SEGMENTATION ON OVARIAN CANCER TISSUE MICROARRAY USING FREQUENCY WEIGHTED MEAN SHIFT AND WEIGHTED FUZZY C MEANS ALGORITHMS

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ABSTRACT: *Quantifying the presence and extent of staining on account of a vascular biomarker on tissue microarrays is a laborious, time consuming and error prone job. Therefore there is a need for a powerful image segmentation algorithm. This is achieved using Hierarchical Normalized cuts algorithm which is driven by the use of a hierarchically represented data structure that merges two powerful image segmentation algorithms namely, Frequency weighted mean shift for supervised clustering of the images and Normalized cuts for graph partitioning. A system is designed for high throughput in computing and detecting staining of ovarian cancer on a very large pathology in less time. Hierarchical Normalized cut enables rapid analysis of large images. Weighted fuzzy c means for clustering and frequency weighted mean shift for reduced the color resolution that has to be applied in the Normalized cuts then to check the effienecy of the algorithm .Also it requires specification of only a few pixels from the object of interest and is highly insensitive to changes in users' domain knowledge.*

KEYWORD: Fwms, HNCuts, fuzzy clustering, feature weighted

INTRODUCTION:

Image processing is a technique in which the input image is converted to a digital image on which various mathematical operations are performed to extract some useful information from it. Image segmentation partitions these digital images into two or more regions to simplify the representation of the images making it easier to analyze. It is also widely used in the field of medical imaging, in the creation and segmentation of images of the human body such as tissues and organs to reveal, diagnose and examine them for treatment planning and various other clinical purposes.

Image segmentation is done on ovarian cancer tissue microarrays to quantify the presence and extent of staining on them with the use of a robust and flexible supervised segmentation algorithm called the hierarchical normalized cuts (HNCuts).This algorithm merges two powerful image segmentation algorithms,a frequency weighted mean shift and the normalized cuts algorithm.HNCut gains its strength by performing clustering and partitioning in the color space.

PROPOSED METHOD

The proposed algorithm combines Frequency Weighted Mean Shift (FWMS) and NCuts algorithm and is specifically designed for the rapid extraction of pixels of interest which is insensitive to the user's domain knowledge. The FWMS unlike the mean shift algorithm works directly in the color space merging points of similar values that lie within the neighbourhood of each other and exhibits novelty in convergence allowing faster computation with few steps. The Weighted FCM cluster the image depends on the membership function weight has to calculated. To combine FWMS and WFCM algorithm to find the efficiency use NCuts algorithm .

SYSTEM ARCHITECTURE

FWMS for Reducing the Number of Colors for NCut

1) Theory: The MS algorithm is used to detect modes in data using a density gradient estimation. By solving for when the density gradient is zero and the Hessian is negative semidefinite, we can identify local maxima. For a more detailed explanation of the algorithm, we refer the reader to [24].

We startwith the fixed point iteration update $\forall j \in \{1, \ldots, N\}$
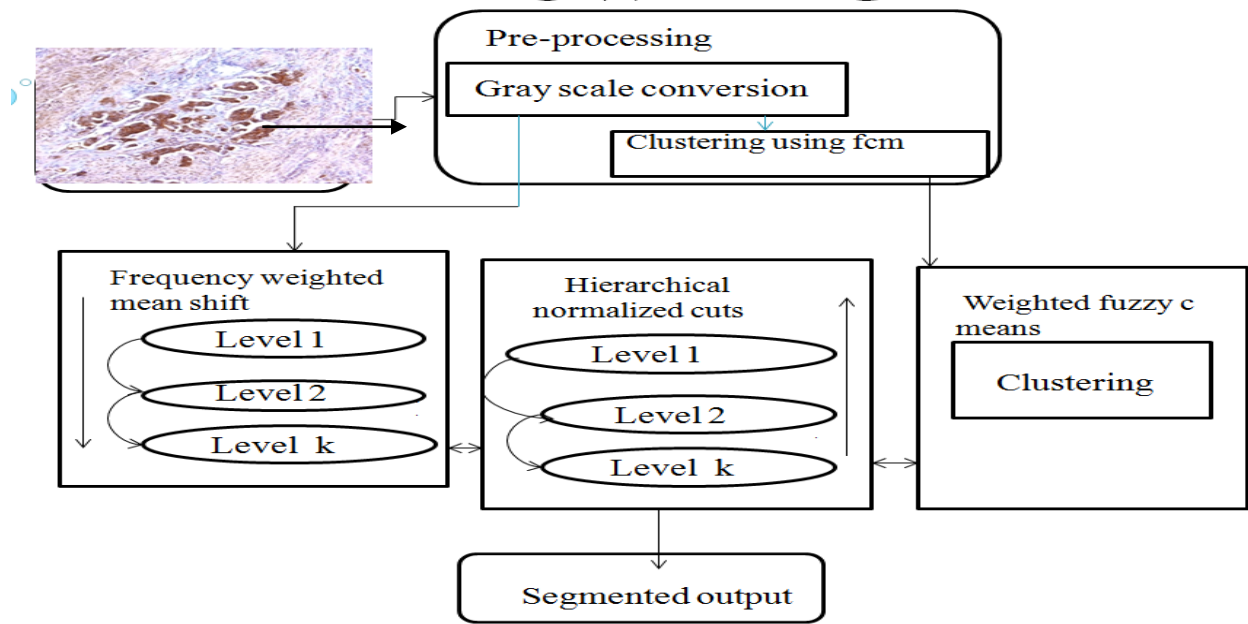
$$f_{k+1,j} \leftarrow \frac{\sum_{i=1}^{N} f_{k,i} G(f_{k,j} - f_{k,i})}{\sum_{i=1}^{N} G(f_{k,j} - f_{k,i})}$$

where G is a Gaussian function with a bandwidth parameter σMS, which is used to compute the kernel density estimate at

$$G(f_{k,j} - f_{k,i}) = \exp\left(-\frac{\|f_{k,j} - \hat{f}_{k,i}\|_2}{\sigma_{MS}^2}\right)$$

with $\cdot_2$ representing the L2 norm. $k \in \{1, \ldots, K\}$ represents various levels of color resolution produced at each iteration. The overall computation time for (1) is $O(N^2)$. By employing the IFGT

we can reduce the computation complexity to $O(N)$ with minimal precision loss..

System Architecture of Process

NCuts on FWMS Reduced Color Space

1) Theory: NCuts [15] is a graph partitioning method, used to separate data into disjoint sets. For our problem, the hierarchical pyramid created by FWMS at various levels of color resolution

($\hat{F}1$,$\hat{F}2$, . . . ,$\hat{F}K$) serves as the initial input to the NCut algorithm. The NCut takes a connected graph**G**= (*E, V*), with vertices (*V*) and edges (*E*) and partitions the vertices into disjoint groups. By setting *V* equal to the set of color values $\hat{F}K$, and having the edges represent the similarity (or affinity) between the color values, we can separate the vertices into groups of similar color values. The NCut is defined as the process by which the removal of edges leads to two disjointed partitions *A* and *B* such that the variance of values (in our case colors) in *A* and *B* are minimized and the difference in average value (intensity of colors) between *A* and *B* is maximized.We present the high-level formulation as described in [15]:

$$NCut(A, B) = \frac{cut(A, B)}{assoc(A, V)} + \frac{cut(A, B)}{assoc(B, V)}$$

where cut describes the affinity between the sets, encouraging higher dissimilarity between sets, and assoc describes the affinity between a set and the whole system, encouraging sets of significant size. The ψ function is used to define the affinity between two points. Our ψ function is defined as

$$\psi(\hat{f}_{k,i}, \hat{f}_{k,j}) = \exp\left(-\frac{\|\hat{f}_{k,i} - \hat{f}_{k,j}\|_2^2}{\sigma_{\text{Ncut}}}\right)$$

with σNcut as a bandwidth parameter. It is worth noting that in the traditional NCut paper [15], their affinity calculation took into account both a spatial and color component. For even small images, this made the affinity matrix intractable. As a result, the ψ function had a spatial constraint introduced such that (9) is set to zero if the associated pixels are farther away than a userspecified distance. This constraint forced the affinity matrix Ψ to typically be sparse, making its storage and subsequent operations applied to it less burdensome. Nevertheless, for large images, the affinity matrix is still too large (in spite of the spatial constraints), and as such we choose to operate solely in a significantly reduced color space, without the imposition of spatial constraints. In Fig. 3, we can see at the bottom of the hierarchical pyramid for a color image with original dimensions of 1200×1200, we would have an affinity matrix of only 7×7, and at the highest level a size of 1572×1572. 2).

Algorithm: The main steps comprising the HNCut technique are shown in Algorithm 2.We begin by applying NCut on the lowest image resolution generated in the previous section, by setting $k = K$, $Vk = \{\,\hat{}\,fk,1\,,\,\hat{}\,fk,2\,,\,\ldots\,,\,\hat{}\,fk,Mk\,\}$, i.e., the set ofunique color values present at level K from FWMS

FIGURE 1: ovarian cancer image -input.

Gray scale image

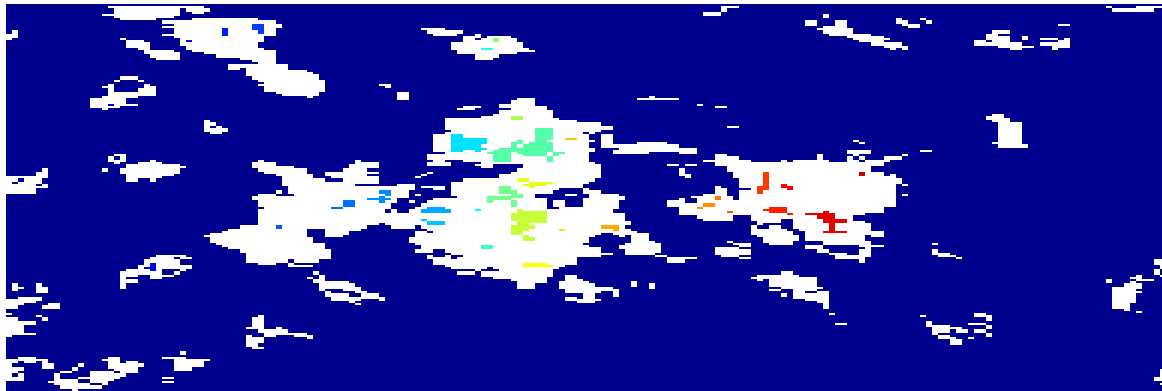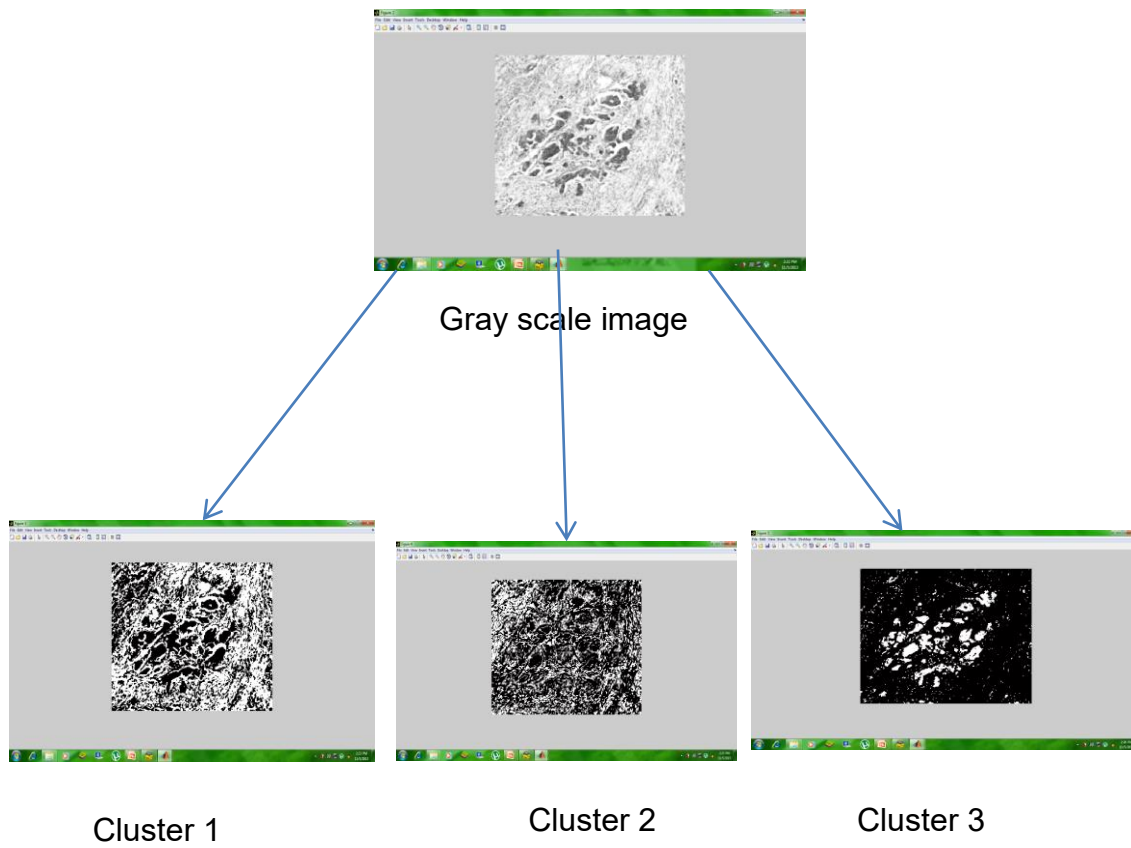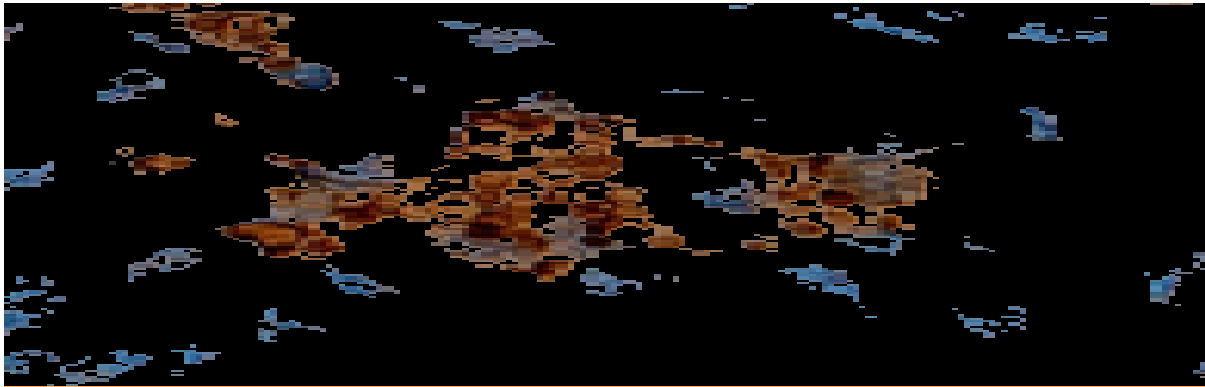Cluster 1   Cluster 2   Cluster 3

FIGURE 2: FWMS

FIGURE 3: HNCUTS

The table below shows the various inputs with which our system is tested.

Input Given	Output Obtained	Expected Output
Any .jpeg image or.gif image is placed in the target database and selected as input image.	The image is not processed when selected.	Resized image ready for processing if it is a .bmp image.
User presses cancel after selecting the image.	A dialog box showing a display that user has pressed cancel.	The input image selected is displayed in the first handle if the user has pressed ok.
The Normalized Cuts button is clicked before FWMS.	No image appears in the third handle.	Normalized Cuts performs partitioning of the image leading to segmentation if clicked after FWMS.
The Segmented output is clicked after FWMS.	No image appears, showing an error in the command window.	The Segmented output is generated only when it is clicked finally after FWMS and NCuts.

Table.1 Test Inputs and Expected Outcomes

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