



# Logo Matching and Recognition for Avoiding Duplicate Logos

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**Abstract:** Logo matching and recognition is mainly done in order to reveal duplicate logos which have a slight difference from the original logos in order to deceive customer. In this paper an effective logo matching and recognition method called Context-Dependent Similarity method is performed. Firstly dataset of logo images are created for the reference images, then another test image which have logos in it is taken as the input and start matching with the dataset logo images to check whether the input image is fake or genuine logo based on the dataset image. For this features of logos images for both the reference and test images are extracted and based on their extracted features matching is performed using Context-Dependent Similarity method.

**Keywords:** Key-points extraction, Computation of context, Logo matching and recognition.

## I. INTRODUCTION

Logos are mainly a visual object which is used for representing the identity of an organisation, industry, company, schools or institutions and an individual. They are graphical objects which can be either represented by names of the respective organisations or it can be a real world object or symbols. The graphic designers carefully studied the distinctiveness of logos because their differences is only seen in few details. Logo matching and recognition is important for brand advertising and surveillance applications and it discovers either improper or non-authorized use of logos. Some logos may have similar layout with only few details of differences that can be seen on the spatial disposition, the size and shapes and even on the orientations. Every organisations or companies have their own logos which is a legal symbol for the identification of their products. And some other organisations or individuals used the duplicate logos that have small variations from the original ones in order to deceive customers. So this has motivated in the discovery of an image analysis system in order to reveal the non-authorized used of logos.

A generic system for logo detection and recognition in images taken in real world environments must comply with contrasting requirements. On the one hand, invariance to a large range of geometric and photometric transformations is required to comply with all the possible conditions of image/video recording [1]. Fig.1 shows an example of real world famous logos which can either be text, symbols or combination of both in order to identify a company or an a. And Fig 2 is the example showing the comparison of duplicate logos with the originals ones that are found in the real world.

Some logos are found in images and videos that are embedded on other objects like shirts, vehicles, mugs etc. In these cases they are subjected to other objects therefore they may have deformations, often corrupted by noise or partially occluded. So there are several logo recognition systems which are found in the history some of which are detection of duplicate logos to reveal non-authorized used of logos [2] and advertisement of logos in sport events [6] etc.



Fig. 1 Example of some popular logos found in the real world.



Fig. 2 Example of logo with slight differences from the original logos in order to deceive customers



The proposed system is divided into three steps: 1) Interest key-point extraction 2) Context computation 3) Key-point matching. This paper is divided into five sections. The discussion in the next section is about related work performed by other researchers. Section III is about the proposed system in detail and Section IV shows the experimental results. The last section or Section V is the conclusion of this paper.

## II. RELATED WORKS

Jau-Ling Shih et al (2001) proposed a new trademark segmentation and retrieval system. First the shape of those representative objects called mask in each trademark are extracted by semi-automatic segmentation method. Then, some features are selected to describe the mask. A similarity measure is provided based on the rank of the feature distance to do the similar trademark retrieval [2].

Serge Belongie et al (2002) proposed a novel approach for measuring similarity between shapes and exploit it for recognition. In their work, a similarity measurement was performed by attaching a descriptor or shape context to each point to solve the correspondences between two points on the two shapes. The shape context captures the distance of the remaining points relative to it and thus two similar shapes will have similar shape context. And dissimilarity is computed as sum of matching errors between corresponding points [3].

David G. Lowe et al (2004) proposed method for extracting invariant features from images that can be used to perform reliable matching between different views of an object or scene. The recognition was done by matching individual features to a database of features from known objects using a fast nearest-neighbour algorithm which was followed by a Hough transform to identify clusters belonging to a single object [4].

David Crandall et al (2006) proposed a spatial-colour joint probability function called the colour edge co-occurrence histogram (CECH). Their algorithm employed perceptual colour naming to handle colour variation and pre-screening to limit the search scope (i.e., size and location) of the object. Their proposed algorithm was in-sensitive to object rotation, scaling, partial occlusion, and folding, outperforming a closely related algorithm by a decisive margin [5].

Lamberto Ballan et al (2008) proposed trademark detection and recognition system while advertising trademark in a sports videos. a semi-automatic system was proposed for detecting and retrieving trade-mark appearances in a sports videos. A human annotator supervises the results of the automatic annotation through an interface that shows the time and the position of the detected trademarks [6].

The above works are the related works performed by different researchers in the field of object recognition and

matching based on different algorithms. The proposed system however used Context Dependent Similarity (CDS) algorithm. This method enhances the performances of logo matching and recognition in terms of accuracy.

## III. PROPOSED SYSTEM

### A. System Design

The flow diagram for context dependent similarity algorithm is as shown in Fig. 3. The first step is pre-processing the test image. Then extraction of interest key-points using Scale Invariant Feature Transform Algorithm. Then computation of context for the interest key-points and then similarity design for matching and recognizing.

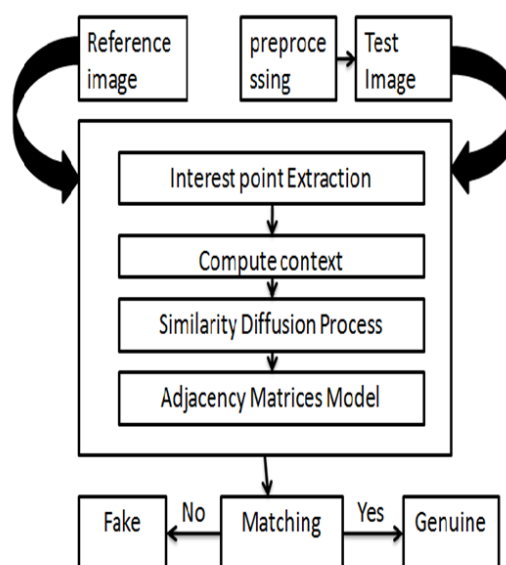


Fig. 3 Context-Dependent Similarity Algorithm.

### B. Pre-processing

Pre-processing is performed for the test image or the input image in order to improve the quality of the image. Which consists of processes such as the geometric and radiometric correction, enhancement or standardization of imagery.

### C. Interest Points Extraction

The interest point extraction is done using Scale Invariant Feature Transform Algorithm (or SIFT). It is an algorithm in computer vision to detect and describe local features in images. It transform image data into scale-invariant coordinates relative to local features.

The following steps are followed in scale invariant feature transform algorithm:

1) *Scale space extrema detection:* In this first stage the minimum or the maximum point among all the different scales is detected. This is done by performing Difference of Gaussian (DOG). Here first, for different scales the image undergoes convolution with Gaussian filters. And then the difference of Gaussian-blurred images are taken. Then key-points are selected where the



maxima/minima of the Difference of Gaussians (DOG) occurred on the multiple scales. The DOG of an image  $D(x,y,\sigma)$  is given by

$$D(x,y,\sigma) = L(x,y,k_1\sigma) - L(x,y,k_2\sigma) \quad (1)$$

Where  $L(x,y,k\sigma)$  is the convolution of the original image  $I(x,y)$  with the Gaussian blurred  $G(x,y,k\sigma)$  at scale  $k\sigma$

$$\text{i.e., } L(x,y,k\sigma) * I(x,y) \quad (2)$$

Once we find the DOG of the images, the local minima/maxima of the DOG images for multiple scales is found by comparing each pixel in the DOG images to its eight neighbours at the same scale and nine corresponding neighbouring pixels in each of the neighbouring scales. If the pixel value is the maximum or minimum among all compared pixels, it is selected as a candidate key-point.

2) *Key-point localization:* At each candidate location, a detailed model is fit to determine location and scale. Key-points are selected based on measures of their stability. This information allows points to be rejected that have low contrast (and are therefore sensitive to noise) or are poorly localized along an edge. Determine location and scale for each interest point and eliminate weak key-points

3) *Orientation assignment:* This is the step where one or more orientations are assigned to each key-point location based on local image gradient directions. Histogram of gradient directions is created within a region around the key-point, at selected scale by:

$$m(x,y) = (L(x+1,y) - L(x-1,y))_2 + (L(x,y+1) - L(x,y-1))_2 \quad (3)$$

$$\theta(x,y) = \text{atan2} (L(x,y+1) - L(x,y-1), L(x+1,y) - L(x-1,y)) \quad (4)$$

where  $m(x,y)$  is the magnitude and  $\theta(x,y)$  is the orientation. The highest peak obtained from the histogram of orientation is taken as the respective key-point. In case of peaks within 80% of highest peak, multiple orientations assigned to key-points. So one key-point can have more than one orientation assigned to it.

4) *Keypoint descriptor:* The local image gradients are measured at the selected scale in the region around each keypoint. Here a 16 x16 window around detected interest point is taken and divided into a 4x4 grid of cells. Histogram is computed in each cell. Hence out of 4x4 grid of cells and 8 bin of histogram it gives 128 features for the respective interest point.

*D. Context Computation*

The context is defined by the local spatial configuration of interest points in both  $S_x$  and  $S_y$ .  $S_x$  corresponds to the reference image and  $S_y$  corresponds to testing image. Formally, in order to take into account spatial information, an interest point  $x_i \in S_x$  is defined as

$$x_i = (\psi_g(x_i), \psi_f(x_i), \psi_o(x_i), \psi_s(x_i), \omega(x_i)) \quad (5)$$

Where the symbol  $\psi_g(x_i) \in \mathbb{R}^2$  stands for the 2D coordinates of  $x_i$  while  $\psi_f(x_i) \in \mathbb{R}^c$  corresponds to the feature of  $x_i$ . The orientation of  $x_i$  is denoted  $\psi_o(x_i) \in [-\pi, +\pi]$  and the scale of the SIFT descriptor is denoted by  $\psi_s(x_i)$ . Finally,  $\omega(x_i)$  is used to identify the image from which the interest point comes from.

The context is of  $x_i$  is defined by the following:

$$N_{\theta,\rho}(x_i) = \{ x_j : \omega(x_j) = \omega(x_i), x_j \neq x_i \text{ s.t. (6), (7) hold} \} \quad (6)$$

and

$$(\theta-1)/N_a \pi \leq ((\psi_o(x_i), \psi_g(x_j) - \psi_g(x_i))) \leq \theta / (N_a) \pi \quad (7)$$

where  $(\psi_g(x_j) - \psi_g(x_i))$  is the vector between the two point coordinates  $\psi_g(x_j)$  and  $\psi_g(x_i)$ .

The radius of a neighbourhood disk surrounding  $x_i$  is denoted as  $\epsilon_p$  and obtained by multiplying a constant value  $\epsilon$  to the scale  $\psi_s(x_i)$  of the interest point  $x_i$ . In the above definition,  $\theta = 1 \dots N_a$ ,  $\rho = 1 \dots N_r$  corresponds to indices of different parts of the disk.  $N_a$  and  $N_r$  correspond to 8 sectors and 8 bands in Fig. 4 is the definition and partitioning of the context of an interest point  $x_i$  into different sectors (for orientations) and bands (for locations).

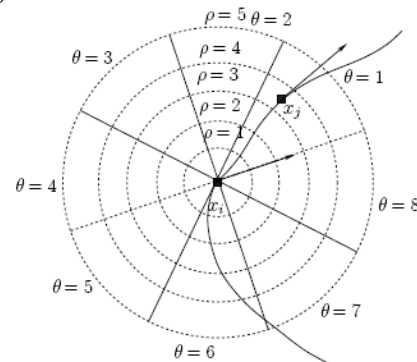


Fig. 4 Definition and partitioning of interest point  $x_i$  into different sectors and bands.

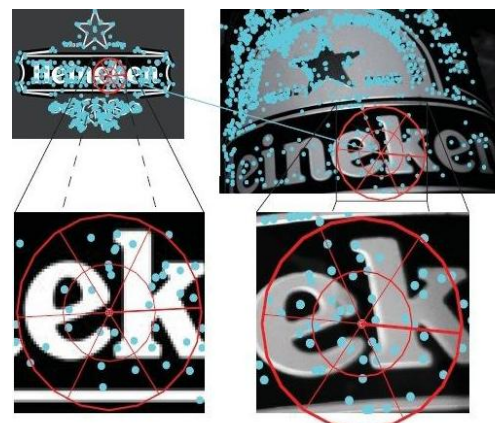


Fig. 5 Example of a real context definition.



**E. Similarity Design**

Here  $k$  is defined as a function in which when two interest points  $x \in S_x \times S_y$  are given, they provides a similarity between them. The function  $k$  when given as a matrix  $K$  it represent the similarity between  $x$  and  $y$ . The dissimilarity between the interest points features are measured by

$$d(x, y) = \|\psi_f(x) - \psi_f(y)\|_2$$

And now the similarity  $K$  between two objects  $S_x, S_y$  is found by using the minimization problem.

$$\min_k \text{Tr}(K D') + \beta \text{Tr}(K \log K') - \alpha \sum_{\theta, \rho} \text{Tr}(K Q_{\theta, \rho} K' P'_{\theta, \rho})$$

In the above equation there are three terms, the first term represents the matching quality between the features. The second term represents the regularization criterion so that the entropy is minimized. And the last term represents the neighbourhood criterion.

**IV. EXPERIMENTAL RESULTS**

The logo matching and recognition based on context dependent similarity algorithm is performed and the results are shown below:

Fig. 6 is the reference logo image which is taken as the input and Fig. 7 gives the reference logo with its key-points mapped onto it.



Fig. 6 Reference Logo Image.



Fig. 7 Reference Logos with key-points mapped onto it.



Fig. 8 Genuine Logo which is recognised.

Fig. 8 shows a genuine logo which is recognized and Fig. 9 shows a fake logo which cannot be recognised based on the input image.



Fig. 9 Fake logo not recognized.

**V. CONCLUSIONS**

An effective logo matching and recognition algorithm is proposed based on Context-Dependent Similarity method. In which SIFT algorithm was implemented for the extraction of scale and rotation invariant key-points. The advantage of this method is that it can tolerate certain problems like partially occluded logos, it also has the ability to detect both near-duplicate logos as well as logos with small variation in their appearances, the probability of success of matching and detection is high.

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