International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:5, No:4, 2011

Harris Extraction and SIFT Matching for Correlation of Two Tablets

Ali Alzaabi, Georges Alquié, Hussain Tassadaq, Ali Seba

Abstract**—**This article presents the developments of efficient algorithms for tablet copies comparison. Image recognition has specialized use in digital systems such as medical imaging, computer vision, defense, communication etc. Comparison between two images that look indistinguishable is a formidable task. Two images taken from different sources might look identical but due to different digitizing properties they are not. Whereas small variation in image information such as cropping, rotation, and slight photometric alteration are unsuitable for based matching techniques. In this paper we introduce different matching algorithms designed to facilitate, for art centers, identifying real painting images from fake ones. Different vision algorithms for local image features are implemented using MATLAB. In this framework a Table Comparison Computer Tool "TCCT" is designed to facilitate our research. The TCCT is a Graphical Unit Interface (GUI) tool used to identify images by its shapes and objects. Parameter of vision system is fully accessible to user through this graphical unit interface. And then for matching, it applies different description technique that can identify exact figures of objects.

Keywords**—**Harris Extraction and SIFT Matching

I. Introduction

SPATIAL-Temporal image matching is very much required for Art Museum to differentiate images made by different artists. Art exhibition centers endow with a guide which is interrogated by visitors to locate an object on a tablet. Small variation in image such as color density, brush use differences, etc… can affect an image and allows us to identify a fake one.

However manual technique of information retrieval is tedious and there is a high risk of false judgment. Therefore a high image comparison application is required in order to solve the problems mentioned above.

Considering matching results, we can finalize identification of objects and prove image as original image. We integrate in our TCCT system (Figure 1) different image recognition algorithms. TCCT is a based GUI system, by which user can set best parameters regarding condition and situation. A lot of image matching techniques based on local features and global features are available. We designed TCCT to give opportunities to programmers to integrate more image recognition algorithms of their own.

Ali Alzaabi is with UPMC, France (e-mail: aljawal1@yahoo.com)

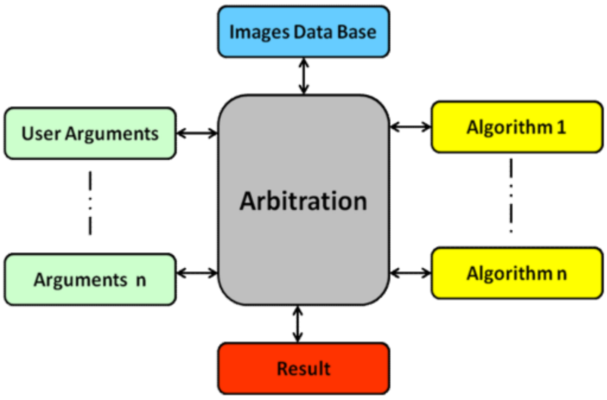

Fig. 1 Table Comparison Computer Tool (TCCT)

Seven [1] method used feature histograms intended for content-based image retrieval. These methods have achieved relative success with 2D object extraction and image matching. Mikolajczyk and Schmid [2] used differential descriptors to approximate a point neighborhood for image matching and retrieval. Van Gool [3] introduced the sweeping color moments to explain shapes and intensities of different color channels in a local region. David Lowe [4] proposed Scale Invariant Features Transform (SIFT), that is robustly flexible to a number of common image transforms. Lowe's [5] Scale Invariant Features Transform (SIFT), is geometrically invariant to similarity transforms and invariant to intensity changes. Our goal is to design a highly distinctive recognition system that can benefit of best matching algorithm for image recognition. We provide an environment that uses local descriptor for matching purpose. Front end of application is a GUI system, that can incorporate different image recognition algorithms such as SIFT. This system provides to users an access to all parameters required for matching as users are best arbitrators of any scenario.

II. Proposal

In this work we encode distinctive local structure of a collection of image points for the purpose of matching to similar patterns in other images.

The efficiency of the algorithms depends on the environment. The complex algorithms are more robust but on the other hand they require more execution time.

International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:5, No:4, 2011

Fig. 2 Images taken from [8] for evaluation

For our specific application where efficiency is critical and where robustness is also mandatory, we find a trade off in the existing algorithms to develop application that gives matching algorithm maximum advantage. After applying basic image adjustment techniques i.e. alignment, cropping etc… we use the following techniques in order to reach our goal:

- Features Point Descriptors,
- Local Features Descriptors,
- Invariant Features Descriptors,
- Matching Descriptors.

Fig. 3 Variant features marked in red color

III. Features Point Descriptor

Discontinuity of spatial gray value function *g(x)* in the image plane is an efficient edge. The primary job of features point descriptor “edge detection” is to analyze the properties of the edges enclosed in the chosen image. A model is formulated that determines accuracy of edges. In certain conditions it is possible to detect an edge and to optimize edge detection. Edge detection is always based on differentiation in one or other form. In discrete images, differentiation is replaced by discrete difference that only approximates differentiation [6].

IV. Variant Features Descriptors

In variant features descriptors we inquired about how to represent a segmented object. We studied the representation of binary objects with run-length code [7], quad tree code [8], and chain code [9]. A dense illustration of objects shape is not very useful if it takes a lot of effort to compute it and if it is cumbersome to compute shape parameters directly from it. Shape parameters are extracted from objects in order to describe their shape, to compare it to the shape of template objects, or to separate objects into classes of different shapes.

Thus it is of interest to discover shape parameters such as scale and rotation in variant or even invariant under perspective projection.

Harris corner detector is used to find local features in image. The Harris corner detector is a popular interest point detector due to its strong invariance to: rotation, scale, illumination variation and image noise. The Harris corner detector is based on local auto-correlation function of a signal that measures local changes of signal with patches shifted by in indifferent directions.

Usually Harris is used on scale gray image. In our work we use it on color image and our process follows these four different steps that we use for features extraction:

A. Separate Color Domain

At this step we convert (RGB) image from color domain to separate domain.

Red Image = 1 * R + 0 * G + 0 * B
Green Image = 0 * R + 1 * G + 0 * B
Blue Image = 0 * R + 0 * G + 1 * B

We do apply steps listed below over several (RGB) image domains. Results are merged into same image.

B. Apply Corner Detectors

This step takes three different (RGB) image domains. For each input image pixel (RGB), corner operator is applied to obtain a corner. Step output is (RGB) corner maps. Since, for each (RGB) input image pixel, corner operator is applied to obtain a corner measure. Corner map has the same geometry as input image and can be considered as a version of input image.

C. Apply threshold on corner map

At this point the corner map holds numerous local maximums that have comparatively small corners measures that are not true corners. To avoid considering these points as corners, corner map is usually applied with threshold. All values in corner map under threshold are set to zero.

D. Non maximal values suppression

Threshold corner map contains only non-zero values around the local maximums that need to be marked as corner points. To locate the local maximums, non-maximal suppression is applied. For every (RGB) point in threshold corner map, non-maximal suppression sets the corner measure to zero, but only if its corner measure is not larger than the corner measure of all points within a definite space. After non-maximal suppression is applied, the corners are simply the non-zero points remaining in the corner map.

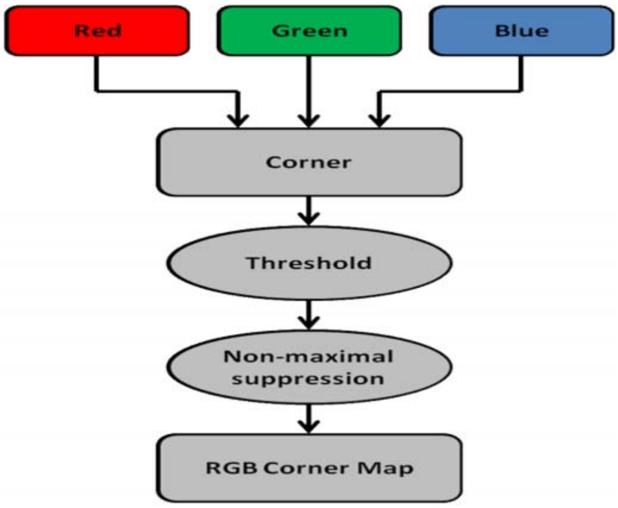

Fig. 4 Flow Graph to Extract Variant Features

V. Invariant Features Descriptors

We have defined pattern that represents features descriptors. A pattern class includes different patterns information. Local feature techniques implemented includes differential approach that we have studied here: SIFT technique and correlation-based method. The conclusion given by local differential method (Lucas, 1981) [10] and phase-based method (Fleet, 1990) [11] offers the most consistent performance on data-sets.

However, there are many variables; not only in the data but also in implementation that might lead to preference for a particular technique. Lowe's algorithm [12] that gives stable features on scale space by repeated smoothing, down-sampling of an input image and subtracting adjacent levels, creates a pyramid of difference-of-Gaussian images.

Features that SIFT algorithm detects represent minimums and maximums in a scale pace for these difference-of-Gaussian images. At each of these minimums and maximums, a comprehensive model is fitted to determine location, scale and contrast, during which some features are discarded, based on measures of their (in) stability.

Once stable feature has been detected, its dominant gradient orientation is obtained, and a key-point descriptor vector is formed from a grid of gradient histograms, constructed from the neighborhood feature gradients.

Key-point matching is performed using a nearest-neighbor indexing method, followed by a Hough transform.

It finds key-points that agree on potential object poses, and therefore a solution for affine parameters that determine specific location and orientation of each recognized object.

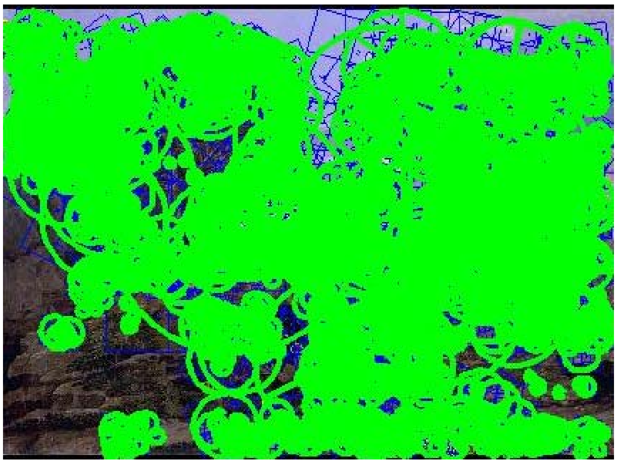

Fig. 5 Invariant Descriptor marked in green circles

VI. Matching Descriptors

We encode the image structure in spatial neighborhoods at each set of feature points chosen at selected scales. By matching such local feature descriptors in other images, we can solve important problems. The use of cross-correlation [7] for pattern matching is irritated by distance measure (squared Euclidean distance) if image and sum of distance measure is over *x*. In that case *y* is under the window containing feature situated at *u* and *v*.

Equation 1 measures the comparison between the picture and the features templates

$$i(x, y) = \sum f(x, y)t(x-m, y-n) \tag{1}$$

Matching technique is used with the specified threshold (THRESH). Descriptor D1 is matched to descriptor D2 if and only if distance d(D1,D2) multiplied by (THRESH) is not greater than distance of D1 to all other descriptors.

VII. Results and Comparison

In this section we compare original images with fake images and gather results in Table 1, Table 2 and Table 3. We used three images: original image, real image and fake image for evolution. Original image corresponds to the original data base image taken from original painting. To create fake image and real image we used a function having features image transducer/scanner source shown in figure 6 below.

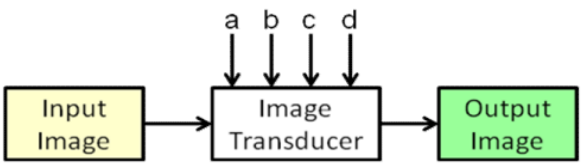

Fig. 6 Image transducer function block diagram

Parameters a,b,c and d have different characteristics than scanner source. Parameter *a* represents color information, parameter *b*: light characteristics, parameter *c:* image resizing and parameter *d*: image compression. For fake image we reduce *a* and *b* features up-to 10% without generating noise.

Real image contains all same features than original image. We use original image from image transducer function and add 1% value to all parameters. Both real image and fake image look identical to human eye.

TABLE I
RESULT TAKEN BY SPECIALIZED CROSS-CORRELATION

T	TS	SZ	OIF	RIF	FIF	RFM	ROM
T 1	**3x3**	**9**	**3907**	**3906**	**3716**	**2565**	**3842**
T 2	**3x3**	**9**	**2212**	**2229**	**1748**	**1206**	**2146**
T 3	**3x3**	**9**	**4049**	**4043**	**3815**	**2573**	**3969**
T 3	**3x3**	**9**	**2830**	**2849**	**2473**	**1693**	**2781**

T: Tablet, TS: Template Size, SZ: Search Size, OIF: Original Image Features, RIF: Real Image Features, FIF: Fake Image Features, RFM: Real vs. Fake Matching, ROM: Real vs. Original Matching.

In Table I we can observe variant features of original, real and fake images (T1, T2, T3, and T4). We used generic setting to collect those features and apply cross correlation. It has been observed that our variant matching algorithm matches more than 95% of features from real image and 50% of features match fake image.

TABLE II
PHASE CROSS-CORRELATION RESULT

T	Sig	TZ	SZ	TH	FOI	RIF	FIF	RFM	ROM
T 1	**0.2**	**3x3**	**9**	**500**	**3906**	**3907**	**3716**	**2627**	**3849**
T 2	**0.2**	**3x3**	**9**	**500**	**2229**	**2212**	**1748**	**1147**	**2149**
T 3	**0.2**	**3x3**	**9**	**500**	**4043**	**4049**	**3815**	**2722**	**3974**
T 3	**0.2**	**3x3**	**9**	**500**	**2849**	**2830**	**2473**	**1748**	**2783**

Sig: sigma, TH: Threshold.

Table II shows phase correlation results of variant features. We found more than 95% accurate results while comparing original images with real image copy. Tool rejects images having less than 80% of matching features.

TABLE III
SIFT FEATURES RESULT

T	TH	DOI	DRI	DFI	RFM	ROM
T 1	**10**	**3055**	**3096**	**2964**	**232**	**2896**
T 2	**10**	**486**	**483**	**433**	**87**	**456**
T 3	**10**	**1930**	**1942**	**1860**	**182**	**1869**
T 4	**10**	**527**	**526**	**488**	**30**	**510**

DOI: Original Image Descriptor, DRI: Real Image Descriptor, DFI: Fake Image Descriptor.

In Table III, we can observe results of Scale Invariant Features Transform matching. SIFT matching gives more than 90% of accurate results where only 7% of features match fake image.

Comparing the three methods we conclude that SIFT matching is more accurate and rigid. Harris method select fake features and consider them as original ones. Whereas SIFT totally discards those features that are not part of original images.

VIII. CONCLUSION AND FUTURE WORK

In this work, we have developed a system which allows strongly museum images recognition with almost identical images but fake ones created by different artists. It is based on using variant (Edges) and invariant (SIFT) features to match images. We did modifications in variant features detections. To gather all used algorithms we have created a GUI tool [TCCT] [12]. With the help of this GUI tool we provide different parameters for users to compare images. Users select best parameters depending upon the environmental conditions.

The most difficult issues that we have faced during our work are features extracting. All images are almost identical. Features extraction requires some compromise. Using SIFT, this problem is mostly solved.As future work we propose to find a solution to deal with the variation in image information such as cropping, rotation, and slight photometric alteration. It will be possible to improve our system with more tablet sample, add more and better algorithms in our GUI system to complete the system of distinguishing.To progress in building a very similar tablet copy, we need to use better digitizing system with high resolution. If we succeed in obtaining a very similar tablet, we can substitute the paper tablet by numeric tablet in order to protect the original tablet or a set of tablets and why not imagine a new museum which integrates numerical painting art.

ACKNOWLEDGMENT

The authors would like to thank M. Bruno Carletto for his assistance in creating this document.

REFERENCES

[1] S. Seven, Feature Histograms for Content-Based Image Retrieval. PhD The- sis, Albert-Ludwigs-University Freiburg. December (2002).
[2] K. Mikolajczyk, C. Schmid. Indexing Based on Scale Invariant Interest Points. In: ICCV, (2001) 525-531.
[3] G. Van, M. Theo, and U, Dorin. “Affine photometric invariants for planar intensity patterns”. European Conference on Computer Vision (ECCV), pp. 642-651, (1996).
[4] D. Lowe, Distinctive Image Features from Scale-Invariant Keypoints.Inter-national Journal of Computer Vision, 60, 2 (2004), pp.91-110.
[5] D. Lowe, Object Recognition from Local Scale Invariant Features. In Proceedings of the International Conference on Computer Vision, pages 1150-1157, Corfu, Greece, September (1999).
[6] S. Kima, J. Leea and J. Kima, new chain-coding algorithm for binary images using run-length codes. Department of Electrical Engineering, Korea Advanced Institute of Science and Technology, P.O. Box 150, Chon gryang, 131, Seoul, Korea.
[7] B. Lucas and T. Kanade, an Iterative Image Registration Technique with an Application to Stereo Vision. Computer Science Department Carnegie-Mellon University Pittsburgh, Pennsylvania.
[8] D. FLEET, Phase-Based Disparity Measurement. Department of Computing and Information Science.
[9] J. Crowley and A. Parker, A representation for shape based on peaks and ridges in the difference of low-pass transform. IEEE Trans. on Pattern Analysis and Machine Intelligence, (1984), 6(2):156-170.
[10] L. Peterson, "Fast Normalized Cross-Correlation," Industrial Light & Magic. http://www.idiom.com/~zilla/Papers/nvisionInterface/nip.html. [11] Grande Galerie. Le journal du Louvre - juin-juillet-août. (2010).
[11] A. ALZAABI, G. ALQUIÉ, H. TASSADAQ, A. SEBA. TCCT: A GUI Table Comparaison Computer Tool. International Joint Conferences on Computer, Information, and Systems Sciences, and Engineering (CISSE 10). Bridgeport, CT, USA, (2010).