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Superpixel Based Color Image Segmentation Techniques: A Review

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Abstract— The basic data unit of image representation, the pixel and encompassing features, form the key for the qualitative and quantitative output of any image processing step. The result of grouping pixels exhibiting similar features within local or global neighbourhood is termed as SUPERPIXEL. Computer vision research experts have conceptualised SUPERPIXEL for many decades and contributed number of superpixel based approaches to improve accuracy and reduce complexities in image processing techniques. The job of grouping pixels into super pixels by comparing the values of each and every neighbourhood pixel within specific connectivity, defining the boundary strength of superpixel, and the center of superpixel called as seed point are of important consideration. The following work introduces conceptual understanding of an image in terms of pixel, superpixel and its features. Further to this, explanation of various SUPERPIXEL grouping methods and superpixel based segmentation techniques that are of great interest to the image vision community are discussed.

Keywords—Image Segmentation, Pixels, Superpixels, Superpixel Segmentation Methods

I. INTRODUCTION

Digital image processing has revolutionised the concepts of multimedia and visual data processing, paving way for normal image to machine vision level research experience and application development. Heavy quality of research results in development of detailed data processing techniques. Likewise image processing techniques are applied to develop wide range of image processing applications catering the need of various industries. The processed information caters the knowledge of domain professionals to micro level information exposure to common society, which was a nightmare for a common man before the image processing era.

The development in image acquisition methods, data storage medium and processing power mutually enhances the methods of digital image processing and information sharing. Based on the image acquisition medium employed, digital image can be a binary image (black and white), gray scale image and color image. The source of the image can be from variety of sources like normal photograph, scanned document, geometric scene sent from satellite, medical images like x-ray, ct scan, ultra scan, lab level details like microscopic image etc.., General property of a digital image is described by the visual property of the eye like hue, saturation, brightness, image size and color space. The specification details of a digital image are detailed by color space, size (memory space required to store the image file in storage medium) and format of storage like bmp, jpeg, png, etc..,

II. IMAGE REPRESENTATION

A. Basic Component of Image

Any digital image is represented as collection of basic data unit called pixels and visually spread across two dimension co-ordinate system with x and y axis. The coordinate system for pixels in a computer window, however, is reversed along the y-axis. (0,0) can be found at the top left with the positive direction to the right horizontally and down vertically.

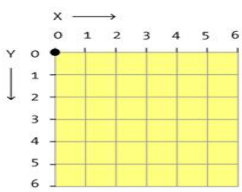
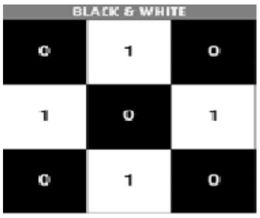


Fig.1 Co-ordinate system

Each (x,y) co-ordinate specifies one pixel of the image. A binary image is arrangement of 0 and 1 value across the co-ordinate system which represents black(background) pixel and white(foreground) pixel. Each pixel is represented by 8bit. The binary image is represented by 1 bit of data as 0 or 1. $2^1 = 2$ different tones as black and white of binary image are represented. The resolution of the image is specified as number of pixels per inch. The size of the image is calculated using number of bits per pixel and number of pixel per inch.

A gray scale represents 256 different tones of pixel value ranging from 0 to 255. Here, 0 implies a black pixel and 255 implies to a white pixel color. Other pixel value between 0 and 255 are intermediate shadows of grey between black and white. To digitally represent pixel value of greyscale image 8bit (1 byte) of memory is required; i.e $2^8 = 256$ different tones of greyscale can be represented with various combinations of 0 and 1.



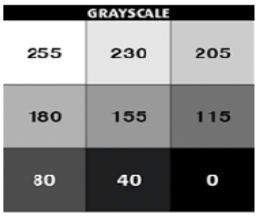


Fig.2 Black and white pixel with value 0 and 1

Fig.3 Different tones of Black and white pixel – grey scale shadows with values between 0 and 255

Color image is digitally represented by RGB color space, where R-Red, G-Green, B-Blue color forms the basic color component. Each pixel of color image is combination of RGB component; implying 3 set of data is required to represent a color pixel. The memory required to represent a color pixel is 3*8 bits = 3*1byte = 3 byte. Each component has $2^8 = 256$ different tones with various combinations of 0 and 1.

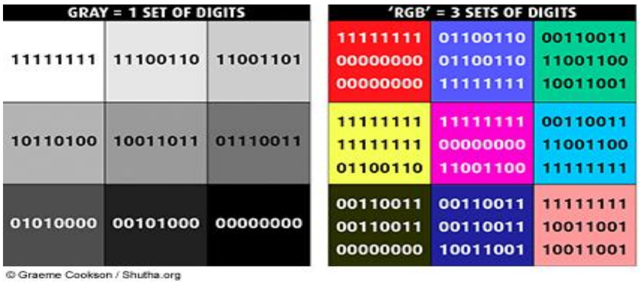


Fig.4 A greyscale image only has 1 set of numbers per pixel, an RGB image has three sets of numbers per pixel and a CMYK image has four sets of numbers per pixel

B. Image Classification

Pixel based: In the past, most digital image classification was based on processing the entire scene pixel by pixel which is commonly referred to as **per-pixel (pixel-based) classification**. Intensity (or pixel value) interpolation (also termed as resampling) is the process of extrapolating data values to a new grid, an important step in rectifying an image that calculates pixel values for the rectified grid from the original data grid. Various interpolation techniques are Nearest Neighbor interpolation, Bi-linear interpolation and Cubic interpolation.

Object based: Object-oriented classification techniques allow the analyst to decompose the scene into many relatively homogenous image objects (referred to as patches or segments) using a multi-resolution image segmentation process. The various statistical characteristics of these homogeneous image objects in the scene are then subjected to traditional statistical or fuzzy logic classification. Object-oriented classification concept applied for image segmentation is often used for the analysis of high-spatial-resolution imagery (e.g., 1 × 1 m Space Imaging IKONOS and 0.61 × 0.61 m Digital Globe QuickBird).

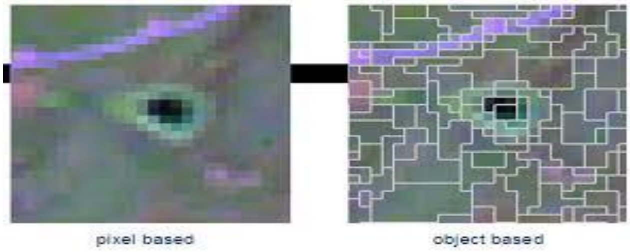


Fig 5 Image representation, pixel based and object based

The concept of object-oriented classification involves two stages. Image segmentation stage merges similar pixels into objects, and classification stage is applied to the objects, rather than individual pixels, to assign them into different classes. Concept of grouping pixels into meaning full entities with respect to classifiers (intensity, color, texture etc.,) is a challenging task. Such grouped in pixels termed superpixels are of commendable use in many image processing areas.

III. SUPER PIXELS

The pixel-grid representation is an "artifact" of a digital imaging process and not a natural one. Most of the image processing algorithms visualise image with the use of pixel-grid, as the underlying representation. Many stochastic models of images are often defined on this regular grid. It would be more natural, and presumably more efficient, to work with meaningful entities obtained from a low-level grouping process. The result of over-segmentation partitions the image into fewer number of segments known as superpixels. Few examples can be visualised in Fig 6 and Fig 7.

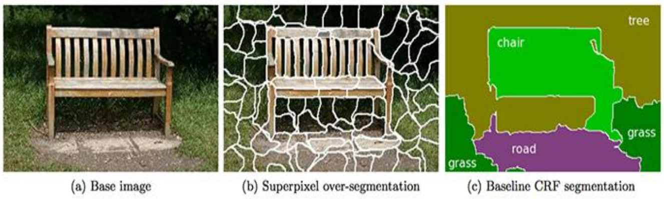


Fig 6 Example of Base Image, superpixels generated by over-segmentation, baseline CRF segmentation

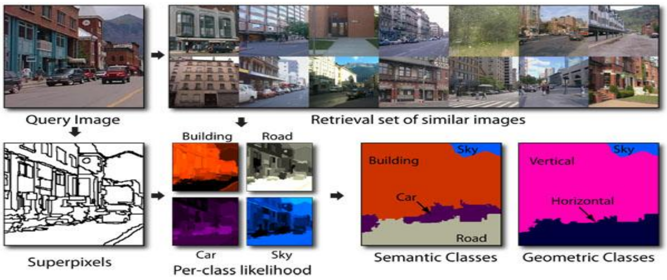


Fig 7 Example of Query Image, Superpixel view of the query image generated by over-segmentation, Per-Class Likelihood and Grouping the superpixels under different classes and objects.

A. Properties of Superpixel

Super pixel map depicts many desired properties:

- **Representational efficiency**: Pixel wise representation of image exhibits pair wise constraints between units, which needs to parse through in-between pixels to interact with target pixels. Connectivity and neighbourhood constraints plays important role. The seed-point in super pixel representation models much longer-range interactions between super pixels.
- **Computational efficiency**: The complexity of images from hundreds of thousands of pixels to only a few hundred super pixels reduces the computational cost and increases the image processing speed.
- **Visual Meaning**: The perceptual view of super pixel gives uniform and meaningful representation of image based on texture and color.
- It is **near-complete**: The structure of the image is mostly conserved, because super pixels are results of an over-segmentation. The loss due from pixel-grid to superpixel map is very little.

B. Why Superpixel way of processing?

Superpixel representation is adapted to the local structure of the image where, small regions that results from conservative over segmentation, or "superpixels," [17, 4, 16] to be the elementary unit of any detection, categorization or localization scheme. Together on the surface, the existence of superpixels as the elementary units seems counter-productive, because aggregating pixels into groups requires a decision that is unrelated to the final task. However, superpixel aggregation captures the local redundancy in the data, and the aim is to minimize the risk of merging unrelated pixels [21]. At the same time, moving to superpixels allows us to measure feature statistics (in this case: histograms of visual words) on a naturally adaptive domain rather than on a fixed window. Since superpixels tend to preserve boundaries, there is an opportunity to create a very accurate segmentation by simply finding the superpixels which are part of the object.

Superpixel approach acts as the key-building-block of many computer vision algorithms, which is applied to various top scoring multiclass object segmentation entries to the PASCAL VOC Challenge [22], [24], [23], depth estimation [25], segmentation [26], body model estimation, and object localization [22]. Every different superpixel generation approach has their own advantages and disadvantages, that may better serve the need for processing the respective image. For example, if adherence to image boundaries is of paramount importance, the graph-based method of [3] may be an ideal choice. However, if superpixels are to be used to build a graph, a method that produces a more regular lattice, such as [14], is probably a better choice.

Since, no one ideal approach exists which constitutes for all applications, the following properties are generally desirable for superpixels:

1) Superpixels should exhibit good adherence to image boundaries.
2) At pre-processing step, superpixels should have reduced computational complexity, should be fast to compute, memory efficient, and simple to use.
3) At actual segmentation step, superpixels should linearly increase the speed and improve the quality of the results as well.

The motivation to superpixel concept is grounded to the following fact of normal pixels. (a) Pixels are not natural, they are merely consequence of discrete representation of query image. (b) Optimisation becomes intractable at pixel level, since even a normal resolution image has good number of pixel. Thus the coherent and local nature of superpixels makes good interest for segmentation at good scale of interest.

IV. IMAGE SEGMENTATION TECHNIQUES

Image segmentation is the process of extracting region of interest from the query image. The approach can be classified as two types: Local Segmentation and Global Segmentation.

Local Segmentation: Local segmentation deals with segmenting sub-images which are small windows on the entire image. The number of pixels available for local segmentation is much lower than global segmentation.

Global Segmentation: Global segmentation is conquered by segmenting a whole image. It consider generally with large number of pixels segment. This makes estimated parameter values for global segment more robust.

A. Methods of Image Segmentation

Image segmentation methods may vary based on the field of application, reason for the process and cause of use of segmentation.

Some of the highlighted image segmentation techniques are

a. Threshold based
   - Threshold selection
   - Histogram based threshold selection
   - EMT technique
b. Region based segmentation
   The two broad approaches in region based methods are
   1. Region growing
   2. Region Splitting and Merging
c. Edge based segmentation
d. Low level segmentation
e. Fuzzy based
f. ANN based

The pixel based image segmentation technique considers all pixel of the image for processing, consumes time and implies heavy computational cost. Accurate image segmentation to separate the object of interest from the background scene is very hard for the kind of images where the color and texture are very complex. Hence semi automatic methods of segmentation which inculcate user inputs as processing parameters are becoming more popular. For example, in the active contour model (ACM) or snake algorithm, the initial curve is selected by the user which could lead to a good convergence to the actual object contour.

Some of the low level image segmentation methods like mean shift, watershed, level set and super-pixel, usually divide the image into many small regions. In spite of several over segmentation, the low level segmentation methods provide a good basis for the subsequent high level operations such as region merging. The ground truth image is initially divided into N number of superpixels based on user defined value. Also, the number of iterations the image should undergo in the process can also be as per user terms. The following chapter introduces and discusses on few state-of-art super pixel based image segmentation methods.

B. Superpixel Based Image Segmentation

Superpixel based image segmentation techniques applies many sophisticated algorithms for fast 2D image segmentation. SUPERPIXELS are commonly defined as contracting and grouping uniform pixels in the image, which are widely used in image segmentation and object recognition [4], [19].The superpixel map is natural and perceptually meaningful representation of the input image. Therefore, compared to the traditional pixel representation of the image, the superpixel representation greatly reduces the number of image primitives and improves the representative efficiency. The convenience and effectiveness of superpixels to compute the region based visual features provides important benefits for the vision tasks such as object recognition [4].

Furthermore to research works by experts, good study of literature reveals various superpixel methods have evolved during last decade. The approaches can be roughly classified into two categories. The **first category** of algorithms that do not consider the compactness constraints during the superpixels generation procedure, such as meanshift [1], and graph based [5] algorithms. These algorithms produce superpixels by over-segmenting the image, In order to avoid the superpixels crossing the object boundaries. Non consideration of compactness constrains produces the superpixels of highly irregular shapes and sizes. The **second category** of superpixel algorithms considers the compactness constrains, such as normalized cuts [2], lattice cut [8], TurboPixels [9], and graph cut [10] approaches.

List of various algorithms and details are discussed in the following section.

- Mean shift algorithm [1]
- Graph-based method [5]
- Normalized cuts [2]
- Lattice Cut [8]
- Turbopixels [9]
- SLIC superpixels [12]
- Optimization-based superpixels [10]
- Random Walk algorithm[6]

In spite of availability, each algorithm has its own advantages and disadvantages that better suits a particular type of application. Development of high quality superpixel algorithm is still a challenging task, which has to answer the under-segmentation task and local grouping of the pixels with respect to the intensity boundaries. An ideal superpixel algorithm should adhere well to object boundaries of image and also maintain the compact constrains in the complicated texture regions. The following section discusses few important algorithms.

C. Normalized Cut[2]

Image segmentation result never matches human perspective when just one cues of image is considered. While segmenting objects the boundaries of the objects play vital fact to make the result more meaningful for analysis. Variety of features including contours, brightness, texture, color and good continuation can be considered. These features are analysed, grouped and classified to result in descent classification of details. Out of many algorithms, the popular n-cut algorithm proposed by Shi and Malik [27] was the basis for original superpixel algorithm of [2]. Ren and Malik [2] originally presented the concept of superpixel as defining the perceptually uniform regions using the normalized cuts (NCuts) algorithm. The proposed approach segments the image into a large number of small compact and homogeneous regions by the normalized cuts.

Graph theory applied along with computer science generates Normalised cut algorithm using graph partitioning methods. In this approach the image is first pre processed to generate superpixels. Ncut approach, views image as a graph model which groups similar pixels into segments. Image represented as set of pixels is predicted as a weighted graph G = (V,E) where V means vertex i.e., image pixels, and e means edges. Each edge E has weight w, where w is the measure of similarity between two nodes i,j. The graph is partitioned to two distinct sub graphs, with the aim to minimise the value of cut by the following equation, with the constraint {A union B = V} and {A intersection B is NULL}.

$$cut(A,B) = \sum_{i \in A, j \in B} w(i,j)$$

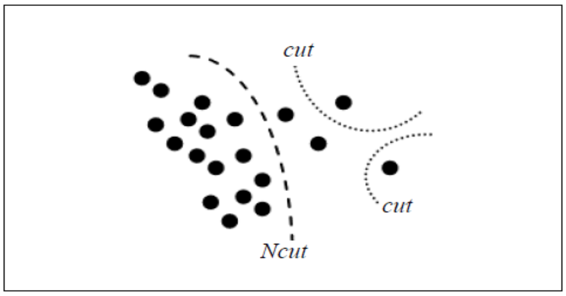


Fig 8 Normalised Cut and Ordinary cut

The groupings of pixels are two-fold step, intra-region-similarity and inter-region-dissimilarity. Then clustering algorithm is applied to generate meaningful segments. Similar and dissimilar pixels are grouped to improve segmentation accuracy. The degree of dissimilarity of sub-graphs A and B are removed using the above equation. Recursive bi-partitioning is applied to generate k sub-graphs, until there exist high similarity within sub graphs and low similarity between sub graphs is reached. This happens with the aim to reduce the maximum cut between sub-graphs. The isolated nodes formed are solved using the disassociation measure for the cut. The graph cut is formulated as fraction of the total edges between all the pixels in the graph. The disassociation measure removes the partitions which cuts the small set of isolated pixels. The relative association and disassociation is formulated by [2]. Then image segmentation results by clustering on the eigenvector.

The NCut method is very powerful in feature extraction for obtaining the regular superpixels in size and shape. However, the computational cost of NCut superpixel approach is very high and expensive when the number of superpixels or the size of image increases greatly. Image of size mxn pixels requires W matrix with size of (mxn)x(mxn) for eigen values computation. Shi and Malik discussed spectral approximation approach with complexity of $O(N^{3/2})$ where N being the number of pixels. Space and runtime complexity are linear with the number of segments.

D. Turbopixels[9]

Levinshtein *et al.* [9] proposed an efficient TurboPixel algorithm using the level set based geometric flow evolution from the uniformly placed seeds in the image. Computationally this applies the concept used in curve evolution techniques in computer vision. The algorithm segments an image into compact regions of lattice like structure, called superpixels by dilating seeds the seeds. There exist many themes for dilating seeds using geometric flows, none of these are used in superpixel segmentation. Turbopixel model combines the technique of curve evolution model for dilation with skeletonisation process on the background region which prevents the merging of expanding seeds.

Turbopixel approach solves the super pixel computational complexity towards solvable geo-metric flow pattern approach. This technique demonstrates its computational efficiency towards (1) megapixel size images with heavy superpixel density (2) comparable segmentation accuracy with Ncut algorithm with respect to low run-time. Main factors that guide the approach are (a) Uniform size and shape of superpixel by covering all the pixels of image, achieved by dilating the properly distributed initial set of seeds. (b) Connectivity of the pixels that groups to a superpixel. (c) Boundary compactness of the superpixel in absence of local edge information, which is maintained by the term that produces constant motion in the direction of the outward normal in regions of uniform density. (d) Smooth and edge preserving flow which insists on the superpixel boundaries to coincide with the image edge while the growth stops. To achieve (d), the flow is formulated with the three properties such that the flow slows down the boundary growth towards to vicinity of the edges, gets attracted to edges and produce smooth boundaries. This formulation implies good shape regularisation of superpixels. (e) Non-overlapping superpixels, enforcing the boundary evolution to halt if two different dilating seed are nearing collision which is achieved by skeleton-based mechanism for collision detection in the background.

Thus with consideration of above characteristics, geometric-flow based turbo pixel algorithm maintain and evolve the boundary between the assigned regions which contain pixels that are already part of superpixel, and unassigned regions containing all other pixels. Conceptually the algorithm places initial seeds in position, iterates the image with further steps until no further evolution is possible. Iteration includes, evolving the boundary for T time steps, estimating the skeleton of unassigned region, updating the speed of each boundary pixel and unassigned pixel in boundary's vicinity.

The turbo pixel framework with combined effect of data-driven curve evolution process and skeletal based constraints produces quality superpixels compared to other ones. The order of magnitude of fastness that turbo pixel works makes it accountable for processing very large megapixel images with heavy superpixel densities within same run time and speed. It employs user-defined measure of affinity between pixels, where affinity measure is entirely domain or purpose dependent. The turbo pixel framework allows the user to have control over the shape and density of the superpixel. Focussing on the task or domain of image, judicial placement of seeds with varying density is possible at the cost of lower superpixel uniformity. The shape of superpixel controlled by compactness constraints clearly reduces under-segmentation with comparable high computation cost. The application of segmented superpixels ranges from image compression, perceptual figure ground grouping and image labelling for images with many pixels.

E. SLIC Superpixels [12]

Achanta *et al.* [12] presented a simple linear iterative clustering (SLIC) algorithm which generates superpixels in the similar manner to [18], by applying k-means clustering with relatively lower computational cost. It yields good adherence to image boundaries on Berkley benchmark [11] when compared with other methods used for segmenting PASCAL[2] and MSRC[15] data sets. It can directly be extended to higher dimensions and freely available across net.

The fact of good pixel packing, and uniformity in size of pixels determine the performance of the proposed algorithm. The efficiency of the algorithm is measured by boundary recall and under-segmentation error measures. The k-means clustering generates superpixels by clustering pixels based on the color similarity and pixel proximity in the image plane. The clustering is done on the five-dimensional [labxy] space, where [lab] is the pixel color vector in CIELAB color space and xy is the pixel co-ordinates. The maximum possible color distance between two nearing colors in the CIELAB space (assuming sRGB input images) is limited and the spatial distance is determined by the image size. The spatial distance is to be normalised in order to apply the Euclidean distance in this 5D space. Hence, new distance measure that considers superpixel size is applied, which enforces color similarity as well as pixel proximity in this 5D space, so that the expected cluster sizes and their spatial extent are mostly equal.

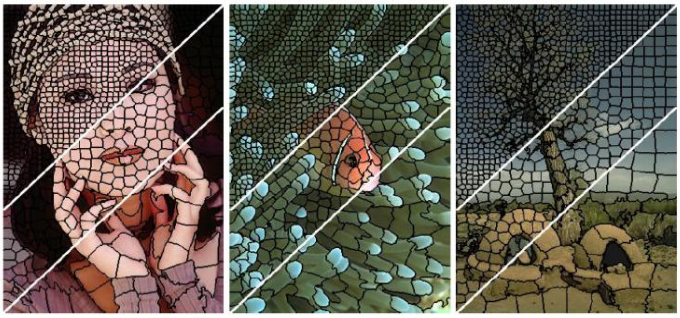


Fig 9 Image segmented using Achanta et al, SLIC algorithm [12], into superpixels of approximate size 64, 256 and 1024 pixels. The superpixels are compact, uniform in size, and adhere well to region boundaries.

The desire number of superpixels, say K, is the input for the SLIC algorithm. A query image with N pixels, generates superpixels with approximate size of N/K pixels. Considering all the superpixels are roughly equal in size, there exist a seed point (center) for every superpixel at the grid internal S=$\sqrt{N}/\sqrt{K}$. The cluster center lies within the safe area of all K superpixels on the xy plane, and become the search area for the pixels nearest to the each cluster center. When the spatial distance exceeds the perceptual color distance limit, the pixel color similarities are outweighed. New distance measure Ds is the sum of the lab distance and the xy plane distance normalized by the grid interval S. A variable m is introduced in Ds allowing us to control the compactness of a superpixel. The value of m can be in the range 1 to 20. As the value of m lies on the maximum scale, more spatial proximity and cluster compactness is promised. It matches meaningful CIELAB distance and good color and spatial proximity.

The complexity of SLIC superpixel segmentation algorithm [12] is measured by O(N), where N is the only input parameter required, the number of desired superpixels. The value of N scales up linearly the value of computational cost and memory usage. Application area concerning to SLIC algorithm are object recognition and electron microscopy as stated in [12]. The experiments done on mitochondrial images and comparative details of VOC score with other algorithms indicates, SLIC adheres to better image boundaries resulting in smoother and accurate segmentations.

V. CONCLUSION

Every different superpixel generation approach has their own advantages and disadvantages based on the need for processing the respective images. Since, no one ideal approach exists which constitutes for all applications, each one is ranked on the nature of analysis. The above review helps as a study material to understand the basic unit of image, the nature of superpixel and various methods for superpixel segmentation and applied approaches towards segmentation.

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