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FEATURE EXTRACTION TECHNIQUES IN MACHINE LEARNING

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ABSTRACT

Object identification is primarily concerned recognition based on specific local features and global features. Image processing and object recognition are subsets of pattern recognition, in which an image is recognized based on extracted features. Traditional approaches were used to identify animals for a variety of applications. With the advent of computer science, researchers considered developing an identification system that could replace traditional methods which physically harm animals and have social implications. Livestock management, cattle census for milk production in the country, insurance claims in banks, and security concerns like avoiding cross borders by the cattle are among the most common applications of cattle identification. In this paper we are going to discuss the feature extraction techniques for identification in machine learning.

KEYWORDS: SIFT, SURF,ORB, LBP, PCA,LDA

1. INTRODUCTION

Feature extraction is a very important step in the construction of any pattern classification that extracts relevant features to identify the class from group of images. To recognizing accuracy depends upon the quality of features extracted from an image. Unique feature extracted has high accuracy in recognizing classes. The accuracy of a system depends upon the number of features and type of feature extracted from an image; relevant features are extracted to form a feature vector. Feature extraction technique extract two types of features namely: local features and global features. Local features extract interesting points that include points, edges, corners, blobs, and ridges. They are an image patch that differs from its surroundings by texture, colour, and intensity. Global features describe the image in a generalized form. It includes contour representation, shape description, and texture features.

2. LITERATURE REVIEW

References	Techniques	Images	Accuracy
Noviyanto andArymurthy(2012)	Speed UpRobustFeature (SURF)	80 Images	90.6%
Awad*etal.*(2013)	Local invariantfeature,SIFT	90 Images	93.3%
CaiandLi(2013)	LBP Texture Feature Extraction	300 Images	95.30%
Kumaret al.(2016)	PCA+LDA+ICA	3000Images	95.87%
Kumar *etal.*(2017)	SIFT	5000Images	96.87%
Kumar *etal.*(2018b)	SIFT, DSIFT,LBP	5000Images	96.56%
Kusakunniran*etal.* (2018)	Bag of Histogram andLBP	217 Images	100%

3. FEATURE EXTRACTION TECHNIQUE

3.1 SHI TOMASI CORNER DETECTOR

The Shi-Tomasi corner detector detects corners, i.e., a junction of two edges defines a change in the image brightness. A corner indicates an image feature that makes the correspondence between two images. Shi and Tomasi proposed this extraction technique based on the concept of the Harris corner detector with a difference in "selection criteria" that achieves good results and is very fast.

3.2 SCALE INVARIANT FEATURES

SIFT, invented by Lowe, is a computer vision algorithm to detect, describe, and match local texture features. SIFT is mainly used as an object recognition algorithm to extract unique features from an input image and locate features in an image and store them in a database. A new image or query image is compared with the already stored images to find the matching candidate features based on Euclidean Distance. Among a full set of matches, a subset of those key points that agree on the object, location, and scale in the new/query image are identified to find the best result.

3.3 DENSE-SCALE INVARIANT FEATURE TRANSFORM (D-SIFT)

This method collects more features at every location and scale in the image, which increases recognition accuracy. This method has a higher computational complexity than normal SIFT. Dense-SIFT feature extraction works by specifying descriptor size by a single parameter. Dense-SIFT is faster than SIFT and does not identify interest points; instead, it divides the image into overlapping cells, describes interest points using a histogram of Oriented Gradients, and generates 128-dimensional feature vectors.

3.4 SPEEDED UP ROBUST FEATURES

SURF was presented by Bay, as a version of the SIFT feature detector with a few improvements on certain factors like rotation, blurred, and transformed images, and is faster than the SIFT algorithm. A feature descriptor is an algorithm to divide the raw data into numerical features to process and preserve the information of the original dataset for analysis and classification. SURF is a patented, local descriptor that works by applying a Gaussian second derivative mask to an image at multiple scales.

3.5 ORIENTED FAST AND ROTATED BRIEF FEATURES

ORB was developed in the OpenCV lab by Rublee, is an efficient, viable, and faster techniques. ORB enhanced the performance using FAST (Features from Accelerated Segment Test), i.e., a corner detection algorithm and a BRIEF (Binary Robust Independent Elementary Feature) descriptor for binary strings. ORB has good features: accurate orientation component, efficient computation, rotation invariance, and multiscale features. ORB creates a multiscale representation of a single image that consists of a sequence of images at different resolutions. A pyramid of images is created. A fast algorithm is used to detect key points from an image.

3.6 LOCAL BINARY PATTERN (LBP)

The LBP presented by Ojalais also a local image descriptor that describes the texture and shape of an image. It labels pixels of an image by thresholding the value of each pixel and results in binary information. The neighbourhoods are assigned a value of "0" if they are less than the threshold, otherwise "1". It is a powerful descriptor to detect all possible edges in the image. The neighbourhoods are assigned a value of "0" if they are less than the threshold, otherwise "1". Then compute the histogram, normalize it, and concatenate all the cells. The result is a feature vector for the entire window.

3.7 BINARY ROBUST INVARIANT SCALABLE KEY POINTS (BRISK)

The BRISK algorithm is a binary descriptor used as a local feature point detection and description algorithm with scale invariance and rotation invariance. Brisk constructs the feature descriptor of an image through the grayscale relationship of random point pairs in the neighbourhood of the local image and then obtains its binary feature descriptor. There are three phases of BRISK. 1) Key point detection-AGAST (Adaptive and Generic Accelerated Segment Test) for Corner Detection to extract stable points. 2) The binary feature descriptor is a key point in the description. 3) Descriptor Matching- Hamming Distance is used for feature matching.

3.8 BINARY ROBUST INDEPENDENT ELEMENTARY FEATURES (BRIEF)

BRIEF is also a binary descriptor that uses binary strings as an efficient feature point descriptor and is based on pairwise intensity comparison. BRIEF converts an image into a binary feature vector, which contains 1 and 0 that describe key points, with each key point represented by a 128–512-bit string. BRIEF is invariant to illumination but not to scaling and rotation.

3.9 HARRISCORNERDETECTOR

An algorithm was presented by Harris and Stephens (1988), and is commonlyused to extract the corners of an image. A corner is a junction of two edgesand has variation in all directions, so it can have unique points. This algorithmprovedto be more accurate atdistinguishing edgesandcorners.Here, asmall window around each pixel *p* in an image is used to identify unique pixelsbyshiftingeachwindow.

3.10 PRINCIPALCOMPONENTANALYSIS (PCA)

Principal Component Analysis, commonly known as PCA, is a holistic feature. It is an unsupervised learning dimensionality reduction algorithm.Itisanefficient tool which can reduce a large set of correlated variables into smallsets of uncorrelated variables called principal components, which still consist of mos to fthe information in a largest identify the object. In simple language, we can say that by dropping the least important part of object and retaining the valuable part. PCA is very much like another multivariate procedure known as Factor Analysis. Often, PCA is confused with factor analysis. PCA checks for linear combinations of variables to extract maximum variance from variables Abdelmajed (2016). Afterwards, it removes the extracted variance in the first step and checks for a second linear combination to explain the maximum proportion of remaining variance and keeps on checking for variances.

3.11 LINEARDISCRIMINANTANALYSIS (LDA)

Linear Discriminant Analysis, commonly known as LDA,is also a holistic feature. It is a supervised learning dimensionality reduction algorithm. An LDA is a type of linear combination that implements a statistical process by applying it to various data items and then applying functions to analyses multiple classes of objects or items. In other words, it finds linear combination of features that characterizes or separates two or more classes.LDA reduces the number of features to some manageable features before the classification process.

4. CONCLUSION

In this paper have discussed numerous feature extraction techniques for identification in machine learning.These methods have replaced the traditional method of identification and has more accuracy to than traditional method of cattle classification. Traditional methods have many implications as it physical harm cattle and handle other application like Livestock, cattle census, insurance claims in banks, and security concerns like avoiding cross borders. These techniques have high accuracy if good features are extracted from the images.

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