Survey on Object Classifications in Image Processing

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Abstract— Object classification important task in image processing. The image processing techniques greatly help to classify object. The goal of object classification is to accurately predict the target. Classification includes image sensor, object preprocessing, object detection, feature extraction from a image and object classification. Feature extraction is useful technique for efficient object classification. This paper presents the survey of various classification techniques with fusion function. The survey presented in this paper can be useful as a quick overview and beginner's guide for the object classification field.

Key words: Object Classifications, Image Processing

I. Introduction

An Image is a square pixels array, or a matrix, arranged in columns and rows. The pixel is a picture element. Image processing is process image data for storage and transmission, which is used enhance the image for improve the image quality and reduce the noise. The enhancement is a process which is used to extracting image feature information. Image classification is easy task for human but it has to be a complex problem for digital devices. The raise of high-capacity computers, the availability of high quality scanning devices and low –priced cameras and the increasing need for automatic object analysis has generated an interest in object classification algorithm. A simple object classification system consists of a camera fixed high above the interested zone in image processing, where objects are detected and consequently processed. Object Classification system consists of extracted feature database that contains predefined patterns that compares with detected object to classify in to proper category. Object classification is an important and challenging task in various application domains, including biomedical imaging, biometry, vehicle tracking, industrial visual inspection, robot tracking and image remote sensing. Image classification represents group pixels to define land cover features. Land cover may be forested, urban, agricultural and other types of features. There are three main object classification techniques in remote sensing.

A. Object Classification Techniques:

- Unsupervised image classification
- Supervised image classification
- Object-based image classification

Object classification uses the reflectance information for individual pixels. Pixels are the smallest unit represent in an image. Unsupervised and Supervised techniques are the most common classification approaches. Pixels are clustered based on the reflectance properties of pixel. Clustering process define the pixel grouping. The user physically specifies each cluster with land cover classes. Multiple clusters characterize a single land cover class. IN supervised classification the user selects delegated samples for each land cover class in the digital image. These sample land cover classes are acknowledged as "training sets". The training set compared with the land cover classes in the entire image by using the image classification software. The Supervised classification of land cover is based on the spectral signature distinct in the training set. The image classification software determines each class on what it resembles most in the training set.

II. Literature Survey

The system describes some textural features computations. Textural features based on the gray tone spatial dependencies. It illustrates their applications in category identification tasks of three different kinds of image feature information data sets. IN each data set was divided into two parts, a training set and test set. Test set identification accuracy is 89% for photo micrographs, 82% for aerial photographs and 83% for the satellite photographs. These results indicate that the easily computable image textural (pattern) features probably have a general applicability for a wide variety of image-classification application. Additional processes are necessary to determine the size of the sub image region and the distances. That distance should be used in computing the gray-tone dependence matrices. Too small sub image region will not have enough textural information (gray-tone spatial-dependence) to separate image categories, while a large sub image region will increase the storage requirements. The pixel distance which must be used in computing the gray-tone spatial-dependencies may be obtained from the autocorrelation function of the image. The distance between pixel auto correlation function of the image becomes too small can serve are an upper bound on the distance which may be used texture feature based on gray-tone spatial-dependence matrices. [1].

This system presents UnECHO, a mechanism of integrating spatial and spectral information in an unsupervised classifier. The techniques of unsupervised enhancement of pixel homogeneity features in a local neighborhood, This techniques will enable an unsupervised contextual classification of multispectral image feature that combine the spectral and spatial information producing results that are more meaningful to the human anylst. This UnECHO is divided in two stages; first one uses the spectral information on a pixel-by-pixel basis. It can be a problem solution from either a clustering algorithm such as C-means or a supervised classification such as ML classifier. Second one uses both spectral information from the original image and the content of the first stage clustering map. Its main advantages are that it simplifies image features by retrieval process of spatial structures. This Enhancement is specially, relevant for the new generation of airborn image process and space borne sensors with high spatial resolution. [2].

This system proposes a trival NN-based classifier – NBNN, (Native-Bayes Nearest-Neighbor), which employs NN distances in the space of the local image descriptors.

The spatial pyramid match kernel of measures distance between histograms of quantized SIFT descriptors, but within an SVM classifier. NBNN computes image to-class distances without descriptor quantization method. Their SVM feature learning phase compensates for some of the feature information loss due to quantization process, raising classification performance up to 64.6%. NBNN is extremely simple, efficient and requires no feature learning/training phase; its performance ranks among various feature learning process-based image classifiers, Empirical comparisons are shown on several challenging databases. However, comparison to the baseline performance of NBNN implies that the information loss incorrectly the descriptor quantization was larger than the gain obtained by using SVM classifier. [3]

The system proposes to image features classification and simultaneously to learn the unique image features in such high-dimensional scenarios. This learning method is based on the automatic feature optimization of a linear combination of kernels dedicated to different meaningful class sets of features, such class sets can be groups of bands, contextual or texture features or bands acquired by different sensors. System presents a kernel framework for combining and assessing the relevance of different sources of information multiple-kernel SVM image classification. The system proposed an efficient model selection procedure based on the kernel alignment. The result is a weight for the model ,experiments carried out in multi-and hyper spectral, contextual and multisource remote sensing image feature classification confirm the capability of the method in ranking the relevant image feature and show the computational efficient of the proposed strategy. It allows to automatically optimizing different kernel parameters and weights per dedicated kernel. Particularly when using kernel alignment for parameters estimation, computational costs is affordable for large –scale remote sensing applications.[4].

In this system proposed a logistic regression-based fusion (LRFF) method. and also design a new marginalized kernel by making use of the output of the regression model. Here the system compares proposed approaches with existing methods that combine color and shape on three datasets. The system proposed learning-based feature fusion process clearly out performs the state-of-the art fusion methods for image classification. In this paper, System presented a new approach to fuse multiple cues by adaptively a set of diverse and complementary visual words for s given class using a sparse logistic regression method and also a marginalized kernel used for better classification. This kernel takes into account not only the learned conditional probabilities of the LRFF method, but also the image-to class image similarity to define the similarity between two images. The system Instead of using all cues like (color, shape, texture….) select set of diverse from image in order to better discriminate. Logistic Using regression here reduces multiple dictionaries the most specific discriminative words. Independent weighting for each cues is impossible in this system.[5].

The system introduce the patch alignment framework to linearly integrate multiple image features in the optimal way and obtain a unified low-dimensional representation of these multiple image features for subsequent image classification. IN this method features has its particular contribution to the unified property determined by simultaneously optimizing the pixel weights in the objective function. The integrated objective functions of each single feature into a unified one by simultaneously optimizing the combining weights. Finally, system have further extended the MFC to its linear version to solve the out of-sample problem in HIS image classification. Some of the advantages of our works are as follows. First MFC considers the spectral, texture and spatial features of a pixel to achieve a physically meaningful low-dimension representation from effective and accurate classification. Second, the weights for feature are optimized in the objective function of MFC simultaneously without using cross-validation, which suggests that the discriminative abilities of image different features and the complementary properties among the multiple image features have been fully considered in the system optimization of MFC, there by achieving the optical classification performance. This system want to focus on how to select optimal radius parameter for each image feature, respectively, contain the best low-dimensional for Multiple Feature Classification. [6].

The system presents a new hierarchical image segmentation method that applies graph laplacian energy as a generic measure for object segmentation. Which reduces the image pixel redundancy in the hierarchy by an order of magnitude with little or no loss of performance. The selected hierarchies using this laplacian energy, they can get a sensible semantic interpretation in terms of image and image features which used to get more robust image classification. IN the classification stage, they apply local self-similarity (LSS) feature fusion method to capture the internal geometric region in an image. The system achieved better performance by using the combination of semantic hierarchical image segmentation and pixel local geometric region description. IN the experimental section, system validates the effectiveness of the system method by showing results on QuickBird and GeoEye-1 image datasets. Using graph laplacian, the redundancy in the image hierarchy by an order of magnitude with little or no loss of performance. System proposed a new hierarchical image segmentation techniques that applies graph Laplacian energy as a generic measure for object segmentation based on pixel energy. This technique provides satellite image analysis and classification that is better than those from alternative methods. Semi supervised learning method is not used in satellite image analysis. Furthermore, traditional spectral features will be incorporated into this system. [7]

III. OBJECT CLASSIFICATION STEPS

Object classification is a division of image detection. It may be larger than object detection .Object classification analyzes the numerical properties of different image feature and organizes data into categories .object classification algorithm normally employ two phases of processing :training and testing. Training set features are isolated, which is extremely important for object classification. Test set is used for testing process.

Object Classification process consists of following steps:

A. Pre-Processing:

Image preprocessing also known as image restoration. Image preprocessing is the technique of enhancing data image. It removes low frequency background noise. Image transformation. Image pre-processing can extensively boost the reliability of an optical inspection. Pre-processing contains numerous image filters for image optimization. It includes numerous functions for image pre-processing like Normalization, Binning, Edge filters, Soft focus etc.

B. Detection and Extraction of an Objects:

It includes detection of pixel position and other characteristics of moving object image selected from camera. Extraction involves dropping the amount of resources required to describe a large set of data.

C. Classification:

Detected object into predefined classes by using suitable classification method. Object Classification is mainly depends upon the features. Image Features are functions of the original measurement variables that are useful for object classification and pattern recognition. Feature extraction defining a set of image features, or object characteristics, which will most efficiently classification or meaningfully represent the feature information that is important for image quality analysis and image classification.

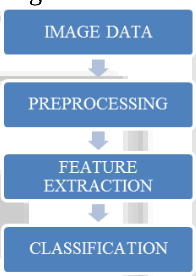

Fig. 1: Object Classification Overview Diagram

IV. CONCLUSION

This paper attempts to study and provide a brief knowledge about the different image classification concepts and different classification methods. Most common approaches for image classification can be categories as supervised and unsupervised or object-oriented, subpixel, per-pixel and perfield or spectral-classifiers, contextual classifiers and spectral-contextual classifiers or hard and soft classification. These surveys give theoretical knowledge about different classification methods and validate the advantage and disadvantages of various object classification methods. Available papers limitations were highlighted in each and every technique. Advance study may be carried out to include find efficient methods to reduce computational cost, increase accuracy and decrease the time required for classify the object. These papers produce the survey of various papers and investigated different classification methods.

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