Edge direction histogram (EDH)

Hariom Verma (CS171026)

[hariom18599@gmail.com]

Sahil Babani (CS171066)

[sahilbabani1997@gmail.com]

Abhiti Darbar (CS171005)

[darbarabhiti@gmail.com]

December 13, 2020

Contents

1. Introduction

- 1.1. What is Histogram
- 1.2. Edge Direction Histogram

2. Mathematical Formulation

- 2.1 Magnitude for local histogram bins
- 2.2 Magnitude for global histogram bins
- 2.3 Formula for similarity matching
- 3. Algorithm
- 4. Documentation of API
- 5. Examples
- 6. Learning Outcome
- 7. References

Introduction

1.1 What is Histogram

The histogram is the most commonly used structure to represent any global feature composition of an image. It is invariant to image translation and rotation, and normalizing the histo- gram leads to scale invariance. Exploiting the above properties, the histogram is very useful for indexing and retrieving images

1.2 Edge Direction Histogram

Edges in images constitute an important feature to represent their content. Also, human eyes are sensitive to edge features for image perception. One way of representing such an important edge feature is to use a histogram. An edge histogram in the image space represents the frequency and the directionality of the brightness changes in the image. To represent this unique feature, there is a descriptor for edge distribution in the image. This Edge Histogram Descriptor (EHD) expresses only the local edge distribution in the image. Edge histogram is designed to contain only 80 bins describing the local edge distribution. These 80 histogram bins are the only standardized semantics for EHD. However, using the local histogram bins only may not be sufficient to represent global features of the edge distribution. Thus, to improve the retrieval performance, we need global edge distribution as well. These histogram bins are used to evaluate the similarity between images.

The sub-image is defined by dividing the image space into 4×4 non overlapping blocks. Thus, the image partition always yields 16 equal-sized sub-images regardless of the size of the original image. The EHD basically represents the distribution of 5 types of edges in each local area called a sub-image. They are vertical, horizontal, 45-degree diagonal, 135-degree diagonal, and non-directional edges. Therefore each local histogram contains 5 bins. Each bin corre- sponds to one of 5 edge types (since there are 16 sub-images in the image, a total of 5×16=80 histogram bins is required). If the maximum value among 5 edge strengths obtained is greater than a threshold then the image-block is considered to have the corresponding edge in it. Otherwise, the image-block contains no edge. However, the local edge histograms alone may not be sufficient to yield efficient image matching therefore we may need edge distribution information for the whole image space. The global edge histogram has 5 bins and each bin value is obtained by accumulating and normalizing the dequantized bin values of the corresponding edge type

of BinCounts[]. This total 85 bins constitute our EHD descriptor which will give us image features.

Mathematical Formulation

2.1 Magnitude for local histogram bins

The respective edge magnitudes mv(i,j), mh(i,j), md-45(i,j), md-135(i,j), and mnd(i,j) for the (i,j)th image-block can be obtained as follows:

```
mv(i,j) = \sum ak(i,j) \times fv (k)
mh(i,j) = \sum ak(i,j) \times fh (k)
md-45(i,j) = \sum ak(i,j) \times fd-45 (k)
md-135(i,j) = \sum ak(i,j) \times fd-135(k)
mnd(i,j) = \sum ak(i,j) \times fnd(k)
```

where ak(i,j) denotes the image block and $f_v(k)$, $f_h(k)$, $f_{d-45}(k)$, $f_{d-135}(k)$ and $f_{nd}(k)$ denotes the filter coefficients for vertical, horizontal, 45-degree diagonal, 135-degree diagonal and non directional edges.

2.2 Magnitude for global histogram bins

The formula for calculating global bins is

```
Mv(i,j) = average(mv(i,j))
Mh(i,j) = average(mh(i,j))
Md-45(i,j) = average(md-45(i,j))
Md-135(i,j) = average(md-135(i,j))
Mnd(i,j) = average(mnd(i,j))
```

Where mx(i,j) denotes the magnitudes of vertical, horizontal, 45-degree diagonal, 135-degree diagonal and non directional edges local histogram bins.

Algorithm

Edge Direction Histogram Algorithm

Input: Image

Output: 1D-Array having 85 features

- 1. Load image in grayscale mode
- 2. Initialize kernels for all 5 edges i.e: horizontal,vertical,diagonal_45, diagonal_135 and non_edge
- 3. Resize image into multiple of 4
- 4. Divide image into 4*4 images i.e Blocks and calculate Bins for each block
 - 4.1 Initialize Bins of 17*5 array with value 0
 - 4.2 divide image into blocks i.e we will get 16 Blocks
 - 4.3 for each Block:
 - 4.3.1 divide Block divide into 2*2 sub_blocks:
 - 4.3.2 for each sub_blocks:
 - 4.3.2.1 multiply with each kernels and sum all the

Values and store its corresponding value in

B0,b1,b2,b3,b4 respectively.

- 4.3.2.2 get the maximum from b0,b1,b2,b3,b4
- 4.3.2.3 if maximum>Threshold=50:

Bin[maximum_edge]+=1

- 4.3.3 return Bin
- 4.4 find the global_bin i.e find the mean for every edge from

Bins[0:15] and store its corresponding value in global bin

4.5 append global bin into Bins

5 flatten Bins into 1-D array which will give us total of 85 features

6 return Bins

Documentation of API

Edge Directed Histogram calculates and returns 85 bins i.e is 80 local bins and 5 global bins.

Syntax:

edge_direction(image)

Parameters:

image : Image for which descriptors to be calculated. (use opency or any other library to read image)

Return type:

2D Array containing 85 Features Bins

Example

```
import cv2
#reading image in grayscale mode
image = cv2.imread('/content/download.jpg',0)
Features=Edge_direction(image)
```

Learning Outcome

- Extracting the "edge direction" descriptor.
- Understanding the concept of histogram in terms of image.
- Concept of local and global bins.

References

[1]:

https://onlinelibrary.wiley.com/doi/pdf/10.4218/etrij.02.0102.0103