iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 2 **Issue:** V **Month of publication:** May 2014

DOI:

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

A Survey on Image Matching Techniques

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***Abstract*— The matching is a difficult task in model based object recognition system because images do not present perfect data, noise and occlusion. Several image matching techniques have been developed to find logos from the real world images. This survey includes some existing parallel matching algorithms for logo matching and recognition. The advantages and disadvantages of the different techniques are also included.**

***Keywords*— Image matching, logo, recognition, trademark**

I. INTRODUCTION

Logos are key elements for companies and play essential role in the industry and commerce. Different logos may similar layout but slight difference in spatial disposition of the graphics elements, difference in orientation, size and shape.

Recent techniques for image matching are discussed here. Image retrieval system using fisher classifier [2] is one of the approaches. Reference [3] proposes an image matching technique based on principle component analysis. Image matching using SURF [5][6] and SIFT [4] algorithms are the commonly used methods. Context is created to find the similarity between two images in [1][7].

II. LOGO MATCHING FOR DOCUMENT IMAGE RETRIEVAL

A. System Overview

Graphics detection and recognition are fundamental research problems in document image analysis and retrieval is presented in [2]. As one of the most pervasive graphical elements in business and government documents, logos may enable immediate identification of organizational entities and serve extensively as a declaration of a document's source and ownership. An automatic logo-based document image retrieval system that handles logo detection and segmentation by boosting a cascade of classifiers across multiple image scales [2] and logo matching using translation, scale, and rotation invariant shape descriptors and matching algorithms. This approach is segmentation free and layout independent and address logo retrieval in an unconstrained setting of 2-D feature point matching. Finally evaluate the effectiveness of this approach using large collections of real-world complex document images.

Detecting and segmenting free-form graphical patterns such as logos are challenging. Due to large variations in logo style and low quality images can make detection of logo is difficult. Complicating matters, the foreground content ofdocuments generally includes a mixture of machine printed text, diagrams, tables andother elements. From the application perspective, accurate localization is needed for logorecognition. Logo detector must consistently detect and extract complete logos while attempting to minimize the false alarm rate. Logo detection and segmentation approach incorporating a two-step, partially supervised learning framework that effectively deals with large variations. First learn the base detector - a Fisher classifier [2] at a coarse image scale, from a small set of segmented images and test on a larger pool of unlabelled training images. Then bootstrap these detections to boost a cascade of classifiers at finer image scales, which allows false alarms to be quickly rejected and the detected logo to be more precisely localized. Logo detection approach is segmentation free and layout independent[2].

Logo as a non-rigid shape, and represent it by a discrete set of 2-D feature points extracted from the object. The shape of a logo is well captured by a finite set of n corner feature points computed from the edge image. It uses two state-of-the-art shape matching algorithms [2] for logo matching. The first method is based on the representation of

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shape contexts. In this approach, a spatial histogram defined as shape context is computed for each point, which describes the distribution of the relative positions of all remaining points. Prior to matching, the correspondences between points are solved first through weighted bipartite graph matching. Second method uses the neighbourhood graph matching algorithm by [4], which formulates shape matching as an optimization problem that preserves local structures, approach has an intuitive graph matching interpretation, where each point represents a vertex and two vertices are considered connected in the graph if they are neighbours. The problem of finding the optimal match between shapes is thus equivalent to maximizing the number of matched edges between their corresponding graphs under a one-to-one matching constraint.

B. Disadvantages

This method has Difficult to detect low quality images. It is difficult to extract high-level features from the images.

III. LOGO MATCHING TECHNIQUE BASED ON PRINCIPLE COMPONENT ANALYSIS

A. System Overview

A novel approach concerned with the specific class of complicated objects matching is presented in [3]. A logo is a complicated object. In complicated object, one means an object which consists of a number of separated components, inner holes, or a combination of both. A complicated object can be represented as a collective set of self-closed contours each of which contains a large number of critical points. This algorithm proposed is based on Principle Component Analysis (PCA) approach [3]. In this technique, the PCA is used to extract the features, kept inherent in the normalized pattern for matching process. In the matching process, the extracted features of unknown pattern are mapped onto formulated feature spaces, and the distance between the source symbol and modelled symbols is used as a decision making tool.

This algorithm contains two steps [3], feature selection process and identification process. In feature selection process first convert the scanned 2-D images into 1-D representation. Calculate the reduced the covariance matrix of ten deviation vectors. Calculate Eigen vectors and Eigen values, and then sort Eigen values. In identification process, firstly compute the deviation vector of unknown logo from the referenced logos mean. Secondly, use this deviation vector to get its weighting coefficients by projecting these values onto the Eigen profiles space.Finally, use the Euclidean distance to detect the minimum distance of the recognizable logo.

By changing the sizes, locations, and resolutions, it is obvious that the quality of images is either improved or degraded. The method applied here was invariant to translation, and scaling. This was done by performing image normalization to each reference and tested logo of different scaling, and translation, prior to the calculation of eigenvectors. It was found that the scaling factor in image normalization case should be around the value of 1, in order to accommodate all the logos. It could also be made invariant to rotation by performing image normalization to rotation.

B. Advantages and Disadvantages

The method preserves salient line features as well as curved features efficiently. Difficult to directly mapping shapes into a feature vector.

IV. IMAGE MATCHING USING SCALE INVARIANT FEATURE TRANSFORM

A. System Overview

The work in [4] describes effectiveness of the Scale Invariant Feature Transform (SIFT) for image matching. There is a popularly used interest point detection method often applied to image matching, the Harris corner detector. Scale-invariant feature transform is an algorithm for extracting interest point features from images that can be used to perform reliable matching between different views of an object or scene. The features are invariant to image scale, rotation, and partially invariant to change in 3D viewpoint, addition of noise and change in illumination.

The major steps [4] in the computation are Scale-space construction, keypoint localization, orientation assignment and keypoint descriptor.

Scale-space Construction

In this step construct Gaussian and difference-of-Gaussian pyramids [4].Interesting image features or key pointsare detected using a cascade filtering approach that identifies image candidate locations that will be evaluated further later. The first step is to realize image location coordinates and scales that can be repeatable assigned under pose variation of the object of interest.

Finding locations that are invariant to scale is performed by scale function that searches for stable features across

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different scales. The scale space convolution kernel of choice is the Gaussian function used to define the scale space function of an input image according to

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

where* is the convolution operation in **x** and **y** with Gaussian

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma} e^{-(x^2 + y^2)/2\sigma^2}$$

To detect stable keypoint locations in scale space, the difference-of-Gaussian (DoG) function [4] convolved with the imageis computed from the difference of two nearby scales separated by a constant multiplicative factor. The DOG function is a close approximation to the scale normalized Laplacian of Gaussian. It is known that the local maxima and local minima ofthe most stable image features compared to a range of other possible image functions.

Keypoint Localization

Keypoint candidates are chosen from the extrema in the scale space, and keypoints are selected based on measures of their stability.Local maxima and minima of the DoG function are detected as keypoint candidates. To detect local maxima and minima of the DoG function, each sample point is compared to its eight nearest neighbours in the current image and nine neighbours in the scale above and below. To detect extrema reliably, the right frequency of sampling must be chosen in the image and scale domain [4]. Once a keypoint candidate has been realized, the next step is to perform a detailed fit to local image data for location, scale and ratio of principal curvatures. With this information points are rejected that have low contrast because they are sensitive to noise or are poorly localized along an edge. A simple approach of the implementation is to locate keypoints at the location and scale of the central sample point.

Orientation Assignment

Orientations are assigned to each keypoint based on histograms of gradient directions computed in a 16x16 window.

Keypoint Descriptor

Represent keypoint descriptor in a 128-dimensional vector. Keypoint matching is the best candidate match is found by its nearest neighbour. After image location, scale, and orientation have been assigned to each keypoint, it is possible to impose a two dimensional coordinate system to describe the local image region and provide invariance with respect to these parameters.

B. Advantages and Disadvantages

The main advantage of the method is thatSIFT algorithm is widely used in image recognition and retrieval system. SIFT contains 128 descriptors. SIFT is slow and not good at illumination changes. The main disadvantage is that high dimensionality.

V. CONTENT BASED IMAGE RETRIEVAL USING SURF AND COLOUR MOMENTS

A. System Overview

The aim of the work in [5] is to image retrieval using SURF algorithm. SURF (Speeded-Up Robust Feature) is one of the most and popular interest point detector and descriptor. It is widely used in most of the computer vision applications. The SURF has been proven to achieve high repeatability and distinctiveness. It uses a Hessian matrix-based measure for the detection of interest points and a distribution of Haar wavelet responses within the interest point neighbourhood as descriptor. An image is analysed at several scales, so interest points can be extracted from both global and local image details. In addition to that, the dominant orientation of each of the interest points is determined to support rotation-invariant matching. SURF is one of the best interest point detectors and descriptors currently available.

The feature vectors are extracted from the images in the database and described by multidimensional feature vectors, which form a feature database. To retrieve images, the feature vectors are extracted from the given query image. The similarities between the feature vectors of the query image and the feature vectors of the database images are then calculated. And the retrieval is performed with the aid of an indexing scheme and matching strategy, which provide an efficient way to search the image database [5]. In this work, SURF algorithm is used to extract the features and the first order and second order colour moments is calculated for the SURF key points to provide the maximum distinctiveness for the key points. The KD-tree with the Best Bin First (BBF) algorithm

ISSN: 2321-9653

is used to index and match the similarity of the features of the images.

The Speeded up robust features algorithm is a scale and rotation-invariant interest point detector and descriptor which is computationally very fast. It uses Integral images to improve the speed. The key points are detected by using a Fast-Hessian matrix.

B. Advantages

SURF detector is mainly based on the approximated Hessian Matrix. So it is faster than SIFT. It is widely used in the computer vision applications. The SURF has been high repeatability and distinctiveness.

VI. SPEEDED-UP ROBUST FEATURES (SURF)

A. System Overview

The framework in [6] aims to extract the interest points using SURF algorithm. In feature detection, SURF is faster than SIFT which is the main requirement of the today's real time application. It is the robust image detector and descriptor. SURF detector is mainly based on the approximated Hessian Matrix. On the other hand, the descriptor gives a distribution of Haar-wavelat [6] responses within the interest point neighbourhood. Both the detector and descriptor are used to reduce the computation time because descriptor has low dimensionality. So that SURF is better than previously used schemes with respect to repeatability, distinctiveness, robustness and speed. Approach for interest point detection uses a very basic Hessian-matrix approximation. Integral images fit in the more general framework of boxlets.

The SURF feature detector is based on the Hessian matrix [6]. The determinant of the Hessian matrix is used to determine the location and scale of the descriptor. The SURF descriptor is extracted from an image in two steps: the first step is assigning an orientation based on the information of a circular region around the detected interest points. The orientation is computed using Haar-wavelet responses in both x and y direction. Once the Haar-wavelet responses are computed and they are weighted with a Gaussian. In a next step the dominant orientation is estimated by summing the horizontal and vertical wavelet responses within a rotating wedge which covering an angle in the wavelet response space. The resulting maximum is then chosen to describe the orientation of the interest point descriptor.

To improving the efficiency of SURF-based image matching propose a machine learning approach for keypoint pruning which aims to identify the keypoints that are important for the matching. Image matching can be reduced to finding keypoint correspondences in the subsets of important keypoints.To achieve this speed up image matching based on the SURF feature by classifying the extracted keypoints in two categories: 1) Significant keypoints, which are highly salient to distortions; correspondences between such keypoints in different images are strong indicators of similarity. 2) Insignificant keypoints, which are less salient, do not contribute much for establishing visual similarity, and can be practically excluded from the matching process. For this a Random Forest classifier is fed with training data consisting of labeledkeypoints extracted from large collection of images spanning various categories. The decision on the importance of a keypoint is performed by running the feature vector of a test keypoint on the learned model to predict its usefulness for the matching.

Integral Images

SURF algorithm is most applicable in integral images. Integral images allow for fast computation of box type convolution filters [6]. The entry of an integral image I(x) at a location x = (x, y) represents the sum of all pixels in the input image I within a rectangular region formed by the origin and x.

$$I(x) = \sum_{i=0}^{i \le x} \sum_{j=0}^{j \le y} I(x, y)$$

Once the integral image has been computed, it takes three additions to calculate the sum of the intensities over any upright, rectangular area. Hence, the calculation time is independent of its size [6].

Hessian Matrix Based Interest Points

Detector in SURF is Hessian matrix because of its good performance in accuracy. More precisely, detect blob-like structures at locations where the determinant is maximum. The determinant of the Hessian also used for the scale selection [6].

Given a point x = (x,y) in an image I, the Hessian matrix H (x , σ) in x at scale _ is defined as follows

ISSN: 2321-9653

$$H(x,\sigma) = \begin{bmatrix} Lxx(x,\sigma) & Lxy(x,\sigma) \\ Lxy(x,\sigma) & Lyy(x,\sigma) \end{bmatrix}$$

whereL_{xx} (x , σ) is the convolution of the Gaussian second order derivative with the image I in point x

Interest points need to be found at different scales, not least because the search of correspondences often requires their comparison in images where they are seen at different scales. Scale spaces are usually implemented as an image pyramid. The images are repeatedly smoothed with a Gaussian and then sub-sampled in order to achieve a higher level of the pyramid. Due to the use of box filters and integral images, do not have to iteratively apply the same filter to the output of a previously filtered layer, but instead can apply box filters of any size at exactly the same speed directly on the original image and even in parallel. The scale space isanalysed by up-scaling the filter size rather than iteratively reducing the image size. The scale space is divided into octaves. An octave represents a series of filter response maps obtained by convolving the same input image with a filter of increasing size. Each octave is subdivided into a constant number of scale levels [6]. To localise interest points in the image and over scales, non-maximum suppression in a 3x3x3 neighbourhood is applied.

Build on the distribution of first order Haar wavelet responses in x and y direction rather than the gradient, exploit integral images for speed, and use only 64 dimensions. This reduces the time for feature computation and matching. The first step consists of fixing a reproducible orientation based on information from a circular region around the interest point. Then construct a square region aligned to the selected orientation and extract the SURF descriptor from it. Finally, features are matched between two images.

B. Advantages

SURF is faster than SIFT in real time application. It has low dimensionality as compared to SIFT. It reduces the computation time.

VII. CONTEXT DEPENDENT LOGO MATCHING AND RECOGNITION

A. System Overview

The framework in [7] aims to to match and recognizemultiple instances of multiple reference logos in image archives. Extract local features from reference logos and test images and matched by minimizing an energy function mixing, a fidelity term that measures the quality of feature matching, a neighbourhood criterion that captures feature and regularization term that controls the smoothness of the matching solution.Graphic logos are a special class of visual objects extremely important to assess the identity of something or someone. Logo detection and recognition in these scenarioshas become important for a number of applications. Amongthem, several examples have been reported in the literature,such as the automatic identification of products on the webto improve commercial search-engines [7], the verification ofthe visibility of advertising logos in sports events and the detection of near-duplicate logos.

A novel solution for logo detection and recognition which is based on the definition of a "Context-Dependent Similarity" (CDS) kernel that directly incorporatesthe spatial context of local features [7]. I is model-free, that is it is not restricted to any a priori alignment model. Context is considered with respect to each single SIFT keypoint and its definition recalls shape contextwith some important differences: given a set of SIFT interest points *x*, the context of *x* ∈*x*is defined as the set of points spatially close to *x* with particular geometrical constraints. Formally, the CDS function is defined as the fixed-point of three terms: [7] (i) an energy function which balances a *fidelity* term; (ii) a *context* criterion; (iii) an *entropy* term. The fidelity term is inversely proportional to the expectation of the Euclideandistance between the most likely aligned interest points.The context criterion measures the spatial coherence of thealignments: given a pair of interest points in the query and target image with a high alignment score, the context criterion is proportional to the alignment scoresof all the pairs close to interest point but with a given spatial configuration. The "entropy" term acts as a smoothing factor,assuming that with no a priori knowledge, the joint probabilitydistribution of alignment scores is flat. It acts as a regularize factor that controls the entropy of the conditional probability.

The proposed method consists of an alternative matching framework, for logo detection, based on a new class of similarity functions, called context-dependent similarities (CDS) kernel that directly incorporates the spatial context of local features of images. Scale invariant feature Transform (SIFT), are used for extracting features from reference logo and test image. In this method SIFT algorithm is used to extract the interest points from reference logo and test image.

ISSN: 2321-9653

By using this SIFT descriptors, compute the context. Then compute a context similarity matrix. From CDS matrix calculate the similarity function. Using these find the match between reference logo and test image [7].

B. Advantages

The main advantage of the method is that there is a model free context is used for finding logo from real world image. But it has high dimensionality and high computation time.

VIII. CONCLUSIONS

Image matching and recognition methods are mainly used in computer vision application.This work is a survey of some of the selected recent image matching techniques. A brief overview of the different methods, their advantages and disadvantages are included as part of the survey.

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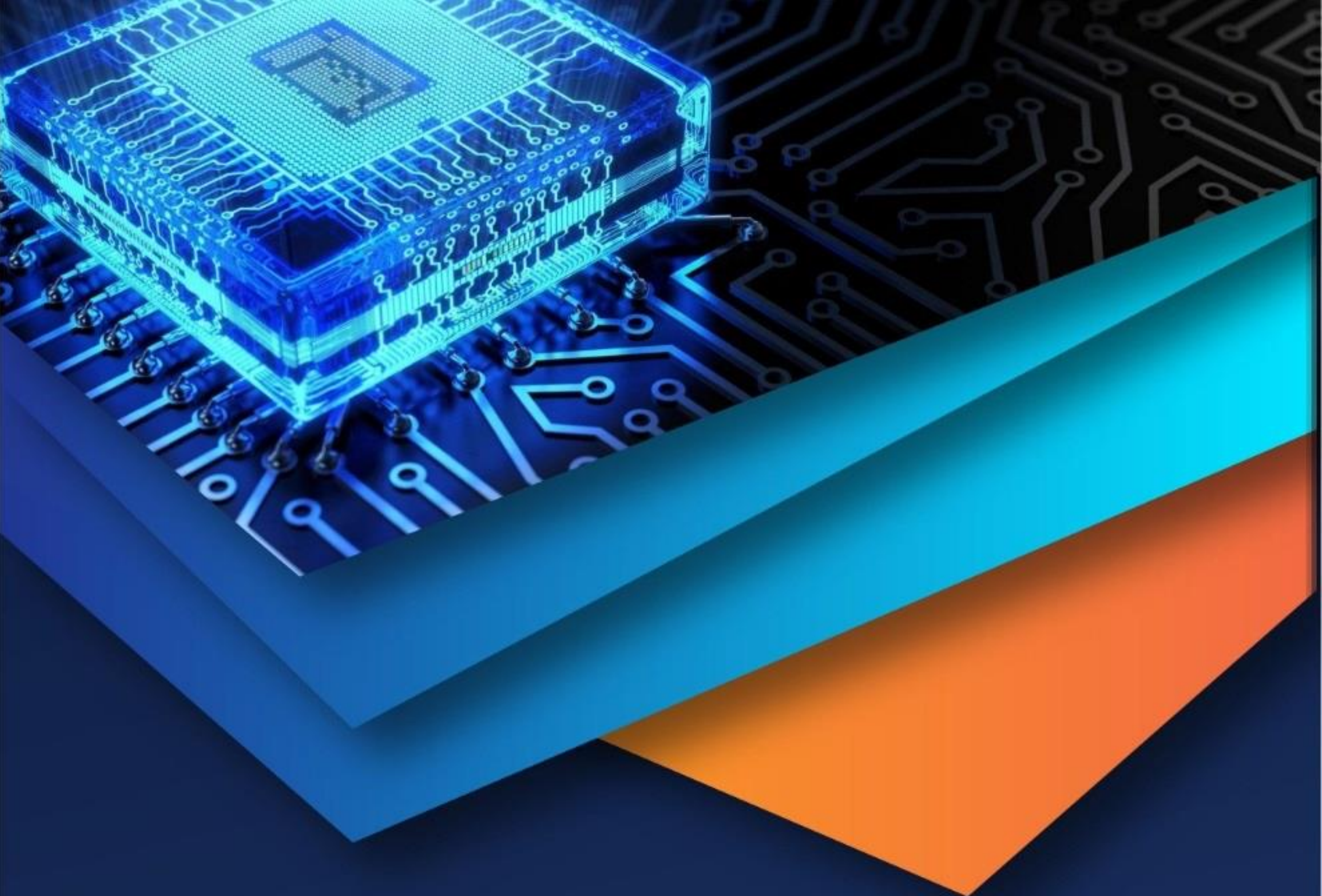

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