IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676,p-ISSN: 2320-3331, Volume 13, Issue 5 Ver. II (Sep. – Oct. 2018), PP 01-05
www.iosrjournals.org

Analysis of Random Projection & Live –Wire For Texture Extraction & Segmentation

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Abstract: *Automatic image segmentation requires a certain degree of depth of work combining image clustering, feature extraction, statistical analysis and iterative feedback. Researchers have been using algorithms like Principal component analysis (PCA) combined with advanced feature extraction techniques like gray level co-occurrence integrated algorithm (GLCIA), along with maximal difference schemes (MDS), have been proposed by researchers, and provide good quality of semi-automatic segmentation. But in these techniques, user intervention is needed in at least 1 of the steps in order to get a proper output. This work proposes a RP-live wire based algorithm which optimizes the segmentation process, and removes the user intervention from the segmentation process in order to produce high quality segmented images with truly automatic segmentation. Our results demonstrate a 20% improvement in overall system speed and 10% improvement in segmentation accuracy when compared with traditional algorithms.*

Keywords: *GLCIA, GMTD, live- wire, MDS, PCA*

Date of Submission: 13-10-2018 Date of acceptance: 28-10-2018

I. Introduction

The Currently instead of labor-intensive manual inspection of power lines, airborne inspection technology is employed by using helicopters to monitor the status of equipment son power lines for the purpose of higher efficiency, accuracy and economy. One of the main tasks of aerial image processing is to segment the insulator and to diagnose whether there is a piece detached. However, the aerial images captured on helicopters often include various cluttered backgrounds such as grassland, farmland, power line towers and small rivers. In these backgrounds, Towers and rivers have similar intensities to insulators. As a result, the difficulty of segmenting insulators is dramatically increased. The goals of this propose work is to segment strings of insulators as a whole from the complex low-contrast aerial images and obtain their closed smooth contours. In the literature review, it has been observed that, few research efforts are reported to deal with the segmentation of insulator images with complex backgrounds. The strings of insulators as a whole are characterized by texture features. The texture-based feature plays an important role in various remote sensing applications.

Our proposed work is focusing on the selection of the best texture feature extraction technique & how to distinguish two texture regions with low contrast, which is a common problem encountered in segmenting insulators from complex aerial images.

A critical shortcoming of determining co-occurrence probability texture features using Haralick's popular grey level co-occurrence matrix (GLCM)[ ] is the excessive computational burden. Grey level co-occurrence integrated algorithm (GLCIA)[ ], is a dramatic improvement on earlier implementations. This algorithm is created by integrating the preferred aspects of two algorithms: the grey level co-occurrence hybrid structure (GLCHS) and the grey level co-occurrence hybrid histogram (GLCHH). The GLCHS utilizes a dedicated two-dimensional data structure to quickly generate the probabilities and apply statistics to generate the features. The GLCHH uses a more efficient one-dimensional data structure to perform the same tasks. Since the GLCHH is faster than the GLCHS yet the GLCHH is not able to calculate features using all available statistics, the integration of these two methods generates a superior algorithm (the GLCIA). The computational gains vary as a function of window size, quantization level, and statistics selected. Using a variety of test parameters, experiments indicate that the GLCIA requires a fraction (27–54%) of the computational time compared to using the GLCHS alone. The GLCIA computational time relative to that of the standard GLCM method ranges from 0.04% to 16%. The GLCIA is a highly recommended technique for anyone wishing to calculate co-occurrence probability texture features, especially from large digital images, and thus is used in this work for feature extraction.

K-means is a commonly used partitioning based clustering technique that tries to find a user specified number of clusters (k), which are represented by their centroids, by minimizing the square error function. Although K-means is simple and can be used for a wide variety of data types. The K-means algorithm is one of the partitioning based, nonhierarchical clustering methods. Given a set of numeric objects X and an integer number k, the K-means algorithm searches for a partition of X into k clusters that minimizes the within groups sum of squared errors. The K-means algorithm starts by initializing the k cluster centers. The input data points are then allocated to one of the existing clusters according to the square of the Euclidean distance from the clusters, choosing the closest. The mean (centroids) of each cluster is then computed so as to update the cluster center. This update occurs as a result of the change in the membership of each cluster. The processes of re-assigning the input vectors and the update of the cluster centers is repeated until no more change in the value of any of the cluster centers. In our approach, we use this k-Means algorithm for segregating the features into weak and strong sets. Strong feature set consists of the cluster of those features which have high variance, while all the other feature sets are clustered into weak feature sets. K-Means provides these 2 clusters and then the weak cluster set is given to the next step for processing. In pseudo code, it is shown by Alpaydin to follow this procedure:

Initialize $\mathbf{m}_i$, i = 1… k, for example, to k random $\mathbf{x}^t$

Repeat

For all $\mathbf{x}^t$ in X

$b_i^t \leftarrow 1$ if $\| \mathbf{x}^t - \mathbf{m}_i \| = \min_j \| \mathbf{x}^t - \mathbf{m}_j \|$

$b_i^t \leftarrow 0$ otherwise

For all $\mathbf{m}_i$, i = 1… k

$\mathbf{m}_i \leftarrow$ sum over t $(b_i^t \mathbf{x}^t)$ / sum over t (b_i^t)

Until $\mathbf{m}_i$ converge

The vector **m** contains a reference to the sample mean of each cluster. **x** refers to each of our examples, and **b** contains our "estimated [class] labels" (Alpaydin).Explained perhaps more simply in words, the algorithm roughly follows this approach:

1) Choose some manner in which to initialize the m_i to be the mean of each group (or cluster), and do it.
2) For each example in your set, assign it to the closest group (represented by m_i).
3) For each m_i, recalculate it based on the examples that are currently assigned to it.
4) Repeat steps 2-3 until m_i converge.

Strong & Weak Discriminative features:

The values from GLCIA are given to a bisecting k-means clustering algorithm in order to find the weak and the strong features. The main advantage of the bisecting k-means clustering algorithm is that, it generates non-empty clusters every time, and usually similar values are clustered into one cluster while dissimilar values are clustered into another. Usually, the similar values are termed as weak features, as they do not change too much, while the dissimilar values of the other cluster are termed as strong features due to their variance. To find out variance from the set of features, we use the following steps,
1. Let the samples in the dataset be termed as data points
2. Add all the data points in the sample together.
3. Divide that number by the number of data points to get the mean.
4. Subtract the mean from each data point and square each result.
5. Add all of the squared values together.
6. Divide that number by n - 1, where “n” is the number of data points, to get the variance.

II. Feature Extraction & Optimization by RP

Texture feature of complex images has extracted using GLCIA. Extracted feature has been clustered into two categories by k-mean. After clustering, texture features with weaker discrimination is optimized by RP [25] which we proposed here.

Proposed Random projection for feature selection

The weak feature set consists of features which are not variant enough in order to describe the different textures of the input image, and thus must be modified in order to be selected. Random projections and random subspace methods are very simple and computationally efficient techniques to reduce dimensionality for learning from high dimensional data. Since high dimensional data tends to be prevalent in many domains. Random projections (RP)[3],[15],[16],[17]are motivated by their proven ability to preserve inter-point distances. By contrary, the random selection of features (RF) appears to be a heuristic, which nevertheless exhibits good performance in previous studies. We find that RP[12],[13],[14],[24],[25] tends to perform better than RF in terms of the classification accuracy in small sample settings , although RF is surprisingly good as well in many cases. Random Projections [21],[22],[23] is a very simple yet powerful technique for dimensionality reduction. In this method the data is projected on to a random subspace, which preserves the approximate Euclidean distances between all pairs of points after the projection. The Johnson Lindenstrauss lemma (JLL) guarantees that for a set of N points in p dimensions there is a linear transformation to a q dimensional random subspace that preserves the Euclidean distances between any two data points up to a factor of $1+e$ if the number of projected dimensions $q > (\log \frac{n}{e^2})$ where e is a small constant such that $0<e<1$. This result implies that the original dimensionality is irrelevant as far as the distance preservation is concerned. What matters is the number of points that get projected and the accuracy with which we want to preserve the distances. An important thing to note is that the bounds provided by Johnson-Lindenstrauss are rather loose, and in practice the number of dimensions to project to in order to preserve the relevant distances may be much lower. The original result of Johnson & Lindenstrauss was an existence result that did not say how to get the linear transform. Later work by Dasgupta has shown that certain random matrices fulfill the JLL guarantee with high probability, and there are several ways to generate a random projection matrix. The method used in this work is to generate a random matrix with Gaussian entries. There are certain properties of this matrix, which may help us intuitively understand this: Any two rows in the random projection matrix are approximately orthogonal to each other, and have approximately the same length. In essence the random projection is an approximate Isometry. Thus, there is no need to normalize the vector to unit length or to orthogonalise the random projection matrix in practice.

The following are the steps to reduce the dimensionality of the data by random projections:

Suppose that we have a data set $X = \{X_{1,} X_{2,} ......X_n\}$ where each data point is a p dimensional vector such that X_i is a subset of Rp and we need to reduce the data to a q dimensional space such $1 < q < p$ that,

- Arrange the data into a $p \times n$ matrix where p is the dimensionality of the data and n is the number of data points
- Generate a $q \times p$ random projection matrix R* using the MATLAB randn (q , p) function.
- Multiply the random projection matrix with the original data in order to project the data down into a random projection space

Thus we can see that transforming the data to a random projection space is a simple matrix multiplication with the guarantees of distance preservation. Hence, the random projection technique is much more efficient than PCA with a run time complexity of only O (pqn). To summarize, we can say that the RP[3][18][19][20] technique, selects random features from the weak feature set, and normalizes them between the values 0 and 1. These normalized feature sets are then equally divided into values ranging from 0 to 1 in the interval of 1/m, where m is the number of randomly selected features. These values are then assigned to each of the randomly selected features, and then the features are de-normalized by multiplying them with the max value of the given feature. This process ensures that the feature values are evenly separated, and have good variance as compared to the previously weak features Thus by passing the weak features to this technique; we are able to obtain a feature reduced set which contains only strong features. These sets are then given to the live wire algorithm for segmentation.

III. Proposed Livewire Segmentation Algorithm

The Intelligent Scissors Algorithm based on the Live Wire Paradigm

The Intelligent Scissors algorithm uses a variant of Dijkstra's graph search algorithm to find a minimum cost path from a seed pixel to a destination pixel (the position of the mouse cursor during interactive segmentation).

1) Local costs

Each edge from a pixel p to a pixel q has a local cost, which is a linear combination of the local costs (adjusted by the distance between p and q to account for diagonal pixels):

- Laplacian zero-crossing f_Z(q)
- Gradient magnitude f_G(q)
- Gradient direction f_D(p,q)
- Edge pixel value f_P(q)
- Inside pixel value f_I(q)
- Outside pixel value f_O(q)

Some of these local costs are static and can be computed offline. f_Z and f_G are computed at different scales (meaning with different size kernels) to better represent the edge a pixel q. f_G, f_P, f_I, f_O are dynamically (or have a dynamic component as is the case for f_G) computed for on-the-fly training.

2) On-the-fly training

To prevent snapping to a different edge with a lower cost than the current one being followed, the algorithm uses on-the-fly training to assign a lower cost to neighboring pixels that "look like" past pixels along the current edge.

This is done by building a histogram of image value features along the last 64 or 128 edge pixels. The image value features are computed by scaling and rounding f'_G (where f_G = 1 - f'_G), f_P, f_I, and f_O as to have integer values in [0 255] or [0 1023] which can be used to index the histograms.

The histograms are inverted and scaled to compute dynamic cost maps m_G, m_P, m_I, and m_O. The idea is that a low cost neighbor q should fit in the histogram of the 64 or 128 pixels previously seen.

The paper gives pseudo code showing how to compute these dynamic costs given a list of previously chosen pixels on the path.

3) Graph search

The static and dynamic costs are combined together into a single cost to move from pixel p to one of its 8 neighbors q finding the lowest cost path from a seed pixel to a destination pixel is done by essentially using Dijkstra's algorithm with a min-priority queue

Both the strong and the weak features are given to the live wire algorithm. The live wire algorithm works in the following steps,

- The input image is converted into a hyper complex representation using a quaternion function

- The pixels of this converted image are evaluated for entropy
- Pixels with highest entropy are selected and a resultant image is formed
- This image is iterated N times into a Gaussian filter unit in order to smoothen the image
- The smooth image is given to a border cut block in order to obtain sharp borders for the segmented image
- This sharp image is again smoothened using Gaussian filter to obtain a final live wire image mask
- The resultant live wire image mask is multiplied with the input image in order to get the final live wire image

This resultant live wire image is then compared in terms of features from the strong and weaker feature sets, and matching of every feature set is obtained. The feature sets of the input image which matches the stronger feature sets of the live wire image are selected and produced at the output, while the other feature sets which do not match the live wire image are masked out of the output image. This obtained output image is then compared with a standard segmented image in order to evaluate the accuracy of segmentation. The next section describes the results obtained by our proposed segmentation and compares them with standard techniques in order to check the optimization level of our results in comparison with other techniques.

IV. Results And Analysis

We selected a database of general texture including Brodatz dataset images & more than 100 satellite images, and compared the results of PCA with GMTD, RP with GMTD & RP with Livewire. The following table shows the comparative analysis between the algorithms,

TABLE I. COMPARISION OF DELAY

Image Type	Number Of Images	Mean Delay (s) PCA+GMTD	Mean Delay (s) RP+GMTD	Mean Delay (s) RP+Livewire
General textures	15	6.35	6.14	5.84
Close satellite	25	2.63	2.55	2.17
Moderate satellite	25	2.97	2.89	2.23
Far satellite	30	3.82	3.67	2.51

From TABLE I it can be seen that the delay for the livewire and random projection algorithm is reduced when compared with the other techniques. This is due to the fact that livewire combines the best properties of segmentation in order to produce a real time fast map of the segmented image which is then used on the weak and strong features for faster segmentation, the RP algorithm also helps in improving the overall system speed due to random selection of weak features. The accuracy comparison can be observed in table II as follows,

TABLE II. ACCURACY COMPARISON OF TECHNIQUES

Image Type	Number Of Images	Mean Acc (%) PCA+GMTD	Mean Acc (%) RP+GMTD	Mean Acc (%) RP+Livewire
General textures	15	88.5	89.2	91.5
Close satellite	25	88.9	89.4	91.7
Moderate satellite	25	88.4	89.7	91.9
Far satellite	30	88.6	89.5	91.9

The accuracy of the livewire based algorithm is superior when compared to the standard existing techniques. Accuracy is evaluated by checking the results of the given algorithm and comparing them with the actual results. The images are selected randomly for all the comparisons so that the results can reflect the performance under any type of image. The general textured images are the ones which contain various gray level textures, while the close satellite images are the ones in which is object is close to the satellite camera, and moderate and far satellite images have the object at a moderate and from far distance the camera respectively.

The proposed RP_live- wire based segmentation algorithm has many advantages-

- Improve segmentation accuracy
- Reduce delay of segmentation
- Better texture extraction than other technique like PCA, MRF.
- Improve weight parameter which leads to improve segmentation.
- Random projection is computationally faster than PCA due to random selection of 'best' basis vector which improves the computational speed of RP.
- Due to randomized selection of basis vector in RP,dramatic improvement in computing time has been achieve in RP for Gaussians[29][30]data.
- Higher efficiency, accuracy and economy

V. Conclusion

From the obtained results we can conclude that the proposed algorithm is better in terms of accuracy of segmentation and also faster in terms of delay of segmentation under varying image conditions. The algorithm is tested for a wide variety of images, and gives consistent results, thus it can also be used in real time scenarios. Another advantage of using this technique is that the process is fully automatic thus can be used for training of machine learning and AI based algorithms.

VI. Future work

Thus far, the results seem to be promising, but there will be cases where the algorithm might not be able to produce good quality results. In those cases, the researchers can try and extend this research by adding machine learning based segmentation technique, and check its performance on both types of images.

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