( P_{iF}^{PV}, P_{iF}^{PV}, ..., P_{iF}^{PV} \right), i = 1, 2, ..., N_F
\]

Similarly, the 2D valley features are normalized as:

\[
P_{iF}^{PV} = \left( x_{iF}^{PV} - x_{iF}^{PV}, y_{iF}^{PV} - y_{iF}^{PV} \right), i = 1, 2, ..., N_F - 1
\]

\[
P_{iF}^{NV} = P_{iF}^{PV} / \max\left( P_{iF}^{PV}, P_{iF}^{PV}, ..., P_{iF}^{PV} \right), i = 1, 2, ..., N_F - 1
\]

The minimum Euclidean distances between the automatically detected pattern and all the reference patterns are computed as:

\[
d_i = \arg \min_{\theta \in [0, 45^\circ]} \left( d_{iF}^{PV} + d_{iF}^{PV} \right), k = 1, ..., K
\]

where \( K \) is the total number of patterns in the dataset. \( d_{iF}^{PV} \) is the average distance between the peak features in detected pattern after rotating \( \theta \) angle and the corresponding peak features in the reference pattern. \( d_{iF}^{PV} \) is the average distance between the valley features in detected pattern after rotating \( \theta \) angle and the corresponding valley features in the reference pattern. \( d_{iF}^{PV} \) and \( d_{iF}^{PV} \) are computed as follows.

\[
d_{iF}^{PV} = \frac{1}{N_F} \sum_{i=1}^{N_F} \left( \left( x_{iF}^{PV} - x_{iF}^{PV}(k) \right)^2 + \left( y_{iF}^{PV} - y_{iF}^{PV}(k) \right)^2 \right)^{1/2}
\]

\[
d_{iF}^{PV} = \frac{1}{N_F - 1} \sum_{i=1}^{N_F - 1} \left( \left( x_{iF}^{PV} - x_{iF}^{PV}(k) \right)^2 + \left( y_{iF}^{PV} - y_{iF}^{PV}(k) \right)^2 \right)^{1/2}
\]

The detected gesture is classified as the \( k \)th pattern with the minimum distance \( d_k \) to it.

III. EXPERIMENTAL RESULTS

Firstly, the SDD threshold selection method is tested with the medical image computing and computer assisted intervention (MICCAI) 2009 databases. The quantitative comparison of the SDD threshold selection method with state of the art methods on the MICCAI 2009 databases are shown in Table 1. As can be seen, the SDD method achieved significantly better accuracy than state of the art methods although many state of the art methods need extremely large efforts and manually delineated ground truths to train their methods.

Table 1. Quantitative comparison of proposed coarse-to-fine SDD threshold selection method with state of the art methods on the MICCAI 2009 challenge databases

| Method | APD | DICE |
|--------|-----|------|
| SDD    | 1.21| 94.7%|
| [4]    | 1.36| 90.7%|

The quantitative classification accuracy of the SDD method on the NUS subset A is compared with state of the art method in Table 2. The SDD hand gesture recognition method achieved 100% recognition accuracy for all the 240 images, which is significantly better than state of the art method.

Table 2. Quantitative comparison of the achieved recognition accuracies by the proposed method and state of the art method on the NUS subset A [5].

| Method | Accuracy (%) |
|--------|--------------|
|       | [5] 94.36 |
| Proposed | 100 |

The quantitative classification accuracy of the SDD method on the NI dataset is compared with state of the art method in Table 3. The SDD gesture recognition method achieved 100% recognition accuracy for all the images.

Table 3. Quantitative comparison of the achieved recognition accuracies by the proposed method and state of the art method on the NI dataset [6]

| Method | Accuracy (%) |
|--------|--------------|
|       | [6] 99 |
| Proposed | 100 |

The quantitative classification accuracy of the SDD method on the Kimia99 dataset is compared with state of the art method in Table 4. The SDD object recognition method achieved 100% recognition accuracy for all the images.

Table 4. Quantitative comparison of the achieved recognition accuracies by the proposed method and state of the art method on the Kimia99 dataset [7].

| Method | Accuracy (%) |
|--------|--------------|
|       | [7] 94.85 |
| Proposed | 100 |

CONCLUSION

Slope difference distribution find derivatives that do not
exist in the original curve and calculates the threshold or feature point robustly. Its advantages have been verified by a lot of simulations and practical datasets. Although slope difference distribution is still very young in computer vision, it has achieved state of the art accuracy in several critical computer vision applications. I am looking forward to its success in other applications.

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