Summit Navigator: A Novel Approach for Local Maxima Extraction

Abhijeet Aditya
dept. Electrical Engineeering
IIT Kharagpur
Kharagpur,India
aditya.abhijeet@kgpian.iitkgp.ac.in

Saurabh Chatterjee
dept. Electrical Engineering
IIT Kharagpur
Kharagpur,India
saurabhchatterjee@kgpian.iitkgp.ac.in

Chandrashekhar Maurya
dept.Electrical Engineeering
IIT Kharagpur
Kharagpur,India
shekhar96@kgpian.iitkgp.ac.in

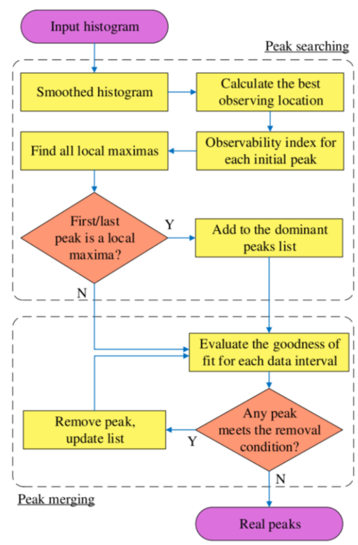
***Abstract*—This article introduces a novel method for multi-object picture segmentation dubbed the Summit Navigator. It is designed to effectively extract local maxima of an image's histogram. After the generated histogram has been smoothed using a moving average filter, an analysis of the data density and distribution is performed in order to locate the optimal place for observation. An observability index has been presented for each initial peak in order to determine whether or not it may be regarded as dominating when utilising the calculated observing location as the basis for the evaluation. After that, recursive algorithms for peak finding and merging are developed in order to get rid of any false detection of peaks that are placed on one side of each mode. The results of the experiments proved the benefits of the technique that was proposed in terms of its accuracy and consistency across a variety of reliable datasets.**

***Index Terms*—Terms— Multi-thresholding, histogram analysis, histogram segmentation, image segmentation, summit navigator.**

I. INTRODUCTION

Image segmentation remain essential tasks, for which the automatic extraction of local maxima is a crucial procedure not only for extracting the foreground for post-processing, but also for separating objects from the background for identification and classification. Techniques for extracting local maxima vary according on the data representation chosen, but can generally be grouped into histogram analysis, clustering, and entropy-based approaches [5, 6]. Histogram shape-based thresholding is extensively accepted due to its simplicity, effectiveness, and computing economy [7]. Approaches in this direction are often rely on grey-level histograms to establish segmentation thresholds in an image. The thresholds may be single or multiple values, corresponding to a bi-level or multilayer thresholding mechanism, respectively. In this research, a novel technique is created to automatically find and pinpoint real peaks in grayscale histograms of images without the need for manual inputs. In this paper, the strategic planning of mountain explorers inspires the formulation of two location-based picture segmentation parameters: offset distance and observability index. These parameters are used to search for all possible dominating peaks at the optimal sites for observation. Notably, this non-heuristic method does not require prior knowledge of the number of processing modes or the distance between modes.

II. APPROACH



The algorithm comprises three main steps: (i) preprocessing with initial peak detection, (ii) searching for dominant peaks, and (iii) merging dominant peaks found on the same side of a mode.

III. PROPOSED METHOD

A. Prepossessing

In the preprocessing phase, a moving average filter is used to the input histogram to reduce high-frequency noise and preserve peaks for further identification. For computational efficiency and efficacy on unprocessed data, the kernel width of the filter is set to 03, the smallest interval that can account for the previous, present, and subsequent intensity levels. Intensity of pixel h_i at level i after application of moving average filtering is calculated as follows:

$$h_i = \left(\frac{h'_{i-1} + h'_i + h'_{i+1}}{3} \right) \tag{1}$$

where h'_i is the intensity at level i of the input histogram. Let S represent the collection of initial peak positions. Local maxima are among the early peaks, therefore it serves as a rough blueprint for the development of the travel strategy. The next step is to identify real summits from S, the fundamental building block of the Summit Navigator algorithm.

B. Peak Searching

The explorer needs to find a good place to watch before starting a new search. This should be a place where you can see several peaks and compare them to find the strongest one. The goal of peak searching is to find the best place to observe the first peaks so that the dominant peaks can be found.

let P be the number of initial peaks and s_k , $0 \leq k \leq P$, the k-th element of vector S. Given that the first peaks satisfy $h_{s_k} > h_{s_{k-1}}$, the observing location, L_k, is the point on the intensity axis.

meeting the following criteria:

$$L_k \leq S_k - L_k \tag{2}$$

where L_k is the distance from the current peak to the place where the observations are being made. This offset distance is calculated based on the location and frequency of two consecutive peaks, k and $k-1$.

$$L_k = \frac{h_{sk}\left(s_k - s_{k-1}\right)}{\epsilon + |h_{sk} - h_{sk-1}|} \tag{3}$$

Where ϵ is small arbitrarily value.

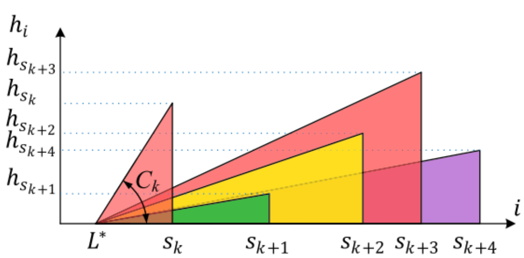


Fig. 2. Illustration of the peak searching mechanism.

observability index is definrd as:

$$C_k = \frac{h_{sk}}{L_k} \tag{4}$$

This index shows each peak's view angle from the observation position; a larger number indicates a higher likelihood of being a dominant peak. Fig depicts a case where S_k and S_{k+3} are prominent peaks to be discovered against the initial ones. In this case, the observing site is L and observability indices are calculated.$C_{sk} > C_sk+1$ makes S_k the dominant peak. The next dominant peak is S_{k+3} because it blocks the sight from the observing point to the next peak, $C_{sk+3} > C_{sk+4}$, while not hiding its prior peak, $C_{sk+3} > C_sk+2$. To extend the notion to different initial peaks, we calculate observing positions for each at S_k.

$$L_k = X_k - (Y_k \odot \Delta X_k) \oslash Y_k \tag{5}$$

Where,

$$X_k = [S_k \quad S_k ... S_k] \tag{6}$$

$$Y_k = [h_{sk} \quad h_{sk} ... h_{sk}] \tag{7}$$

$$\Delta X_k = X_k - [S_1 \;\; S_2 \; ... S_{k-1}] \tag{8}$$

$$\Delta Y_k = Y_k - [h_{s1} \;\; h_{s2} \; ... h_{sk-1}] \tag{9}$$

Then, for any peak S_k, the best place to look at the sky L^* is given by:

$$L^* = min\left\{min\left\{L_{k,m}\right\}\right\} \tag{10}$$

The observability indices for all initial peaks are then computed as:

$$C = Y_p \oslash (X_p - L^*) \tag{11}$$

,

$$Y_p = [h_{s1} \quad h_{s2} ... h_{sp}] \tag{12}$$

$$\mathbf{L}^* = [L^* \quad L^* ... L^*] \tag{13}$$

Lastly, an initial peak k is considered a dominant peak if the following is true:

$$C_k = max\left\{C_{j+1}, C_{j+2}, ..., C_{k+1}\right\} \tag{14}$$

IV. ALGORITHM

for $i \leftarrow 2, P$ **do**
  $\mathbf{L} \leftarrow \mathbf{x} - (\mathbf{y} \circ \mathbf{\Delta x}) \oslash \mathbf{\Delta y}$
  $L_{tmp}(i-1) \leftarrow min(\mathbf{L})$
end for
$L^* \leftarrow min(L_{tmp})$
$\mathbf{C} \leftarrow \mathbf{Y_P} \oslash (\mathbf{X_P} - \mathbf{L}^*)$
Find all local maxima of $\mathbf{C}$, save to $\mathbf{v}$
if $C(1) > C(2)$ **then**
  $\mathbf{v} \leftarrow \begin{bmatrix} 1 & \mathbf{v} \end{bmatrix}$
end if
if $C(end) > C(end-1)$ **then**
  $\mathbf{v} \leftarrow \begin{bmatrix} \mathbf{v} & \text{length}(C) \end{bmatrix}$
end if

V. SIMULATION RESULT

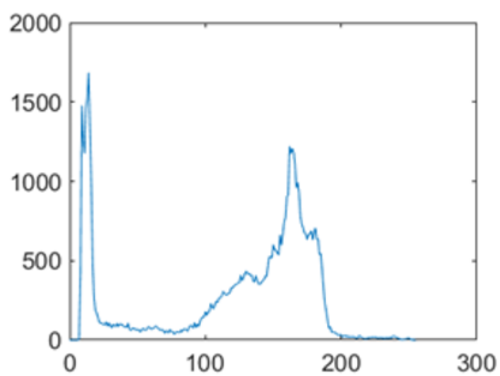


Fig 1. Input Histogram

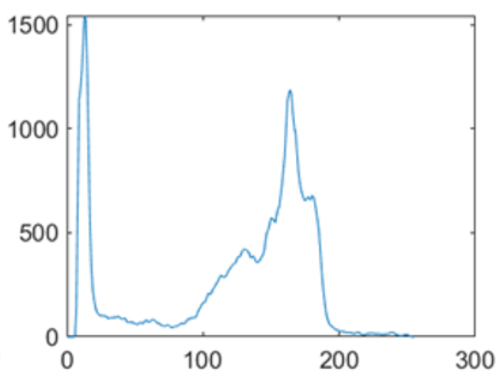


Fig 2. Histogram after applying Moving Averaging Filter

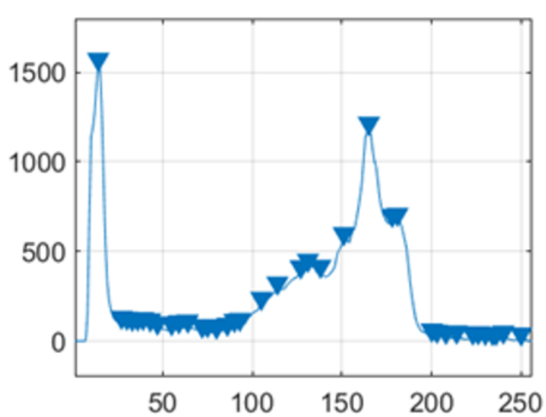


Fig 3. Initial Peaks

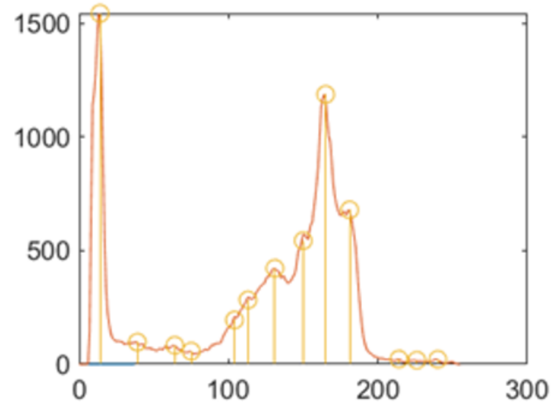


Fig 4. Local Maxima points after using Summit Navigator approach

VI. CONCLUSION

The Summit Navigator is a revolutionary method that was introduced in this research to locate real peaks automatically and accurately from multi-modal grayscale histograms of images. This method does not require a priori knowledge of the number of modes or the distance between modes in processing. In order to determine where the optimal site for observation is, the suggested algorithms use a strategy similar to that used in mountain exploration. Additionally, they take into account the density and intensity of the early peaks. When starting from this point, the observability index can be computed to identify which peaks are most prominent. The method has been successfully proven on credible datasets, and the results have suggested that it outperforms the current approaches in terms of accuracy and robustness. These existing approaches include FTC, HTFCM, MATLAB, Otsu, FTH, ITTH, SDD, and SFFCM. Because of this, there is potential for useful applications in vision-based diagnostics, in particular in robotics and automation systems for surface inspection.

VII. REFERENCES

Tran Hiep Dinh , Student Member, IEEE, Manh Duong Phung , and Quang Phuc Ha , Senior Member, IEEE: Summit Navigator: A Novel Approach for Local Maxima Extraction. https://ieeexplore.ieee.org/document/8794719