A novel solution for logo detection and recognition based on CDS

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***Abstract* - In this technical demonstration, we present a new solution for logo detection and recognition which is based on the definition of a ―Context-Dependent Similarity‖ (CDS) kernel that directly incorporates the spatial context of local features. The proposed method is model-free, i.e. it is not restricted to any a earlier alignment model. Context is considered with respect to each single SIFT key point Formally, the CDS function is defined as the fixed-point of three terms: (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 Euclidean distance between the most likely aligned interest points. The context criterion measures the spatial coherence of the alignments. The entropy term acts as a smoothing factor, assuming that with no a earlier knowledge, the joint probability distribution of alignment scores is flat.**

***Keywords- Local features, special context,* spatial coherence, interest points.**

I. INTRODUCTION

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 fake or non-authorized use of their logo, unveil the malicious use of logos that have small variations with respect to the originals so to deceive customers, analyze videos to get statistics about how long time their logo has been displayed.

Logos are graphic productions that recall some real world objects or emphasise a name, simply display some abstract signs that have strong belief appeal. Color may have some relevance to assess the logo identity. But the distinctiveness of logos is more often given by a few details carefully studied by graphic designers, semiologists and experts of social communication. The graphic layout is equally important to attract the attention of the customer and communicate the message appropriately and permanently. Different logos may have similar layout with small different spatial disposition of the graphic elements, localized differences in the orientation, size and shape, or in the case of malicious tampering differ by the presence/not present of one or few traits.

Objective

In this paper we use ensemble based frame work. This is used to choose the best combination of preprocessing methods and candidate extractors.

II. MODULES

2.1 Interest points Extraction

Interest point detection 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 histogram method.Input images are reference and test logo images and the output is interest points extracted images.

2.2. Context computation

The context is defined by the local spatial configuration of interest points. Context is used to find interest point correspondences between two images in order to tackle logo detection.

Input is interest points extracted images and output is extraction of context.

2.3 The similarity diffusion process

Resulting from the definition of context, similarity between interest points is recursively and anisotropically diffused. The adjacency matrices $\{\mathbf{P}\theta,\rho\}\theta,\rho$, $\{\mathbf{Q}\theta,\rho\}\theta,\rho$ related to a reference logo SX and a test image SY respectively, each of which collects the adjacency relationships between the image interest points for a specific context segment θ, ρ.

Input is context image and the output is extraction of similarity between the reference and test images.

2.4. Matching Process

Our designed similarity may be interpreted as a joint distribution (pdf) which models the probability that two interest points taken from $S_x \times S_y$ match. In order to guarantee that this similarity is actually a pdf, a partition function is used as a normalization factor taken through all the interest points in $S_x \times S_y$. Logo detection is achieved by finding for each interest point in a given reference logo S_x its best match in a test image S_y; if the number of matches is larger than $\tau \mid S_x \mid$ (for a fixed $\tau \in [0, 1]$), then the reference logo will be declared as present into the test image. Input is total number of similarities between the reference and test image. Output is identifying whether the logo is genuine or fake.

III. SYSTEM ARCHITECTURE

Trademark recognition deals with the problem of content-based indexing and retrieval in logo databases, with the goal of assisting in the detection of trademark infringement by comparing a newly designed trademark with archives of already registered logos. This solves the problem of image registration by ensuring that similar images will receive identical classification codes. Logo detection and recognition in these scenarios has become important for a number of applications .Among them, several examples have been reported in the literature, such as the automatic identification of products on the web to improve commercial search-engines, the verification of the visibility of advertising logos in sports events the detection of near- duplicate logos and unauthorized uses. Special applications of social utility have also been reported such as the recognition of groceries in stores for assisting the blind. Logo recognition has been specifically used in application areas including website summarization by image content, enterprise identification, entertainment advertising, vehicle recognition, road sign reading, and content-based image retrieval.

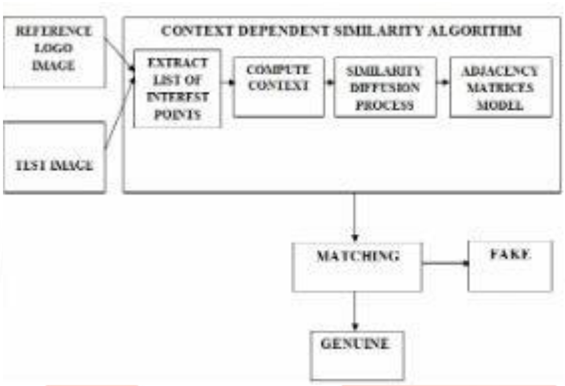

Fig.1.CDS system Architecture.

IV. ALGORITHM

Input: Reference logo image: I_x, Test image: I_y, CDS parameters: *Na, Nr, α, β, τ*.
Output: A Boolean value determining whether the reference logo in I_x is detected in I_y.
Extract SIFT from I_x, I_y and let S_x: = $\{x_1. \; . \; . \; x_n\}$, $S_y := \{y_1, . . . , y_m\}$ be respectively the list of interest points taken from both images;

for i=1:n
    Compute the context of *xi*, given Na, Nr;
end
for j =1: *m*
    Compute the context of *y j*, given Na, Nr;
end
t =1, *max* =30;
if (convergence == 0 || t>max)
    for i=1:n
        for j=1:m
        Compute CDS matrix entry **K***(t)xi ,y j*, given *α, β*;
        end
    end
end
K = **K***(t)*;
for i=1:n
    for j =1:m
    $\mathbf{K}y_j|x_i$ **=** $\mathbf{K}x_i,y_j$ / sum of (for s=1:m compute $\mathbf{K}x_i,y_s$);
    if ($\mathbf{K}y_j|x_i$ >= sum of (for **s~=**j:m compute $\mathbf{K}y_s|x_i$)
    A match between x_i and y_j is declared.
    end
end
if *number of matches in* $S_y > \tau|S_x|$
return *true;*
else

return *false*;
end

V. CONCLUSION

We introduced in this work a new logo detection and localization approach based on a new class of similarities referred to as context dependent. The effort of the proposed method present in several aspects: (i) the inclusion of the information about the spatial configuration in similarity design as well as visual features, (ii) the ability to control the influence of the context and the regularization of the solution via our energy function, (iii) the tolerance to different aspects including partial block, makes it suitable to detect both near-duplicate logos as well as logos with some variability in their appearance, and (iv) the theoretical roundedness of the matching framework which shows that under the hypothesis of existence of a reference logo into a test image, the probability of success of matching and detection is high.

REFERENCES

[1] Alexander M. Bronstein , Michael M. Bronstein, "Spatially-sensitive affine-invariant image descriptors".
[2] Y. Jing and S. Baluja, "Pagerank for product image search," in *Proc. WWW*, Beijing, China, 2008, pp. 307–316.
[3] L. Ballan, M. Bertini, and A. Jain, "A system for automatic detection and recognition of advertising trademarks in sports videos," in *Proc. ACM Multimedia*, Vancouver, BC, Canada, 2008, pp. 991–992.
[4] Yannis Kalantidis, Roelof van Zwo "Scalable Triangulation-based Logo Recognition" This work was supported by the European Commission under contract FP7-215453.
[5] Hichem Sahbi, Jean-Yves Audibert and Renaud Keriven, "Context-Dependent Kernels for Object Classification" This work was supported in part by a grant from the Re- search Agency ANR (Agence Nationale de la Recherche) under the AVEIR and the MGA Projects.
[6] Till Quack ,Vittorio Ferrari ,Bastian Leibe, Luc Van Gool1, "Efficient Mining of Frequent and Distinctive Feature Configurations," We acknowledge support from EU project CLASS, IST 027978 and Swiss NSF project IM2.
[7] J. Rodriguez, P. Aguiar, and J. Xavier, "ANSIG—An analytic signature for permutation-invariant two-dimensional shape representation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Anchorage, AK, Jun.2008, pp. 1–8.
[8] J. Luo and D. Crandall, "Color object detection using spatial-color joint probability functions," *IEEE Trans. Image Process.*, vol. 15, no. 6, pp.1443–1453, Jun. 2006.
[9] J. Matas, O. Chum, M. Urban, and T. Pajdla, "Robust wide-baseline stereo from maximally stable extremal regions," *Image Vis. Comput.*, vol. 22, no. 10, pp. 761–767, 2004.
[10] D. Lowe, "Distinctive image features from scale-invariant keypoints," *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, 2004.
[11] H. Bay, A. Ess, T. Tuytelaars, and L. Van Gool, "Speeded-up robust features (SURF)," *Comput. Vis. Image Understand.*, vol. 110, no. 3, pp.346–359, 2008.
[12] A. D. Bagdanov, L. Ballan, M. Bertini, and A. Del Bimbo, "Trademark matching and retrieval in sports video databases," in *Proc. ACM Int. Workshop Multimedia Inf. Retr.*, Augsburg, Germany, 2007, pp. 79–86.
[13] O. Chum, M. Perdoch, and J. Matas, "Geometric min-hashing: Finding a (thick) needle in a haystack," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Miami, FL, Jun. 2009, pp. 17–24.
[14] Z. Wu, Q. Ke, M. Isard, and J. Sun, "Bundling features for large scale partial-duplicate web image search," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Miami, FL, Mar. 2009, pp. 25–32.
[15] G. Carneiro and A. Jepson, "Flexible spatial models for grouping local image features," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2.Washington, DC, 2004, pp. 747–754.
[16] O. Chum and J. Matas, "Unsupervised discovery of co-occurrence in sparse high dimensional data," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, San Francisco, CA, 2010, pp. 3416–3423.
[17] Jim Kleban, Xing Xie, Wei-Ying Ma ,"SPATIAL PYRAMID MINING FOR LOGO DETECTION IN NATURAL SCENES.
[18] E. Mortensen, H. Deng, and L. Shapiro, "A SIFT descriptor with global context," in *Proc. Conf. Comput. Vis. Pattern Recognit.*, San Diego, CA, 2005, pp. 184–190.