ISSN 2229-5518

A Review on Various Techniques of Features Extraction

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Abstract— Due to tremendous growth in the number and sizes of digital images is making necessary for transmission and storage. So a fundamental problem in computer vision is object recognition: given an image composed of a grid of raw pixel values, one needs to design a computer system that identifies the objects present in this image. Motion in images carries important information about the external world and changes of its structure. The existing technique implemented for the extraction of Features from Gray as well as Color images.

Keywords—SIFT, Sparse Coding Model, Gabor Filter Decomposition Spatial, Feature Extraction techniques.

I. Introduction

The automatic recognition of human actions a fundamental but challenging task in computer vision research for a wide variety of applications including autonomous surveillance, law enforcement, health care monitoring systems, and human computer interfacing. Automatic image features detection is another important task for many applications. The main challenge of such systems is their ability to extract image features in unconstrained environments. Images of human actors can vary by their sizes, shapes, poses, occlusions, viewpoint variations, noise, and lighting. Additionally, action classification systems would need to account for action execution speed requiring spatio-temporal representations that are invariant to such factors.

The most common approaches to classification involve extracting meaningful features from images or video and applying statistical or machine learning tools to make classification decisions. Optimal action representations are those that can capture both the spatial structure of an activity and its temporal arrangement at the end of the day. Despite the fact that many image features can characterize spatial and temporal domains separately, there are spatio-temporal features that are proficient of characterizing both domains, such as space-time importance points and 3D Harris corner detectors. Such image features are well-suited for difficult applications such as multi-view and 3D action classification systems. Within these domains are an extensive range of illustrations concerning normalization, invariance, and comprehensive search. In the same way, face image representations are anticipated to be strong an adequate amount of to differentiate between a extensive range of human subjects and below unconstrained circumstances such as variations in explanation and facial appearances. Local binary patterns and local ternary patterns are among the most popular face image representations.

The method developed in this work has provide several strategies for computing images queries that specify the features, sizes and arbitrary spatial layouts of regions, which include both absolute and relative spatial location. We also address several case spatial queries involving adjacency, overlap and encapsulation regions. In this case, a query returns any number of images depending on the bounds defined by the threshold of features similarity to extract, stores and index.

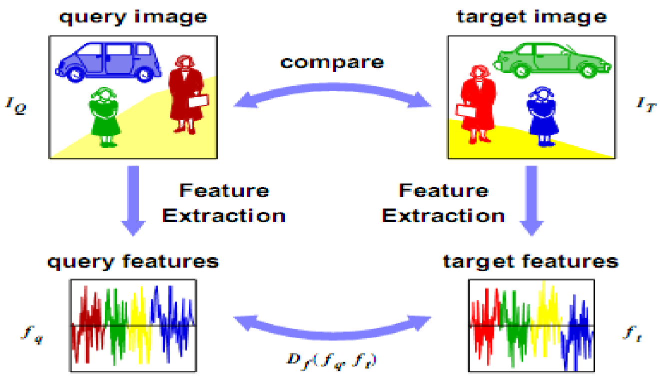

Figure-1: Image Features Comparison.

Many vision applications, including visual SLAM [1], [2] and 3D dense reconstruction [3], rely heavily on accurate feature detection and matching. Feature detection must be robust, stable, and invariant to changes in scale and viewpoint. Feature descriptors need to be able to characterize features uniquely. If real-time operation is desired, both detection and matching must be quick to execute [4].

Scale Invariant Feature Transform

Scale-invariant feature transform (or SIFT) is an algorithm in computer vision to detect and describe local features in images. The algorithm was published by David Lowe in 1999.
Applications include object recognition, robotic mapping and navigation, image stitching, 3D modeling, gesture recognition, video tracking, individual identification of wildlife and match moving.
IFT keypoints of objects are first extracted from a set of reference images and stored in a database. An object is recognized in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based on Euclidean distance of their feature vectors. From the full set of matches, subsets of keypoints that agree on the object and its location, scale, and orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient hash table implementation of the generalized Hough transform. Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and subsequently outliers are discarded. Finally the probability that a particular set of features indicates the presence of an object is computed, given the accuracy of fit and number of probable false matches. Object matches that pass all these tests can be identified as correct with high confidence.

II. Image and its Features

The images we used were a collection of 308 high-resolution ability images acquire from a variety of resources. Here we examine the value of two types of methods – fixed and adaptive – for providing descriptions of the stylistic qualities of art images. Furthermore, we compare these methods to the "expected" stylistic distinctions, in addition to to psychophysical researches that observed perceptual relationship between efforts of art [5]. The two image decomposition methods we utilize in this paper are a Gabor filter decomposition of images and the sparse coding model [6]. Several features are extracted from the decompositions obtained using each of these models and are described in more detail in the corresponding sections.

Gabor Filter Decomposition

Gabor functions are localized, oriented, and bandpass, and as such are sensitive to constructs of lines and edges at particular orientations and spatial frequencies. In our experiments, we created a set of Gabor functions at eight orientations (0 to 7π/8 radians), four spatial frequencies (something like 5, 9, 12 and 16 cycles-per-picture), and two phases (0 and p radians), for a total of 64 filters.

Once an image patch size (e.g., 64×64 pixels) and filter size (e.g., 32×32 pixels) were determined, we imposed a grid on the images and extracted as many patches of the specified size as possible. Each of these patches was convolved with the Gabor filters to generate a set of 64 filter answers. Usually, we let the filters have a region length equal to one-half the side length of the image patches. This allowed us to obtain a section of the convolution image equal in size to the filter, disregarding parts of the image where zero-padding would have been necessary.

Once the response images for each patch were obtained, a feature vector was generated for each patch using the energy contained in each filter response:

$$E(I, f_{k,\theta,\phi}) = \sum_i |(f_{k,\theta,\phi} * I)[i]|^2$$

Where I am the image patch and $f_{k\Theta,\ \phi}$ is a Gabor filter with preferred spatial frequency k, preferred orientation q and spatial phase f, and i indexes pixels in the image patch. Other features are of course possible, but for our purposes here we considered only this method of feature extraction. Distances between works of art were determined by the correlation distance (i.e., 1- Pearson's r) between the averages of the feature vectors associated with a particular image.

Sparse Coding Model

The sparse coding model of Olshausen & Field [6], which is equivalent to independent component analysis (ICA) [7], was originally proposed to explain the response properties of cortical "simple cells" in the early visual system. The model learns a set of basis functions tuned to the higher-order statistical characteristics of a particular image space via maximum likelihood estimation. Since a sparse prior is used on the coefficients for any particular representation, the model attempts to maximize sparseness while guaranteeing a suitable level of reconstruction (i.e., one with relatively low reconstruction error).

For our purposes, we seek to take advantage of two important characteristics of this model: its sparseness, determined by non-Gaussian filter response distributions which allow the learned functions to be non-orthogonal and probably over complete, and its adaptiveness, which insures that the learned functions are optimal regarding the data. Sparseness is significant with the intention that the functions do not become those that would be determined by a principal component analysis [8] decomposition of the image space, since such functions, which resemble the Fourier basis in two dimensions [6] and thus contain no localized information, are usually tuned to a narrow range of spatial frequencies and are generally not separable in terms of orientation and spatial frequency. Adaptiveness is also key: in contrast to fixed decomposition such as a set of Gabor functions, the functions learned by the sparse coding model are data-dependent, and the discrepancies in the possessions of the functions themselves should be reflective of the underlying inputs.

Because of their adaptiveness to the input image space, we use the functions themselves as a proxy through which to analyze properties of the higher-order statistical characteristics of the images. Olshausen & Field showed that the learned functions reflect properties of the input image space [6]. We derive several features from the functions in order to analyze and compare these properties. In all of our experiments, we trained a set of 256 i.e. 16×16 pixel basis functions on each image individually using the sparse coding model. It was from this set of functions that we derived features representing each image.

We compared images according to several metrics, which depend on the features extracted from the basic functions. They are as follows:

- **Peak orientation:** given the two-dimensional Fourier transform F (w; θ) of a basis function (viewed as a function of frequency w and angle θ), we find the orientation θ* at which peak amplitude (or power) occurs, averaged across all spatial frequencies, i.e.,

$$\theta^* = \arg\max_{\theta} \frac{1}{|\Omega|} \sum_{\omega \in \Omega} |F(\omega, \theta)|$$

  This is a reliable way of determining the orientation selectivity of a basis function.
- **Peak spatial frequency**: given the two-dimensional Fourier transform F (w; θ) of a basis function, we find the spatial frequency w* at which peak amplitude (or power) occurs, averaged across all orientations, i.e.,

$$\omega^* = \arg\max_{\omega} \frac{1}{|\Theta|} \sum_{\theta \in \Theta} |F(\omega, \theta)|$$

  This is a reliable way of determining the spatial frequency selectivity of a basis function.
- **Orientation bandwidth:** given the two-dimensional Fourier transform of a basis function, we find the bandwidth in octaves (measured by full width at half-maximum) of the function, averaged across all spatial frequencies, centered on its peak orientation θ *. This measure quantifies how discriminating a base function is for its preferred orientation.
- **Spatial frequency bandwidth:** given the two-dimensional Fourier transform of a basis function, what is the bandwidth in octaves (measured by full width at half-maximum) of the function, averaged across all orientations, centered on its peak spatial frequency w*. This quantity measures how selective a basis function is for its preferred spatial frequency. These quantities are computed for each of the 256 basis functions trained for each image. Since there is no usual method to evaluate individual functions with one another, we employ distributional methods to do so. In particular, we use symmetrized Kullback-Leibler divergence (KLD) to compare distributions of these quantities, defined in the following way:

$$\mathrm{KLD}(P,Q) = \frac{1}{2} \sum_{\omega \in \Omega} \left[P(\omega) \log \frac{P(\omega)}{Q(\omega)} + Q(\omega) \log \frac{Q(\omega)}{P(\omega)} \right]$$

Since the values above are continuous quantities, we estimate KLD by binning, and we determine bins once for a particular quantity (e.g., spatial frequency bandwidth), and this determines the binning for all subsequent computations of the KLD. Thus, given the quantities above, we derive distances between all images using KLD for the following distributions:

- sharing of peak orientation
- sharing of peak spatial frequency
- Joint allocation of peak orientation and spatial frequency
- sharing of orientation bandwidth
- sharing of spatial frequency bandwidth
- Joint allocation of orientation and spatial frequency bandwidth

Furthermore, we compute distances between images based on a distance metric defined directly on the sets of basic functions [9]. The final feature we compute, from which we derive a distance, is the slope of the log rotational average of the amplitude spectrum for each image. Ultimately, including Gabor filter energy, all of the distances derived from the sparse coding model basis functions, and the slope of the log rotational average of the amplitude range, we have in entirety ten distances with which we measure up to images in our dataset. We incorporate an eleventh, the distance matrix originated by aggregating the distance matrices after rescaling each so that the maximum distance was 1.

III. Image Representation

Image representations are encodings that describe facial images and, ideally it should be robust enough to distinguish between human subjects. Eigenfaces is an approach based on finding principal components of face images that linearly project the image space to a low dimensional characteristic space. Even though efficient less than ultimate lighting conditions, frontal pose and neutral facial expressions, eigenfaces are not forceful and outliers from varying lighting conditions, view angles, and expressions can result in undesired classification errors. Fisherfaces maintain the Euclidean structure while maintaining high between class discrimination and being less sensitive to lighting and expressions. Laplacianfaces [10] preserve the local structure of the image space and detects the face manifold structure.

A challenge for Eigenfaces, Fisherfaces, and Laplacian faces is robustness to lighting conditions and facial expressions. Tann and Triggs [11] identify three categories for dealing with these factors which are appearance-based, normalization-based, and feature-based methods. Appearance-based methods require building a large training set that covers varying enlightenment conditions and appearances. Normalization-based techniques engage the normalization methods for example histograms. This consists of gamma correction, Difference of Gaussian (DoG) filtering, and contrast equalization. Feature-based methods identify

ISSN 2229-5518

illumination and expression invariant image features. One such illustration is Local Binary Patterns (LBP) which has proven to be effective for texture representations while being highly discriminative and invariant to worldwide gray-level transformations for lighting invariance. LBP is based on thresholding image pixel neighborhoods and encoding a binary pattern. The original LBP method applies an operator on each pixel of an image which thresholds the neighboring pixels at the value of the central pixel.

The result of this operator is an image patch with an 8-bit code. An example of a fundamental LBP operator and its effecting 8-bit code is shown in Figure 2. The mid pixel with value 77 is investigated with a 3x3 window. Any adjacent pixel values greater than 77 are allotted a binary value of 1. Any that is a smaller amount than 77 are allocated a binary value of 0. After pertaining the LBP operator, the binary encoding is an 8-bit value read from the top left neighbor clockwise around the mid pixel. The encoding is considered uniform if there is at most one transition from 0 to 1 or 1 to 0 (i.e.: 1110001). The resultant encoding in the example make available is not identical for the reason that there are two transitions for 0 to 1 and 1 to 0. The uniform properties of image scrapes are useful for histograms that recognize uniform and non-uniform patterns.

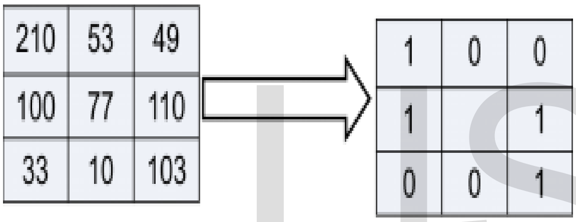

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Figure 2: The LBP operation and the resulting 8-bit encoding of the central pixel [11].

IV. Various Image Feature Extraction Techniques

For the purpose of feature extraction, two-dimensional (2-D) Gabor filters seem to be good candidates because of some outstanding properties like an optimum joint resolution in the space/spatial-frequency domain [12] as well as orientation and occurrence selectivity. Since Gabor filtering necessitates unnecessary computational endeavor, it is necessary to make efficient selection of the proper number of filters and their parameters so that the computation time is minimized while obtaining the best segmentation feature. Illustrations based on multiresolution are very effective for analysing the information substance of images. In computer vision, it is deadly to examine the information content of an image directly from the gray-level intensity of the image pixels.

1) Feature-based methods characterize a texture as a homogeneous distribution of feature values such as gray level cooccurrence matrix (GLCM) and Laws' texture energy (LAWS). Even though both GLCM and LAWS were originally proposed in the context of texture classification, many investigators have practical them to texture segmentation. Spatial/spatial-frequency methods use a technique to generate a group of features from filtered images computed from frequency information at localized areas, such as Gabor functions or wavelet representation.

a) Gray level co-occurrence matrix (GLCM) was introduced by Haralick [13]. A co-occurrence matrix describes how often one gray level appears in a specified spatial relationship to another gray level. The entry at (i, j) of the GLCM indicates the number of occurrences of the pair of gray levels i and j which are a distance d apart along a given direction θ. The values of d and θ are parameters for constructing the GLCM.

b) Laws' texture energy (LAWS) combines predetermined one-dimensional kernels into various convolution masks. The output image of the convolution process is considered as an "energy image", go behind by a texture energy transformation in which each pixel at the centre of a local window (l (i, j)) is replaced by the mean of absolute value in the filter window (f (i, j)) as follows:

$$s(i,j) = 1/(2 \times n+1)^2 \sum_{k=i-n}^{i+n} \sum_{l=j-n}^{j+n} |f(k,l) - l(i,j)|$$

Where n is size of the mask.

c) Gabor multi-channel filtering with Gabor functions (GABOR) was proposed by Jain and Farrokhnia [14]. Many texture-segmentation techniques are based on a filter-bank representation, where the filters, called Gabor filters, are obtained from Gabor basic functions. The aim is to characterize texture discrepancies into measurable filter-output discontinuities at texture margins. By judgment these discontinuities, one can segment the image into another way textured areas.

However if the Gabor filter parameters are suitably chosen distinct discontinuities turn out. Feature images are obtained by presenting each top excellence filtered image to a nonlinear transformation and computing a measure of energy around each pixel. Then, the average absolute deviation from the mean in small overlapping windows is computed. At different resolutions, the details of an image generally characterize different physical structures of the scene. At a coarse resolution, these details relate to the larger structures which provide the image "context". It is therefore obvious to analyse first the image details at a coarse resolution and then gradually increase the resolution. Such a course-to-fine technique is useful for pattern recognition algorithms. It has already been widely studied for low-level image processing such as stereo matching and template matching.

Multichannel filtering approach for texture analysis is intuitively appealing because it allows us to exploit differences in dominant sizes and orientations of different textures. In several papers the successful applications of multichannel filtering for texture segmentation were reported using various filtering techniques, such as isotropic filters discrete cosine transform (DCT) and Gabor filters. The reason for the popularity of Gabor filters is due to their joint optimum resolution in time and frequency. The performance of multichannel segmentation methods based on a more wide-ranging class of filters including Gabor filters. However a large combination of parameters makes texture discrimination using Gabor filters computationally expensive. Recent development in wavelet theory has provided a promising alternative through multichannel filter banks that have several potential advantages over Gabor filters namely,

(i) Wavelet filters cover exactly the complete frequency domain.

(ii) Fast algorithms are readily available to facilitate computation.

2) Wavelet transform: More freshly, learning on doing well application area of wavelet theory on texture analysis has been reported using the multiresolution signal decomposition developed. He used quadrature mirror filters to relate information at different scales of decomposition of the embedded subspace representation. Standard wavelet and characterized the texture by a set of channel variances estimated at the output of the filter bank. The typical or the octave band wavelet decomposition implies finer frequency resolution in the low-frequency region than in the high-frequency region. Laine and Fan [15] carried out studies on texture analysis based on this indication. They used multi-channel wavelet surrounds for feature extraction. One of the drawbacks of standard wavelets is that they are not suitable for the analysis of high-frequency signals with relatively contracted band-width. So the most important inspiration of using the disintegration scheme based on M- band wavelets is to yield improved segmentation accuracies. The typical wavelet decomposition which gives a logarithmic frequency resolution whereas the M-band decomposition gives a mixture of a logarithmic and linear frequency resolution. Additional as another advantage, M-band wavelet breakdowns give way a huge number of sub bands which is necessitated for good excellence segmentation. In the filter-bank example, if an input image encloses two in a different way textured areas, then local spatial-frequency differences between the regions will produce differences in one or more filter-output sub images. Thus, textural differences are transformed into discontinuities in sub image output, where the discontinuities signify transitions between differently textured areas. These discontinuities can then be use, all the way through additional dealing out to division the image into different areas.

V. Literature Survey

When comparing images with different applications such as mosaicking and homography evaluation, the circulation of image features transversely they have common characteristics region have an effect on the correctness of the effective consequence to determine whether points are aggregated at multiple scales. So in this paper author [16] uses the spatial statistics of these image features, calculated by Ripley's K-function, to evaluate whether image feature matches are clustered mutually or extend in the order of the overlap region. Based on this assess, an estimation of a range of modern image feature detectors was achieved; is then carried out using investigation of variance and a large image database observed the imagery and the detector as the two independent variables disturbing exposure, and consequence was evaluated using ANOVA technique. The effects exposed that there is certainly statistical consequence between the performances of modern image feature detectors. SFOP was found to be better-quality to other detectors, while there are also some detectors whose concert differences were not statistically important. These decisions are generally dependable with those acquired by other researchers using unusual move towards, increasing our self-confidence that these concert differences are real. The methodology is implemented for both gray as well as color images.

Here this effort provides work for a statistical computes to approximation reporting and uses a null hypothesis structure to evaluate whether different feature detectors accomplish significantly different coverage's, an essentially conventional approach. Here the main goal of author [16] has to present this as the 'right' approach to compute exposure; to a certain extent, it has been chosen as a corresponding move toward to those that have before now been exploited. This is because, in the wider context of investigating the presentation of vision algorithms, one should predict a strong algorithm, on standard to give up better performance irrespective of the datasets and performance quantity standard used; therefore, the authors challenge that the research community should be using a range of determines on a selection of data and decide which algorithms over and over again shows good. Experimental results evaluated using ANOVA technique show that SFOP introduces significantly less aggregation than the other detectors tested. When the detectors are rank-ordered by this performance evaluate, the order is broadly similar to those obtained by other means, suggesting that the ordering reflects genuine performance differences. Here researches were also executed on stitching overlapping regions into panoramas, authenticating that better coverage yields a better quality consequence. The methodology is implemented for both gray as well as color images.

In this paper [17], firstly author gives a general idea of a large selection of image features for content-based image retrieval and match up to them quantitatively on four different jobs: stock photo retrieval, personal photo collection retrieval, building retrieval, and medical image retrieval. For the researches author have talk about a large range of image features for image retrieval and a set of connections of five different without restraint obtainable databases that can be used to quantitatively compare these features. Widely available image databases are used and the retrieval performance of the image features is analyzed in aspect. These permits for an undeviating evaluation of all image features regard as in this work and additionally will allow an evaluation of recently proposed image features to these in the expectations. Furthermore, the correlation of the image features is examined, which opens the way for a easy and perceptive technique to come across an initial set of suitable features for a new task. The methodology is implemented for both gray as well as color images.

From the experiments accomplished it can be presumed, which image features execute well on which kind of task and which do not appear. On the contrary to other research papers

[17], they will think about tasks from different areas together and straightforwardly evaluate and examine which image features are appropriate for which task and this paper bring to a closes with suggestions which image features execute well for what type of data. Interestingly, the frequently used but much uncomplicated, colour histogram executes well in the evaluation and thus can be suggested as a straightforward baseline for many applications areas.

Here author put another way, so they can efficiently adapt our representation to the higher order statistics of each image or image class, rather than using a standard orthonormal representation. This approach stands in contrast to the “kitchen sink” approach employed by other researchers [18], wherein one or more sets of features are chosen in an ad hoc way e.g., RGB distributions, wavelet coefficients, face detection, etc. to represent or describe a given image. While the latter approach has made important progress related to the analysis of large art databases – succeeding, for example, in separating art of different eras e.g., Gothic vs. Impressionist – there may be more principled ways to address the problems of quantifying style and using this information for image search and organization. Our approach, which includes making use of representations that are optimized for each image, attempts to provide a solution to these problems. The methodology is implemented for both gray as well as color images.

Texture is all-encompassing in natural images and is a dominant indication for a selection of image investigation and various computer vision applications areas like image segmentation, shape recovery from texture, and image retrieval methods. Texture analysis has wide range of applications like medical diagnosis, content-based-image retrieval; satellite imaging and many others research techniques. Since texture is not a local occurrence, one must take into explanation a neighborhood of each pixel with the intention of categorize that pixel accurately. The difficulty of segmenting an image based on texture beginning is submitted to as texture segmentation trouble. The objective [19] of texture segmentation is unscrambling the different uniform regions that represent an input image by charming texture similarity into description. Discovering specific localizations of boundary edges between adjacent regions is a basic objective for the segmentation job, and can only be make sure with comparatively small windows. Consequently, good texture feature extraction necessitates large windows, while specific boundary localization requires small ones. Since both jobs must be functional with the intention of segment textured images, a definite substitution concerning window size must be prepared. Textures may be regular or randomly structured and various structural, statistical, and spectral approaches have been suggested towards segmenting them. The improvement in the last two decades in image analysis and computer vision problem has extended the perceptive of this area; so far it waits an open and difficult predicament. Many traditional methods of texture representation and texture feature extraction are used for this application area. The methodology is implemented for both gray as well as color images.

One of the main disadvantages of using usual wavelets is that they are not appropriate for the analysis of high-frequency signals with comparatively narrow band-width. So the most important inspiration of using the decomposition method based on M-band wavelets is to give way get better segmentation accuracies. The standard wavelet decomposition gives a logarithmic frequency resolution, while the M-band decomposition gives a combination of a logarithmic and linear frequency resolution. Additional as an extra improvement, M-band wavelet decompositions defer a large number of sub bands which is necessitated for good quality segmentation on image features [19]. The methodology is implemented for both gray as well as color images.

VI. Conclusion

A key element in the image features is extracting strong. However representative features from perceptual inputs, usually in the format of raw pixels. Such image features should be proficient to additional sustain high-level understandings such as categorization and detection, and the vision society has meet to explicit structural designs for image feature extraction. Here we have examined two key parts in the computer vision research: to learn better image features with solid hypothetical explanations, and to re-examine the existing vision problem statement to a more convenient and human-like one.

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