International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2018 IJSRCSEIT | Volume 3 | Issue 4 | ISSN : 2456-3307

A Novel Approach for Object Extraction Based On Linear Discriminant Analysis

G. Sukanya[1], S. Swarnalatha[2]
[1]M.Tech Student, Department of ECE, Svuce, Tirupati, Andhra Pradesh, India
[2]Associate Professor, Department of ECE, Svuce, Tirupati, Andhra Pradesh, India

ABSTRACT

Multi view object Extraction plays a major role in tracking and many other applications. Recently different methods are used to extract the object along with boundaries in multi directions. Principal component analysis method is used to extract the object. This method fails due to the high dimensionality and high complexity. So, to overcome the above drawbacks proposed a method called linear discriminant analysis. In this method first extracting the features of the image and converting into the H,S and V planes. k-means segmentation performed to segment the foreground object and extract the boundaries of the object. Experimental results prove to be better and yields better performance when compared to the other state of art methods.

Keywords: Object Extraction, PCA, LDA, k-means segmentation

I. INTRODUCTION

Multi-view object extraction intends to all the while portion a frontal area protest from numerous pictures, each caught at various perspectives of the objective protest. This is a standout amongst the most vital strides in picture based rendering, altering, and numerous PC vision, illustrations, and picture handling undertakings. Early ways to deal with multi-view object extraction regularly expected a very much obliged, indoor studio setup with strict enlightenment and no foundation jumbles Recent methodologies can consequently co-portion a multi-view protest in indigenous habitats by utilizing either basic appearance models in pictures or geometric limitations crosswise over perspectives. Some solid arrangements use three elements: jumping volume earlier from camera postures, appearance models under geometric limitations, and iterative Markov Random Field improvement. In particular, it introduces shading models from projections of a visual body by all cameras. In this technique, divisions of every perspective are geometrically related in the space. The appearance models and frontal area covers are all the while refreshed until the point that they meet in the MRF improvements. In any case, these methodologies just show harsh divisions in moderately low determination pictures and don't perform tangling to determine fragmentary limit issues. Additionally, there is an issue with programmed introduction when the visual appearance of the objective protest can't be basically displayed by shading Gaussian blend models. In this paper, we show a multi-view matte estimation technique over the past methodologies which gauges binary masks, as well as delicate alpha mattes of a forefront protest.

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The Hotelling transform in multivariate quality control, proper orthogonal decomposition (POD) mechanical engineering, empirical orthogonal functions (EOF) in meteorological science, empirical Eigen function decomposition , empirical component analysis ,quasi harmonic modes ,spectral decomposition in noise and vibration, and empirical modal analysis in structural dynamics

Linear discriminant analysis (LDA) is a generalization of Fisher's linear discriminant, a method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification.

II. EXISTING METHOD

2.1 PCA (PRINCIPAL COMPONENT ANALYSIS):

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of distinct principal components is equal to the smaller of the number of original variables or the number of observations minus one. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. PCA is sensitive to the relative scaling of the original variables.

$$t_k(i) = X_{(i)} . w_{(k)} \qquad (1)$$

PCA was invented in 1901 by Karl Pearson, as an analogue of the principal axis theorem in mechanics; it was later independently developed and named by Harold Hotelling in the 1930s. Depending on the field of application, it is also named the discrete Karhunen – Loève transform (KLT) in signal processing, the Hotelling transform in multivariate quality control, proper orthogonal decomposition (POD) mechanical engineering, empirical orthogonal functions (EOF) in meteorological science, empirical Eigen function decomposition , empirical component analysis ,quasi harmonic modes ,spectral decomposition in noise and vibration, and empirical modal analysis in structural dynamics.

Here we use Principal Component Analysis (PCA) to learn a lower dimensional representation of image patches that facilitates easy recognition of the most appropriate patch. Applied to building sequences, we exploit motion cues from the timeline to restrict the number of candidate pixels that will be filled. The problem then becomes one of “building-patch recognition”, akin to the face recognition methods in. The most likely building pixels can then be efficiently retrieved from these candidates using the PCA-based representation. We first explain our PCA-based in painting technique that searches over a much lower dimensional feature space compared to other exemplar based methods. We then extend our synthesis from the spatial domain to include temporal information also and apply it to a vision-based application that aims to recover texture maps of occluded building facades.

III. PROPOSED METHOD

3.1 Feature Extraction

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction.

When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to over fit to training samples and generalize poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

3.2 Converting RGB to HSV

The HSV color space (hue, saturation, value) is often used by people who are selecting colors (e.g., of paints or inks) from a color wheel or palette, because it corresponds better to how people experience color than the RGB color space does. The functions rgb2hsv and hsv2rgb convert images between the RGB and HSV color spaces.

+Color vision can be processed using RGB color space or HSV color space. RGB color space describes colors in terms of the amount of red, green, and blue present. HSV color space describes colors in terms of the Hue, Saturation, and Value. In situations where color description plays an integral role, the HSV color model is often preferred over the RGB model. The HSV model describes colors similarly to how the human eye tends to perceive color. RGB defines color in terms of a combination of primary colors, whereas , HSV describes color using more familiar comparisons such as color, vibrancy and brightness. The basketball robot uses HSV color space to process color vision.

3.3 Texture Feature Extraction

A texture is a repeated pattern of information or arrangement of the structure with regular intervals. In a general sense, texture refers to surface characteristics and appearance of an object given by the size, shape, density, arrangement, proportion of its elementary parts. A basic stage to collect such features through texture analysis process is called as texture feature extraction. Due to the signification of texture information, texture feature extraction is a key function in various image processing applications like remote sensing, medical imaging and content based image retrieval.

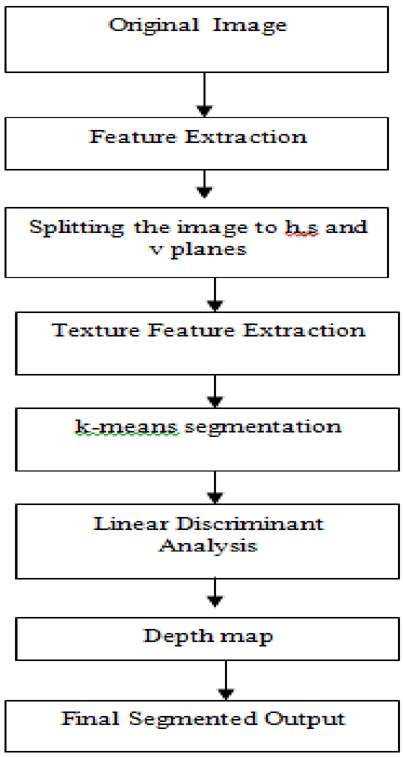


Figure 1. Flow For Proposed Method

There are four major application domains related to texture analysis namely texture classification, segmentation, synthesis and shape from texture. Texture classification produces a classified output of the input image where each texture region is identified with the texture class it belongs. Texture segmentation makes a partition of an image into a set of disjoint regions based on texture properties, so that each region is homogeneous with respect to certain texture characteristics. Texture synthesis is a common technique to create large textures from usually small texture samples, for the use of texture mapping in surface or scene rendering applications. The shape from texture reconstructs three dimensional surface geometry from texture information. For all these techniques, texture extraction is an inevitable stage.

3.4 K-Means Segmentation

Clustering is the process of partitioning a group of data points into a small number of clusters. For instance, the items in a supermarket are clustered in categories (butter, cheese and milk are grouped in dairy products). Of course this is a qualitative kind of partitioning. A quantitative approach would be to measure certain features of the products, say percentage of milk and others, and products with high percentage of milk would be grouped together. In general, we have n data points x_i =1...n that have to be partitioned in k clusters. The goal is to assign a cluster to each data point. K-means is a clustering method that aims to find the positions u_i=1...k of the clusters that minimize the distance from the data points to the cluster. K-means clustering solves

$$\boldsymbol{arg} \underset{\boldsymbol{e}}{\boldsymbol{min}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \sum_{x \in c_i} \boldsymbol{d}(\boldsymbol{x}, u_i)$$

$$= \boldsymbol{arg} \underset{\boldsymbol{e}}{\boldsymbol{min}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \sum_{x \in c_i} \|\boldsymbol{x} - u_i\|_{\boldsymbol{2}}^{\boldsymbol{2}}$$

Where $\boldsymbol{c_i}$ is the set of points that belong to cluster i. The K-means clustering uses the square of the Euclidean distance $\boldsymbol{d}(\boldsymbol{x},u_i)= \|\boldsymbol{x} - u_i\|_{\boldsymbol{2}}^{\boldsymbol{2}}$. This problem is not trivial (in fact it is NP-hard), so the K-means algorithm only hopes to find the global minimum, possibly getting stuck in a different solution

3.5 Linear Discriminant Analysis

Linear discriminant analysis (LDA) is a generalization of Fisher's linear discriminant, a method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification.LDA is closely related to analysis of variance (ANOVA) and regression analysis, which also attempt to express one dependent variable as a linear combination of other features or measurements.

$$(x - \mu_o) \sum\nolimits_{o}^{-1} (x - \mu_o) + \ln |\sum_{i=0} | - (x - \mu_0) > T \qquad (2)$$

However, ANOVA uses categorical independent variables and a continuous dependent variable, whereas discriminant analysis has continuous (independent variables and a categorical dependent variable . Logistic regression and probit regression are more similar to LDA than ANOVA is, as they also explain a categorical variable by the values of continuous independent variables. These other methods are preferable in applications where it is not reasonable to assume that the independent variables are normally distributed, which is a fundamental assumption of the LDA method.

$$s = \frac{\sigma_{between}^2}{\sigma_{within}^2} \qquad (3)$$

LDA is also closely related to principal component analysis (PCA) and factor analysis in that they both look for linear combinations of variables which best explain the data. LDA explicitly attempts to model the difference between the classes of data. PCA on the other hand does not take into account any difference in class, and factor analysis builds the feature combinations based on differences rather than similarities. Discriminant analysis is also different from factor analysis in that it is not an interdependence technique: a distinction between independent variables and dependent variables (also called criterion variables) must be made.

$$c = \omega.\frac{1}{2}\,(\mu_o + \mu_1) \qquad (4)$$

LDA works when the measurements made on independent variables for each observation are continuous quantities. When dealing with categorical independent variables, the equivalent technique is discriminant correspondence analysis.

3.6 Depth Map

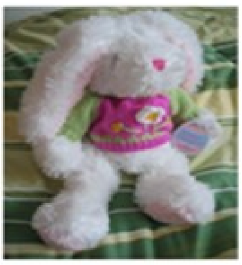
In 3D computer graphics a depth map is an image or image channel that contains information relating to the distance of the surfaces of scene objects from a viewpoint. The term is related to and may be analogous to depth buffer, Z-buffer, Z-buffering and Z-depth. The "Z" in these latter terms relates to a convention that the central axis of view of a camera is in the direction of the camera's Z axis, and not to the absolute Z axis of a scene.

$$E_d = \rho.E_a + (1-\rho).E_g \qquad (5)$$

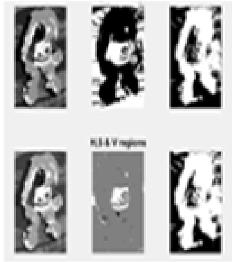
$$E_n = \lambda_{nc}.E_{nc} + \lambda_{ng}.E_{ng} \qquad (6)$$

IV. RESULTS AND DISCUSSION

4.1 Input as Rabbit Image

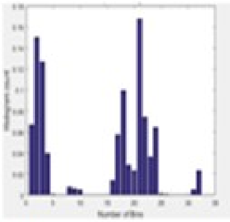


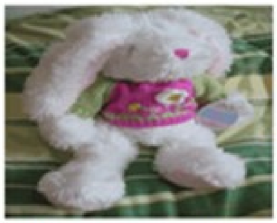
(a) Original image , (b) Bounding mask



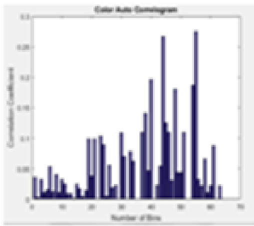
(c) Binary mask, (d) Quantized levels of H,S and V

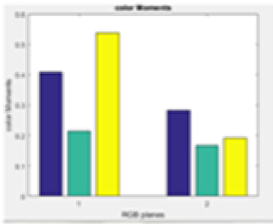
Considering input as rabbit image and bounding box is used to select the particular object. Next converting the image into binary mask which represents the black and white regions, then converting the image into HSV color model for easy processing





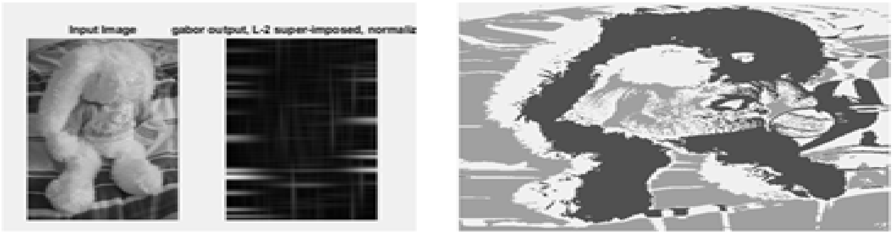
(e) Color autocorrelogram, (f) Color correlogram





(g) Color auto correlogram, (h) color moments

Color auto correlogram is used to represent the histogram of the image; a color correlogram (henceforth *correlogram*) expresses how the spatial correlation of pairs of colors changes with distance. Based on the color auto correlogram representing the color moments in terms of different separations which are used to represent the color distribution in the image.



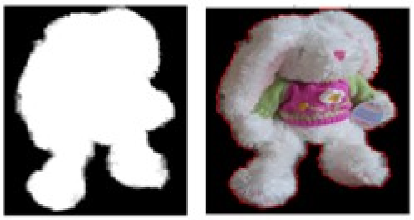
(i)Color output L2 ImposedNormalized,(j) Initial labels

(k)Sum of auxillary node in each iteration,(l) MRF reconstruction for segmentation

For the output the initial labelling is used to extract the particular object. For each iteration calculating the nodes and then applying the MRF segmentation for the better segmentation of the object from background .

(m) Depth map ,(n)Binary mask and trimap or scale level 2 (o) Binary mask and trimap of scale 3,(p) binary mask and trimap of scale 4

Depth map and trimap are used before image matting where matting refers to the segmentation of the object. Using this trimap scale 2 and scale 3 ,depending on the scale the image size gets enhanced.

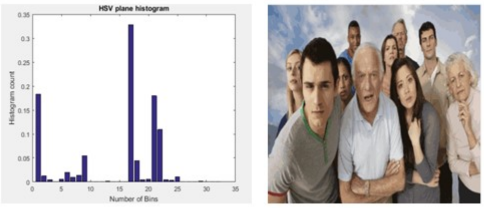


(q) Segmented tri-map, (r) Final segmented Image

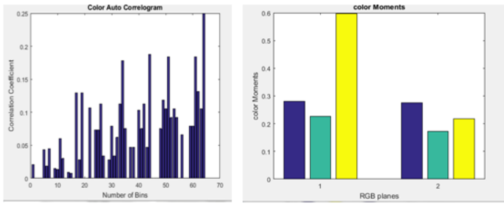
Finally the segmented trimap obtained and then matting applied to remove the background of the image and then finally segmented image can be obtained.

4.2 Input as Family Image

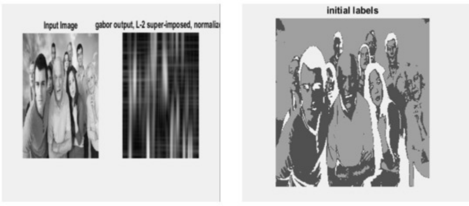
(a)Original image , (b) Bounding mask (c) Binary mask, (d) Quantized levels of H,S and V

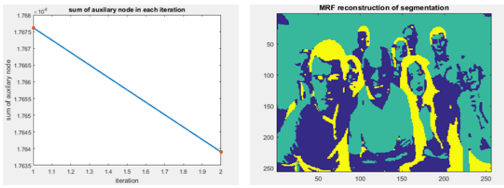


(e) Color auto correlogram,(f) Color correlogram

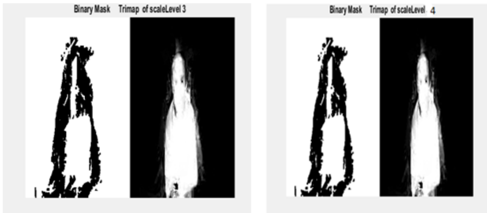


(g) Color auto correlogram, (h) Color moments

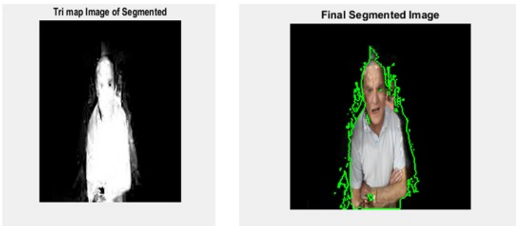




(i)Color output L2 Imposed Normalized,(j)Initial labels (k) Sum of auxillary node in each iteration ,(l) MRF reconstruction for segmentation



(m) Depth map ,(n) Binary mask and trimap or scale level 2 (o) Binary mask and trimap of scale 3,(p) Binary mask and trimap of scale 4



(q) Segmented trimap, (r)Final segmented Image

4.3 Input as Baby Image

(a) Original image, (b) Final Segmented Image

4.4 Input as kid

(a) Original image ,(b) Final Segmented Image

4.5 Input Image as Robot

(a)Original image (b) Final Segmented Image

V. CONCLUSION

In this paper the use of linear discriminant analysis is very advantageous .using LDA the elapsed time of the system reduced .the performance of the system is also improved. This method proves to be better and provides accurate and valid results.

S.Swarna Latha received B.Tech in Electronics and Communication Engineering from JNTU Ananthapur in the year 2000; M.Tech in Digital Electronics and Communication Systems from JNTU Ananthapur in the year 2004; and pursuing Ph.D in Image Processing from Sri Venkateswara University, Tirupati. Currently, she is an Associate Professor in the Department of Electronics and Communication Engineering, SVUCE, Sri Venkateswara University, Tirupati, India.

G.Sukanya received B.TECH degree in Electronics and Communication Engineering from Annamacharya Institute Of Technology And Sciences(jntua), Tirupathi, India in 2015;M.TECH degree pursuing in Sri Venkateswara University College Of Engineering,, Tirupati ,India.

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