MULTI-CLUSTER OBJECT FILTERING USING LAPLACIAN BASED MARKOV RANDOM FIELD

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ABSTRACT

In image processing, data transformation and representation is an important aspect to be considered. The data transformation and representation is possible only if the clarity of the image is high. Several techniques have been presented earlier to perform high dimensional data representation in image processing. Previous work presented a technique for multi-clustering process to identify and evaluate the higher and lower dimensional values of the clustered objects in the clustered centre to estimate the object similarity of the given image derived from datasets. The downside of the previous work is that the cluster purity is less because of the evaluation of dimensional values. To enhance the efficiency of multi-cluster objects for a given image, in this work, we implement a Laplacian optimized Markov Random Field for aggregation of optimal subspace. At first, a Laplacian filter is used to filter the image by enhancing the edge detection process and smoothing the image without any noise and enhances the linear features of the image. Laplacian filter separates the thin layers of the area and determines the differences of each pixel accurately. Then, Markov random field model is used for image segmentation process after the image has filtered. Using Markov Random Field, the filtered image is segmented based on optimized value. The optimized valued for each cluster is computed based on the average cluster values. Then the object aggregation is done possibly with optimal subspace efficiently. Experimental evaluation is made with bench mark real data set obtained from UCI Repositories to estimate the performance of the proposed multi-cluster object filtering using laplacian optimized Markov Random Filed [MFLOMRF] in terms of Filtering efficiency, effectiveness of cluster, Memory consumption.

Key words: Image filtering, Laplacian Filter, Image segmentation, Markov Random Field, Multi-clustering.

1. INTRODUCTION

Many contemporary imaging applications engage self-motivated or video images, in which the features of significance are confined in space and emerge only elaborately in time. Most present image study algorithms, nevertheless, have a tendency to over-smooth such temporary features, which are accordingly badly expected or even gone altogether. The problem is chiefly sensitive for non-invasive atmosphere, which construct oblique data, and which are critical for progresses in areas such as high dimensional imaging. High dimensional imaging presents measurements only about the pixels. The contrary problem comprises in utilizing these meandering outer data which cumulate movement about or transversely the object to improve the inner neural activity. The data are greatly composite and present both spatial and temporal relationship as well as significant noise from diverse sources.

Image segmentation is an imperative untimely image task where pixels with analogous features are clustered into standardized regions. Image segmentation is a decisive system for image examination and it has been genuinely studied. Normally, there are two major strategies to image segmentation: Employing edge information and regional information. The boundary-based strategies engage the recognition of luminance discontinuities for instance lines and edges, and endeavor to guess their direction and location. Noise or random fluctuations obstruct with the recognition of the genuine features. Several approaches have been endeavored in an attempt to attain noise immunity, for instance averaging over a superior region.

Clustering algorithms are managed and employed in many different fields, counting data mining, pattern recognition, machine learning, image analysis and bioinformatics. Clustering engrosses recognizing subsets (clusters) of ‘‘analogous’’ explanation—similarity often being termed by a distance measure.

In actual life we normally have to compact with untypical values, called ‘‘outliers’’, happening in data sets. These may contact significantly the geometric tools that can be utilized for clustering. Centroid-based methods, for instance, group clarification about a representative illustration, which can frequently be termed as a subjective mean of the cluster. One solution absorbs using a substitute centric supported on a strong marker for instance the median. More and more frequently, data sets in frequent research areas enclose a very huge number (from hundreds to tens of thousands) of features, by giving a dominant appropriate explanation of the experimented occurrence. Some features, nevertheless, are not applicable, since their occurrences can incomprehensible central structures and commonly confound the description process.

In this work, a laplacian filter is used with Markov random field to cluster the object efficiently by filtering the image using Laplacian filter in order to aggregate the multi-cluster object with optimal subspace.

2. LITERATURE REVIEW

A segmentation process frequently comprises of two steps. The first step is to select a appropriate position of features which can recognize the similar contented regions and in the meantime distinguish different-content sections; the second process is to affect a segmentation technique to the selected features to realize a segmentation map. A simple Markov random field model [4] with a novel completion system is projected for unsubstantiated image segmentation based on image features

The recognition of the methods of entity detection based image sets has been mounting since of their superior accuracy and sturdiness as contrast with the strategies developing a distinct image as input and it can be efficiently utilized with semantic subspace position [12]. In [7] an incremental learning method of orthogonal subspaces is planned by updating the primary components [6] of the class association and total association matrices unconnectedly.

Content-based image retrieval (CBIR) [1] has been an energetic examination area in the last decade. In the CBIR pattern, an image is regularly symbolized supervise [10] by a position of low-level visual features, which frequently do not have shortest association to high-level semantic concepts. Significance Aggregation Projections (RAP) [8] for learning efficient subspace projections in a semi-supervised method is used. A constrained multi-space method [3] is used with it. In account of this, a kernel method utilized for instead of a nonlinear type of HQ-PCA [11] is offered to deal with nonlinearly distributed data [9]. The major design of kernel deception [2] is to design the input data to a further higher dimensional Hilbert space during a nonlinear mapping and then accomplish the linear algorithm in a new feature space [8]. In this work, we used Laplacian filter and MRF for image filter and segmentation process for object aggregation in optimal subspace.

3. PROPOSED MULTI-CLUSTER OBJECT FILTERING USING LAPLACIAN BASED MARKOV RANDOM FIELD

The proposed work is efficiently designed for enhancing the process of object aggregation with optimal subspace. Before aggregation, it is necessary to cluster the object in a reliable manner for converting the aggregation process to be simpler. Before clustering, the image filtering is done to smoothing the image by extracting the features with less noise. The proposed multi-cluster object filtering using laplacian optimized Markov Random Filed [MFLOMRF] operates under three phases. The first phase describes the process of filtering the image using Laplacian filter. The second phase is to perform multi-clustering using Markov Random Field. The third phase describes the object aggregation with optimal subspace based on Laplacian based Markov Random Field. The architecture diagram of the proposed multi-cluster object filtering using laplacian optimized Markov Random Filed is shown in fig 3.1.

The first phase describes the process of filtering the given image which is derived from the datasets. The Laplacian filtering technique is applied to the given image to produce an image with a good quality by smoothing the image in terms of detection of edge. Spatial development measures produce an alteration of an image pixel value, supported on the pixel values in its instant neighborhood (local enhancement). Laplacian filters are commonly used to:

1) Accurate and return images exaggerated by system broken,

2) Develop the images for visual explanation and

3) Mine features.

The second phase describes the process of implementing a Markov Random Field to a filtered image for clustering the given image in a multiple ways. MRF represent the information about the spatial relations among the regions in an image, so the probability of occurrence of a certain spatial relation between each pair of labels could be used to obtain the most probable label for each region in a given image.

The third phase describes the multi cluster object aggregation with optimal subspace in a reliable manner by filtering and enhancing the segmentation process.

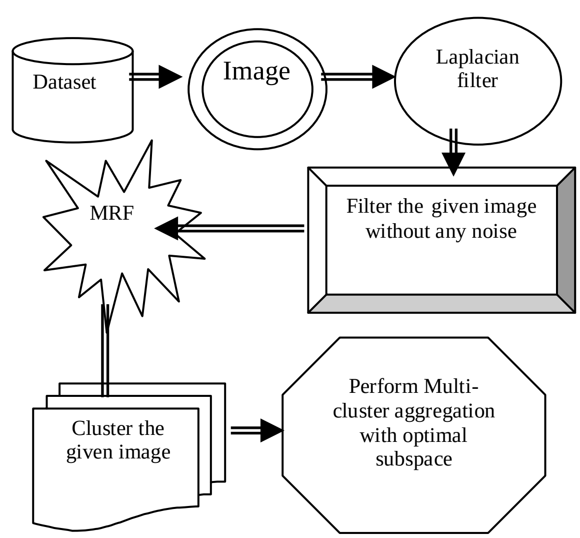

Fig 3.1 Architecture diagram of the proposed MFLONRF

3.1 Laplacian Filter

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Laplacian filters are non-directional filters since they develop linear features comprising roughly any course in an image. The Laplacian is a 2-D isotropic determination of the 2nd spatial derived of an image.

The Laplacian of an image highlights provinces of speedy intensity transform and is consequently often employed for edge detection. The Laplacian is frequently practical to an image that has initially been curved with impressive resembling a Gaussian smoothing filter consecutively to diminish its sensitivity to noise. The Laplacian $L(x, y)$ of an image with pixel strength values $I(x,y)$ is specified by $$L(x,y)=\frac{\partial^2 I}{\partial x^2}+\frac{\partial^2 I}{\partial y^2}$$ ……….. (eqn 1)

This can be considered using a convolution filter. A strain typically comprises of a 3x3 array of coefficients or weighting aspects. It is also achievable to utilize a 5x5, a 7x7 or still a better odd numbered array. The filter can be measured as a window that progress transversely an image and that appears at all dominant values falling within the window. Every pixel value is multiplied by the consequent coefficient in the filter. For a 3x3 filter, the 9 resultant values are added and the consequential value restores the innovative value of the essential pixel. This operation is called convolution. Since the input image is symbolized as a set of distinct pixels, we have to discover a distinct convolution kernel that can estimated the second derived in the definition of the Laplacian.

For instance, for a given image I, apply Laplacian filter to filter the image and the filtered image sequence is shown below (fig 3.2).

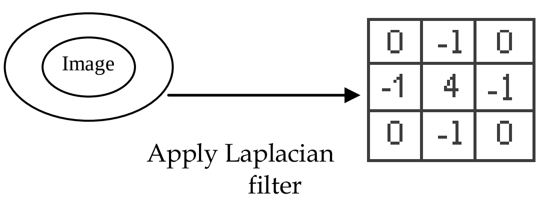

Fig 3.2 Applied Laplacian filter

For an image v (a,b), 0 <= a; b < B, where B = 2 ^ , 0 < l < B, the Laplacian filter can be expressed in terms of difference of the level l of the given image and the original image size and it is shown as.

$$L(a,b)=g_0(a,b)-E(g_1)(a,b) \quad \text{…… eqn (2)}$$

Where E (G)-expanded version of the image i.e., it tests the level of the objects in the image.

Through Laplacian filter, the image is efficiently filtered based on the intensity of the image.

3.2 Markov Random Field for image segmentation

After the image has been filtered using Laplacian filter, the obtained image should be segmented using Markov Random Field. The laplacian filter filtered the image without any noise and the image clarity will also be clear. In this section, filtered image segmentation is made for aggregating the object with an optimal subspace.

Let S={s = (a, b) | 1<= a < H , 1<= b < W , a, b , H , W∈I } be the set of filtered image pattern sites, where H and W are the figure height and width in pixels.

In the two dimensional figure pattern S, the pixel values x = {x_s | s ∈ S}. The spatial possessions can be reproduced through diverse features, between which, the *contextual constraint* is a universal and authoritative one. Markov random field (MRF) theory presents a expedient and dependable technique to form context-dependent things such as image pixels and connected features. This is accomplished by exemplifying mutual authorities between such entities using restrictive MRF distributions. In an MRF, the sites in S are connected to one an added via a neighborhood system.

A neighborhood system N = {N_s, s ∈ S} is a compilation of subsets of S for which s ∉ N_s and r ∈ N_s ⇔ s ∈ N_r. N_s are the neighbors of s.

A clique c is a separation of S for which each pair of sites are neighbors

A random field *X* said to be an MRF on $\mathcal{S}$ with regard to a neighborhood system N if and only if

i) P(X=x)>0 for all $x \in \Omega_x$ Where Ω_x is the set of all possible x on S

ii) P ($X_s = x_s$ | $X_r = x_r$, r ≠ s) = P($X_s = x_s$ | $X_r = x_r$, r ∈ N_s)

Where P(X) – prior of X used to implement the substantial restraints of the segmentation P (X | x) – likelihood of X determines that two contiguous pixels are probable to belong to the similar class except there is an edging among them. The image segmentation has been illustrated based on estimating the value of x supported on X in P (X | x). The image (fig 3.3) shows the MRF based filtered image segmentation. Based on the notation of neighborhood system, the image segmentation is done efficiently. If the neighbor hood system is multi-

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dimensional, a MRF can equivalently symbolized by a Gibbs distribution with a notation as

$$P(z) = Z^{-1} \exp[-\beta U(z)] \text{ ……… Eqn (3)}$$

$$U(z) = \sum_{c \in C} V_c(z) \text{ ……….. eqn (4)}$$

Where

U (Z) – Energy function

Z – Normalization factor

B – Positive control parameter

C – All probable cliques

Vc – Sum of cliques obtained

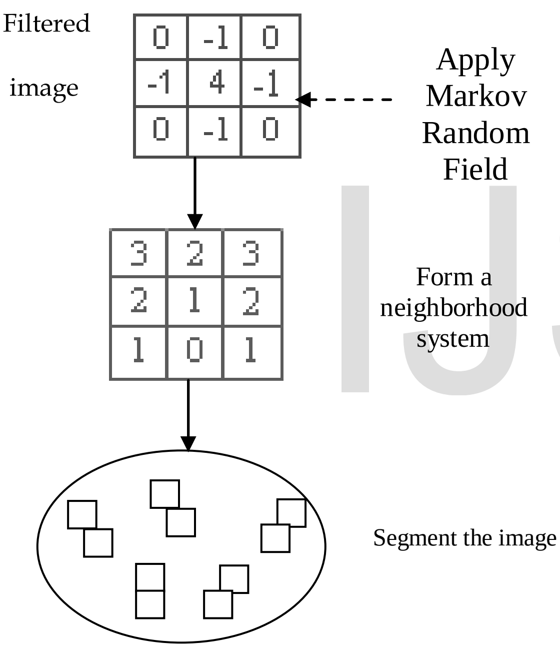

Fig 3.3 Markov Random Filed for filtered image segmentation

The above figure describes the process of filtered image segmentation using Markov random field process. The filtered image obtained through Laplacian filter process is given as input and the filtered image is processed to identify the neighborhood pixels of the given image and segmented based upon this. The Markov Random field is normally integrated with Gibbs distribution process, when the neighborhood system met with multi-dimensional pixels in given image.

After segmentation, the proposed scheme allows the objects in the image to be aggregated with optimal subspace. Since the images are efficiently filtered, the object identification is easily made and necessitate objects are aggregated in the optimal subspace.

4. EXPERIMENTAL EVLAUTION

Extensive experimental studies have been conducted to examine the proposed multi-cluster object filtering using laplacian Markov Random Filed. We have implemented the proposed multi-cluster object filtering using laplacian optimized

Markov Random Filed in Java, and approved out a series of performance experiments in order to monitor the effectiveness of the approaches. The experiments were run on an Intel P-IV machine with 2 GB memory and 3 GHz dual processor CPU. The data sets were accumulated on the local disk. We ran our experiments using bench mark real data set obtained from UCI Repositories. The proposed multi-cluster object filtering using laplacian Markov Random Filed is efficiently designed for aggregating object with optimal subspace based on filtering using Laplacian filter and image segmentation using Markov Random field in image processing. The performance of the proposed multi-cluster object filtering using laplacian Markov Random Filed is measured in terms of

- **i)** Filtering efficiency,
- **ii)** Effectiveness of cluster,
- **iii)** Memory consumption.

Filtering efficiency determines the efficiency of filtering the image in order to remove the noise level of the image and enhancing the edge localization of the given image

Effectiveness of cluster determines the cluster efficiency of the image after it has been filtered.

Memory consumption defines the consumption of memory necessary for implementing both the Laplacian filter and the Markov Random field.

5. RESULTS AND DISCUSSION

In this work, we have seen that how multi-clustering process has been taken place using Markov Random Field for the filtered image which could be filtered by using the Laplacian filter efficiently filter the image without any noise and the process of identifying the object in the optimal subspace is being easy, since the Laplacian filters filter the image with a clarity. For an experimental evaluation, we used bench mark real data set obtained from UCI Repositories to show the performance of the proposed multi-cluster object filtering using laplacian Markov Random Field with an existing multi-clustering process based PCA on the evaluation of higher and lower

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dimensional threshold values. The below table and graph will estimate the performance of the proposed MFLOMRF.

No. of pixels	Filtering efficiency (%)	
	Proposed MFLOMRF	Existing Multi-cluster PCA
100	50	25
200	70	36
300	88	48
400	90	56
500	98	69

Table 5.1 No. of pixels vs. Filtering efficiency

The above table (table 5.1) describes the efficiency of filter for enhancing the image quality. The outcome of the proposed multi-cluster object filtering using laplacian Markov Random Field is compared with an existing multi-clustering process based PCA.

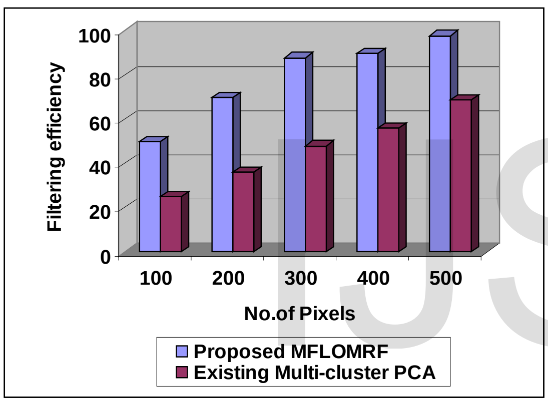

Fig 5.1 No. of pixels vs. filtering efficiency

Fig 5.1 illustrates the efficiency of filter when number of pixels in the image increases. In the proposed MFLOMRF, the filtering of an image is considerably done using Laplacian Filter. Since the Laplacian filter supports isotropic measure, the image has been efficiently filtered without any noise and improves the edge localization for image processing. The filtering efficiency is measured in terms of how clear the image would be without noise, if more number of pixels present in the given image. Compared to an existing multi-clustering process based PCA, the proposed multi-cluster object filtering using laplacian Markov Random Field efficiently perform the filtering process even when number of pixels increases in the given image.

Filtered image in pixels	Clustering efficiency (%)	
	Proposed MFLOMRF	Existing Multi-cluster PCA
25	30	10
50	50	20
75	68	34
100	79	45
125	89	55

Table 5.2 Clustered image vs. Clustering efficiency

The above table (table 5.2) describes the efficiency of cluster for enhancing the image segmentation. The outcome of the proposed multi-cluster object filtering using laplacian Markov Random Field is compared with an existing multi-clustering process based PCA.

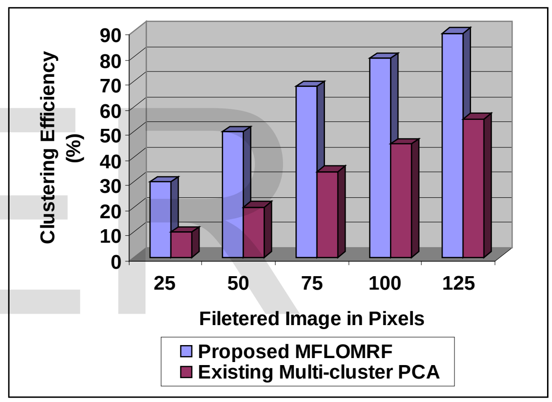

Fig 5.2 Clustered image vs. Clustering efficiency

Fig 5.2 describes the effectiveness of the cluster for filtered image segmentation when number of pixels in the given image increases. In the proposed MFLOMRF, the filtering image is done, after that, the segmentation process is being processes using Markov Random Field based on the neighborhood system of the image.

The filtered image has been segmented efficiently which brings out a clear object viewpoint. The clustering efficiency is measured in terms of how clear the clustered image would be with a clear object. Compared to an existing multi-clustering process based PCA, the proposed multi-cluster object filtering using laplacian Markov Random Field efficiently perform the clustering process even when number of pixels increases in the filtered image.

Clustered parts of image	Memory Consumption	
	Proposed MFLOMRF	Existing Multi-cluster PCA

2	2	5
4	3.8	8.3
6	4.9	10.2
8	5.2	11.2
10	5.8	12.3

Table 5.3 Clustered image vs. Memory consumption

The above table (table 5.3) describes consumption of memory for object aggregation in optimal subspace. The outcome of the proposed multi-cluster object filtering using laplacian Markov Random Field is compared with an existing multi-clustering process based PCA.

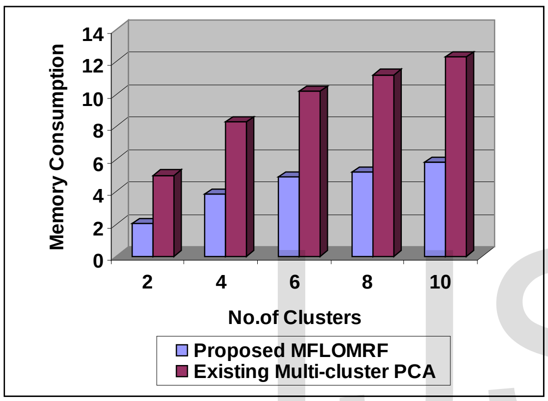

Fig 5.3 Clustered image vs. Memory consumption

Fig 5.3 illustrates the consumption of memory charges when a clustered part of the filtered image increases. Since the proposed MFLOMRF filtered the image at first, the memory consumption would be somewhat less. Then the clustering process takes place based on the neighborhood system of the pixels which is to be obtained through the clustering image. . Compared to an existing multi-clustering process based PCA, the proposed multi-cluster object filtering using laplacian Markov Random Field consumes less memory since the Laplacian filter has been used.

Finally it is being observed that the proposed work reliably achieved the object aggregation by computing the two major activities. The first activity efficiently filtered the given image using Laplacian filter and the second one assumed the segmentation of filtered image using Markov Random field which allows the efficient object aggregation in optimal subspace.

6. CONCLUSION

The proposed multi-cluster object filtering using laplacian optimized Markov Random Filed efficiently designed to perform the multi-clustering process with less memory consumption to enhance the object aggregation process with optimal subspace. At first, the filtering process of image has taken over using Laplacian Filtering technique. Then, the multi-clustering process is done well with filtered image by evaluating the Markov Random fields.

When compared to an existing multi-clustering based PCA based on the evaluation of lower and higher dimensional threshold values, the proposed multi-cluster object filtering using laplacian optimized Markov Random Filed performed well in object aggregation with optimal subspace. The experimental results showed that the proposed multi-cluster object filtering using laplacian optimized Markov Random Filed outperforms well in terms of filtering process and less negative effects of outlier ranges and improves the efficiency of cluster in a given image. Contrast to an existing multi-clustering based PCA based on the evaluation of lower and higher dimensional threshold values, the proposed multi-cluster object filtering using laplacian optimized Markov Random Filed performance is 75-80% high.

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