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MODIFIED CONTEXT DEPENDENT SIMILARITY ALGORITHM FOR LOGO MATCHING AND RECOGNITION

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Abstract - The wide range application of visual data from Companies, Institution, Individuals and Social system like Flickr, YouTube is for diffusion and sharing of images and Video. There are several issues in processing visual data from an image which was corrupted by noise or subjected to any transformation and also its accuracy in matching Logos are some of the emerging research issues currently. To overcome these issues we have proposed a new class of similarities based on Modified Context Dependent algorithm which enhances the performance in terms of accuracy in logo matching and computation time.

Keywords - Visual data, Matching logos, context, computation time, accuracy.

I. INTRODUCTION

Social media include all media formats by which groups of users interact to produce, share, and augment information in a distributed, networked, and parallel process. The most popular examples include Twitter (short text messages), blogs and discussion forums (commentary and discourse), Flickr (photos), YouTube (videos), and Open Street Map (geospatial data).

Social media produces tremendous amounts of data that can contain valuable information in many contexts. Moreover, anyone can access this data either freely or by means of subscriptions or provided service interfaces, enabling completely new applications.

Graphic logos are a special class of visual objects extremely important to assess the identity of something or someone. In industry and commerce, they have the essential role to recall in the customer the expectations associated with a particular product or service. This economical relevance has motivated the active involvement of companies in soliciting smart image analysis solutions to scan logo archives to find evidence of similar already existing logos, discover either improper or non-authorized use of their logo

A.Smeulders *et al* (1998), Proposed Content based-retrieval system which depends upon Pattern, types of picture, role of semantics and sensory gap. Features for retrieval are sorted by accumulative and global features, salient points, object and shape features, signs, and structural combinations. The CBIR implementation improves image retrieval based on features[14].

J.Matas *et al* (2004), have introduces a Novel rotation invariant detector. It was coined as SURF. A new robust similarity measure for establishing tentative correspondences is proposed. The robustness ensures that invariants from multiple measurement regions (regions obtained by invariant constructions from external regions), some that are significantly larger (and hence discriminative) than the MSERs[10].

Y.Jinget *et al* (2008), have discussed Image ranking, it is done through an iterative procedure based on the page rank computation. Numerical weight is assigned to each image. An algorithm is provided to analyze the visual link and solely rely on the text clues[5].

J.Rodriguex *et al* (2009), Proposed 2D shape representation of shape described by a set of 2D points. Invariant relevant transformation technique is used, Such as translation, rotation and scaling is done.2D shapes in a way that is invariant to the permutation of the landmarks. Within the framework, a shape is mapped to an analytic function on the complex plane, leading to analytic signature (ANSIG)[12].

D.Lowe *et al* (2010), Proposed Distinctive invariant method which is used for feature extraction. Object recognition is done from nearest neighbor algorithm it also describes an approach to using these features for object recognition. The recognition proceeds by matching individual features to a database of features from known objects using a fast nearest-neighbor algorithm followed by a Hough transform[8].

The proposed method uses modified context dependent similarity algorithm which involves preprocessing the test image followed by interest point extraction, context computation and similarity design. This overcome the limitation of processing an unclear or corrupted image which contain logo and check its genunity.

II .SYSTEM DESIGN

A. Block Diagram

The flow diagram for Modified context dependent similarity algorithm is as shown in figure.

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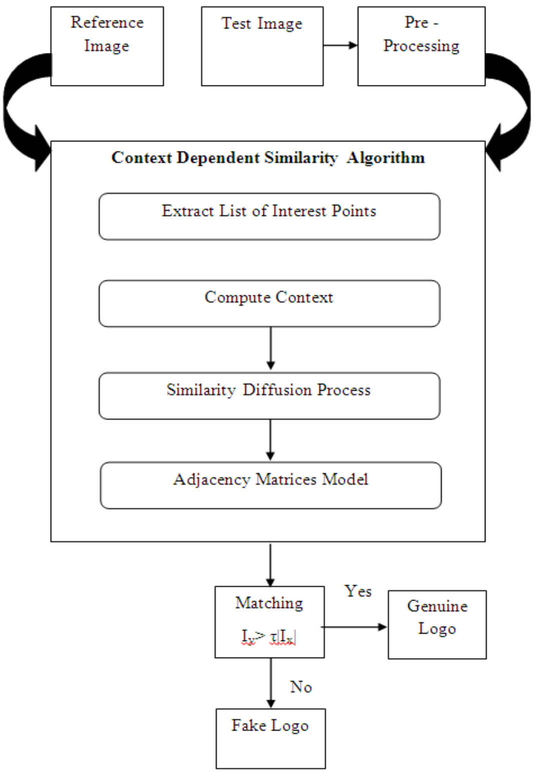


Fig 1. Modified CDS algorithm

B . Pre-Processing

Pre-processing is an important technique which is usually carried out to filter the noise and to enhance the image before any processing. Four filters namely Mean, Median, Gaussian and Weiner filters are used to remove noise here. And their Peak signal to noise ratio is calculated. The image with high PSNR value is used for further processing.

i) Mean filter

The mean filter is a simple spatial filter. It is a sliding-window filter that replaces the center value in the window. It replaces with the average mean of all the pixel values in the kernel or window.

ii) Median filter

Median Filter is a simple and powerful non-linear filter. Median filter is used for reducing the amount of intensity variation between one pixel and the other pixel.

The median is calculated by first sorting all the pixel values into ascending order and then replace the pixel being calculated with the middle pixel value. If the neighboring pixel of image which is to be considered contains an even numbers of pixels, than the average of the two middle pixel values is used to replace.

iii) Weiner filter

The goal of wiener filter is to reduced the mean square error as much as possible. This filter is capable of reducing the noise and degrading function.The Fourier domain of the Wiener filter is

$$G(u,v)=\frac{H^{*}(u,v)}{|H(u,v)|^{2}P_{s}(u,v)+P_{n}(u,v)}$$

Where, H*(u,v) - Complex conjugate of degradation function,
Pn (u, v)-Power Spectral Density of Noise,
Ps (u, v)- Power Spectral Density of non- degraded image.

iv) Gaussian filter

Gaussian filters are used in image processing because they have a property that their support in the time domain is equal to their support in the frequency domain.The Gaussian filters have the 'minimum time-bandwidth product'.

The Gaussian Smoothing Operator performs a weighted average of surrounding pixels based on the Gaussian distribution. It is used to remove Gaussian noise and is a realistic model of defocused lens. Sigma defines the amount of blurring.

The probability distribution function of the normalised random variable is given by

$$g(x)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^{2}}.$$

Where μ is the expected value and σ^2 is the variance.

v) Peak signal to Noise ratio (PSNR)

The Peak signal to noise ratio calculation is performed in order to enhance the image quality and to remove noise present in an image. This simplifies the further processing steps. PSNR is the ratio between maximum possible power of a signal and the power of distorting noise which affects the quality of its representation. It is defined by

$$PSNR=20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

Where MAX_f is the maximum signal value that exists in original “known to be good” image.

Each of the above mentioned filter produces a separate filtering output and the maximum signal value of the best of these filter is calculated and proceeded further for interest points extraction.

C) Interest Points Extraction

Interest point extraction is a recent terminology in computer vision that refers to the detection of interest points for subsequent processing. An interest point is a point in the image it has a well-defined position in image space. The interest points are extracted using key points extracted from Scale Invariant Feature Transform.

For any object in an image, interesting points on the object can be extracted to provide a "feature description" of the object. This description, extracted from a training image, can then be used to identify the object when attempting to locate the object in a test image Such points usually lie on high-contrast regions of the image, such as object edges.Another important characteristic of these features is that the relative positions between them in the original scene shouldn't change from one image to another.

i) 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 make feature detection in the scale space and determine the location of the feature points and the scale.

Algorithm of the scale invariant feature transform follows:

- Constructing a scale space.
- Scale-space extreme value detection (Uses difference-of-Gaussian function)
- Key point localization (Sub-pixel location and scale fit to a model)
- Orientation assignment (1 or more for each key point)
- Key point descriptor (Created from local image gradients).

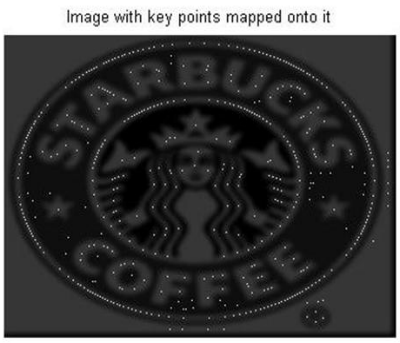


Fig 2. SIFT keypoints mapped

Constructing a scale space:

This is the initial preparation. Internal representations of the original image to ensure scale invariance. This is done by generating a "scale space".

LoG Approximation:

The Laplacian of Gaussian is great for finding interesting points (or key points) in an image.

Finding key points:

With the super-fast approximation, key points can be find. These are maxima and minima in the Difference of Gaussian image.

Assigning an orientation to the key points:

An orientation is calculated for each key point. Any further calculations are done relative to this orientation. This effectively cancels out the effect of orientation, making it rotation invariant.

Generate SIFT Features:

Finally, with scale and rotation invariance in place, one more representation is generated. This helps uniquely identify features.

D) Context

The context is defined by the local spatial configuration of interest points in both SX and SY. Formally, in order to take into account spatial information, an interest point xi ∈ SX is defined as xi = (ψg(xi),ψf (xi),ψo(xi),ψs (xi),ω(xi)) where the symbol ψg(xi) ∈ R^2 stands for the 2D co-ordinates of xi while ψf (xi) ∈Rc corresponds to the feature of xi .

$$\mathcal{N}^{\theta,\rho}(x_i) = \{x_j : \omega(x_j) = \omega(x_i), x_j \neq x_i\}$$

with

$$\frac{\rho - 1}{N_r}\,\epsilon_p \leq \|\psi_g(x_i) - \psi_g(x_j)\|_2 \leq \frac{\rho}{N_r}\,\epsilon_p$$

and

$$\frac{\theta - 1}{N_a}\pi \leq \angle\big(\psi_o(x_i), \psi_g(x_j) - \psi_g(x_i)\big) \leq \frac{\theta}{N_a}\pi$$

where (ψg(xj)−ψg(xi)) is the vector between the two point coordinates ψg(xj) and ψg(xi). The radius of a neighborhooddisk surrounding xi is denoted as $€_p$ and obtained by multiplying a constant value € to the scale ψs (xi) of the interest point xi. In the above definition, θ = 1. . . Na,ρ = 1. . . Nr corresponds to indices of different parts of the disk.

Na and Nr correspond to 8 sectors and 8 bands. In figure 3. Definition and partitioning of the context of an interest point xi into different sectors (for orientations) and bands (for locations).

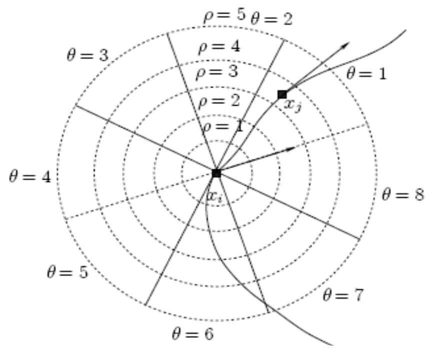


Fig 3.. Partitioning of the context of an interest point into different sectors and bands

E) Similarity design

We define k as a function which, given two interest points $(x, y) \in SX \times SY$, provides a similarity measure between them. For a finite collection of interest points, the sets SX, $SY$are finite. Provided that we put some (arbitrary) order on SX, SY, we can view function k as a matrix **K**,

Let $\mathbf{D}x,y= d(x, y) = \|\psi f (x) - \psi f (y)\|_2$. Using this notation, the similarity **K** between the two objects SX,$SY$is obtained by solving the following minimization problem

$$\min_{\mathbf{K}} \quad \mathrm{Tr}(\mathbf{K}\,\mathbf{D}') + \beta\,\mathrm{Tr}(\mathbf{K}\,\log\,\mathbf{K}') - \alpha \sum_{\theta,\rho} \mathrm{Tr}(\mathbf{K}\,\mathbf{Q}_{\theta,\rho}\,\mathbf{K}'\,\mathbf{P}'_{\theta,\rho}) \quad \text{s.t.} \begin{cases} \mathbf{K} \geq 0 \\ \|\mathbf{K}\|_1 = 1. \end{cases}$$

Here α, $\beta \geq 0$ and the operations log (natural), $\geq$ are applied individually to every entry of the matrix.

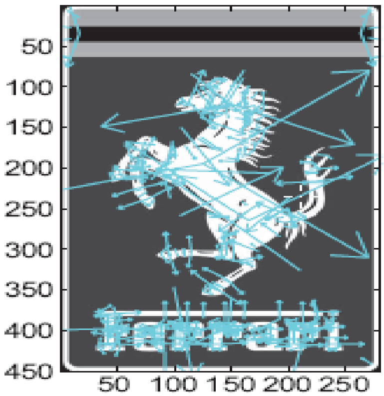


Fig 4. Collection of SIFT points with their locations, orientations and scales

Solution:

Let's consider the adjacency matrices $\{P\theta,\rho\}\theta,\rho$, $\{Q\theta,\rho\}\theta,\rho$ related to a reference logo SX and a test image SY respectively.

$$\zeta = \frac{\alpha}{\beta} \sum_{\theta,\rho} \|\mathbf{P}_{\theta,\rho}\mathbf{u}\mathbf{Q}'_{\theta,\rho} + \mathbf{P}'_{\theta,\rho}\mathbf{u}\mathbf{Q}_{\theta,\rho}\|_\infty$$

Where $\|.\|_\infty$ is the "entry wise" L_∞ norm (i.e. The sum of the square values of vector coefficients).

III. SYSTEM IMPLEMENTATION

The proposed system has been implemented using the following modified context dependent similarity algorithm

Input : Test Logo image.

Output : Detected Logo image.

Step 1: Two Input images are taken namely
Reference logo image Ix.
Test logo image Iy.

Step 2: Convert the color image to gray scale.

Step 3: Extract Scale Invariant Feature ransform [SIFT] from Ix, Iy.

Step 4: Compute the first octave of SIFT
Assume K2=0, k1=0:3, k= sqrt (2)
sigma = [(k^(k1+(2*k2)))*1.6]

Step 5: Compute the CDS matrix by
[1/ ((2*pi)*((k*sigma)*(k*sigma))))*exp(-((x*x)+(y*y))/(2*(k*k)*(sigma*sigma))]

Step 6: Store matrix result and resize the image.

Step 7: Compute second octave and third octave by repeating the above steps only by Changing the values of k2 as 1&2 Respectively

Step 8: Obtain and Plot the key points on the image using kpl

Step 9: Calculate magnitude and Calculate orientation of the key points
p1=mag (k1-2:k1+2, j1-2:j1+2);
q1=oric(k1-2:k1+2,j1-2:j1+2);

Step 10: Plot the keypoint of the test and reference logo image.

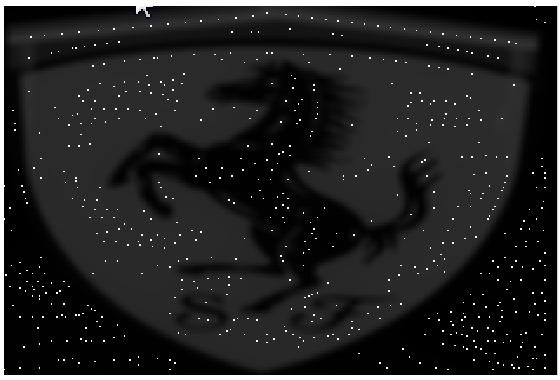
step11: determine the CDS matrix k

step12: Compare keypoint and find the value of tow (tow=(count/length(kp))

IV .RESULTS AND DISCUSSION

The logo matching and recognition using Modified context dependent similarity algorithm is performed and the results are shown below

a) filtered image



b) Test image with keypoint mapped into it

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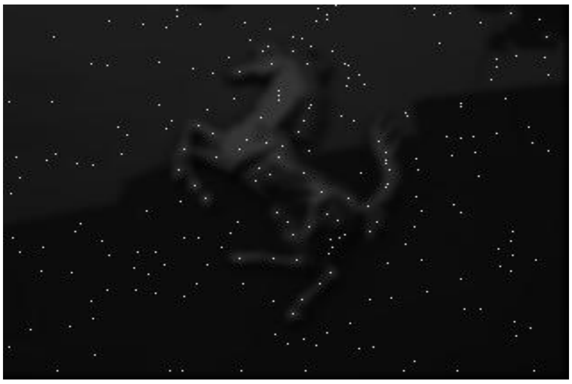
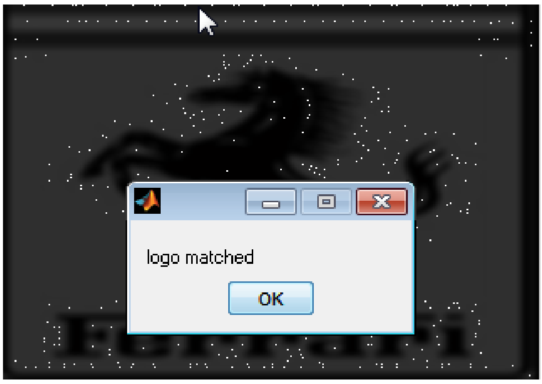
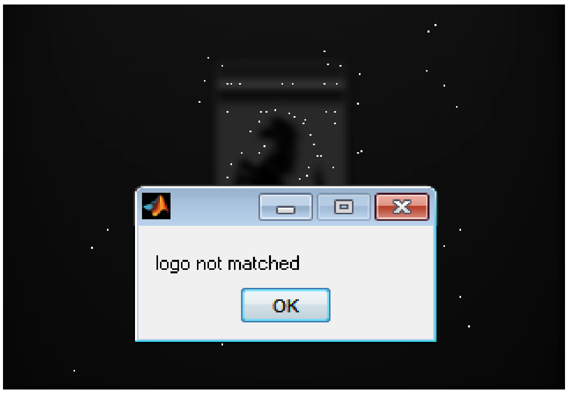


c) Reference image with keypoint



d) Genuine logo detected



e) Fake logo detected

V. CONCLUSION

We have proposed a new class of similarities based on Modified Context Dependent algorithm. We implemented Scale invariant feature transform algorithm for key point extraction and enhanced context computation technique which enhances the performance in terms of accuracy in logo matching and computation time.

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