

Analysis of LDP and LTP with Weber Local Descriptor for Face Recognition

^[1] Asharani Jawale, ^[2] Bhakti Sonawane

Department of Computer Engineering, Shah and Anchor Kuttchi Engineering College Chembur, Mumbai, India

Abstract: - Now days new technologies are booming due to their higher speed and security, large storage and latest applications. Area of Image Processing also enriched with such latest techniques like advanced applications. But as the human face is non-rigid object, the robust face recognition under uncontrolled conditions is still challenging which make it an interesting area of researchers. LDP gives better texture encoding approach than LBP [2] and the generalization of LBP is LTP [5.] This paper analyses performance of Local Directional Pattern (LDP) over Local Ternary Pattern (LTP) in Face Recognition. The illumination invariance is handled by Weber Local descriptor (WLD) and face recognition process is done by Speed up Robust Feature (SURF) technique.

Keywords: WLD, LDP, LTP, SURF, Gaussian Filter, Differential Excitation.

I. INTRODUCTION

Upcoming technologies are influenced with number of innovative techniques like Radio Frequency Identification (RFID), Internet of Things (IOT) etc. Application of these techniques are Material Management, Tool Tracking, Attendee Tracking, Access Control, Smart Home, Smart City, Smart Retail, Connected car respectively. Due to the benefits of such automation many researchers are interested to use such ideas in day to day activities and try to make it more easy.

Automatic Face Recognition system is one of the interesting area for researchers from several decades as it has variety of applications. This is a booming area where lots of work had been done to make this process quick and accurate, but still it has many challenges due to uncontrolled illumination conditions and noise [1]. Lot of methods are developed to solve this problem. One of the most effective ways to handle the illumination invariance and existing noise in input image is the Weber's Law [1]. To extract the features from image and to manage the noise and illumination invariance effect in image are two different things.

Jie Chen et al [14] illustrate the robust weber local descriptor. Ernst Weber, an experimental psychologist in the 19th century, observed that the ratio of the increment threshold to the background intensity is a constant [14]. WLD is consist of two components: differential excitation and gradient orientation.

The rise in interest of Content Based Image Retrieval Technique (CBIR) which operates on totally different principle where the primitive features characterizing image content, such as colour, texture and shape, are computed for both stored and query images. This paper focuses on Image

recognition through texture feature extraction. Various patterns like Local Binary Pattern(LBP) Local directional Pattern(LDP), Local Ternary Pattern(LTP) and Local Tetra Pattern(LTrP) are developed to extract the texture features of an image. [3,6]. S. Anitha et al. [3] states that, LBP act as a non-directional first order local pattern. Another important property of LBP is its computational simplicity, which makes it possible to analyse images in challenging real-time settings. But LBP's are resistant to lighting effects in the sense that they are invariant to monotonic grey-level transformations, and they have been shown to have high discriminative power for texture classification. Bharat Lal et al. [2], attempt the use of LDP for feature extraction. This paper specifies that LDP employs a better texture encoding approach than LBP. Here Kirsch Compass Mask is used and applied in eight directions on grey levels of image for the computation of directional edge values. Then select only high valued edges in calculation of feature vector.

Abdullah Gubbi et al.[7], applies the LTP for feature extraction where the uniform pattern argument applied in the ternary case and coding scheme that splits each ternary pattern into its positive and negative halves. Treating these two halves as two separate channels of LBP descriptors for which separate histograms and similarity metrics are computed. The results combined at the end of the computation to form the feature vector. The LBP and LDP encodes images with only two distinct values (either "0" or "1") and the LTP is able to encode images with three ("0", "-1" or "1") distinct values. LTP encodes the test image into two separate channels of LBP named as LTP Upper and LTP Lower.

This paper analyse the performance of LDP, LTP Upper and LTP Lower without using any feature reduction

technique. Here illumination invariance is handled by Weber Local Descriptor and features of images are extracted by using LDP and LTP patterns. SURF technique is used for recognition process.

The organization of the paper is as follows: Section II introduces the background in which brief description of Weber Local Descriptor, Local Directional Pattern (LDP) method, Local Ternary Pattern (LTP) and Speed up Robust Feature (SURF) Technique is given. Section III explains the Proposed System. Section IV gives Implementation Details while Section V discuss the Result of proposed system and the conclusion is given in Section VI.

II. BACKGROUND

A. Weber Local Descriptor

As per the Weber's law noted in Wang et al.[1] the ratio of the smallest perceptual change in stimulus to that in the background remains constant, which implies that stimuli are perceived in relative terms but not in absolute terms. The algorithm used of calculating weber face in [1] is as below:

Input:-A face image F

Output:- The Weber face WF of F

1.Smoothen F with a Gaussian Filter:

$$F' = F * G(x,y,\sigma),$$

Where * is convolution operator and

$$G(x,y,\sigma) = G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right),$$

Is the Gaussian kernel function with standard deviation σ ,

2. Process F' with Weber local descriptor:

$$WF = WLD(F'),$$

Where WLD (.) is the Weber local descriptor:

$$WLD(F'(x,y)) = \arctan\left(\alpha \frac{\sum_{i \in A} F'(x,y) - F'(x-i\Delta x, y-j\Delta y)}{F'(x,y)}\right)$$

in which $A = \{-1,0,1\}$

The result of implementation of above algorithm of webers law on input image called Weber Face is shown in figure 1.



Fig. 1 Weber Face calculation

Proposed system apply pre-processing, like to convert the colour input image into grey scale and resizing of image which plays an important role in improving results. As per Shutao Li et al. [9] the basic WLD uses two ratios to calculate its two components: differential excitation and orientation. Then a concatenated 2D histogram of them is constructed to represent image. The 'Differential Excitation' of image is calculated, which comes from the ratio between two terms: one is the sum of differences of a current pixel against its neighbours; the other is the current pixel itself. This can be done as follows

$$v1 = I * f1$$

Where, I is the input image, * represents the convolution, v1 is the outputs of filter f1. Then histogram of differential excitation is calculated and mapping of differential excitation is done in 0-255 which gives the output as shown in Fig. 2(1). The orientation component is about the ratio of the change in horizontal direction to that in vertical direction of current pixel. Fig 2 shows the weber face resulted from the calculation of differential excitation and orientation of input image produces the image as shown in Fig. 2



Fig. 2 Weber face with added preprocessing

It is observed that resulting weber face is almost independent of the illumination component and it is same as per the output shown in [2]. This weber face is used for further feature extraction with LDP and LTP methods.

B. Local Directional Pattern (LDP)

There are many methods developed to extract the texture features from input image but Local Directional Pattern is easy to implement and produce effective result in Face Recognition system.

Barat Lal et al.[2] explains how LDP compares the relative edge response values of a pixel in eight different directions. For this purpose, eight directional edge responses $m_0, m_1, m_2, \dots, m_7$ are computed by applying the Kirsch masks in 8 orientations at a pixel. This mask is also called kirsch compass mask. Since responses in different directions vary

a lot in magnitude, only k most prominent directions are used for generating the LDP code at a pixel. An 8 bit LDP code is formed by setting the code to 1 for the top k values of $|m_j|$, and setting the remaining (8-k) bits to 0.[2].The following Fig. 3 shows a sample LDP code generation with $k=3$.

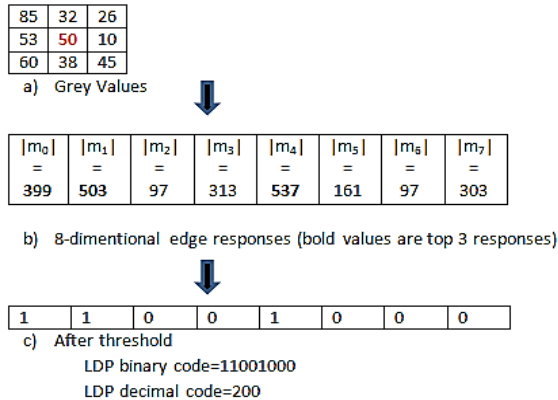


Fig.3 LDP operation [2]

After calculating all eight directions responses at each pixel LDP code get generated with k most prominent values. In proposed system the value of $k=1$ which is maximum out of eight responses.

C. Local Ternary Pattern (LTP)

Local ternary pattern (LTP) is generalization of Local Binary Pattern (LBP). It is more discriminant and less sensitive to noise in uniform regions.[5] LTP extends LBP to 3-valued codes, in which grey-levels in a zone of width $\pm t$ around central pixel i_c are quantized to zero, ones above this are quantized to +1 and ones below it to -1, i.e., the indicator is replaced with a 3-valued function and the binary LBP code is replaced by a ternary LTP code.[5]

Fig. 4 shows the example of LTP code generation with LTP Upper and LTP Lower Patterns. Here proposed system use the threshold $t=0.1$ as it creates full dark image with $t=5$. Treating LTP Upper and LTP Lower as separate channels of LBP descriptors

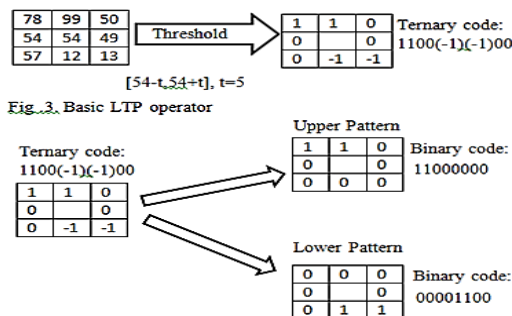


Fig.4. Splitting LTP code into positive and negative LBP code. [5].

According to Abdullah Gubbi et al[6], the Local Ternary Pattern with Booths algorithm avoids the selection threshold that separate the LTP code into two distinct parts, avoids selection of histogram bins even not used any feature reduction technique to reduce the feature vector. The LTPB achieves better result of recognition with KNN classifier.

This survey makes to think of new way to use LTP and observe the result. Here we separate the LTP code into two parts by taking minor threshold as 0.1 which generally has normal range from 3 to 10 as per[6]. Extract the features of input image with pre-processing separately as LTP Upper and LTP Lower without calculating histogram and without using any feature reduction technique. Then compare their performance at recognition step.

D. Surf Matching Technique

Speed-up robust feature (SURF) is a scale and in-plane rotation invariant feature. It contains interest point detector and descriptor. The detector locates the interest points in the image, and the descriptor describes the features of the interest points and constructs the feature vectors of the interest points. SURF uses the determinant of the approximate Hessian matrix as the base of the detector. To locate the interest point, detection of blob-like structures at locations where the determinant is at maximum. Integral images are used in Hessian matrix approximation, which reduce computation time drastically. The SURF used the sum of the Haar wavelet responses to describe the feature of an interest point. Fig.5 shows the Haar wavelet filters used to compute the responses at x and y directions.



Fig. 5. The Haar wavelet filters used to describe the interest points.

For the extraction of the description, the first step consists of constructing a square region centred at the interest point and oriented along the orientation decided by the orientation selection method. The region is split up equally into smaller 4x4 square sub-regions. This preserves important spatial information. For each sub-region, Haar wavelet responses at 5x5 equally spaced sample points. For simplicity, it call dx the Haar wavelet response in horizontal direction and dy the Haar wavelet response in vertical direction. To increase the robustness towards geometric deformations and localization errors, the responses dx and dy are first weighted with a Gaussian centred at the interest point. Then, the wavelet responses dx and dy are summed up over each sub-region

and form a first set of entries in the feature vector. In order to bring in information about the polarity of the intensity changes, it also extract the sum of the absolute values of the responses, $|dx|$ and $|dy|$. Hence, each sub-region has a four-dimensional descriptor vector v for its underlying intensity structure -

$$v = (\sum \sum \sum dx, dy | dx |, \sum | dy |)$$

Concatenating this for all 4×4 sub-regions, this results a descriptor vector of length 64. To speed up matching step, the sign of the Laplacian (i.e, the trace of the Hessian matrix) for the interest point is used. Only the point-pair with the same sign will be matched with the features. Fig.6 shows the example blobs of the sign.

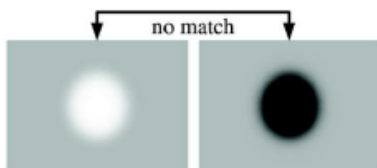


Fig. 6 The fast index for matching.

Thus SURF features should be extracted from images through SURF detectors and descriptors. About 100 interest points are first extracted from face image such as shown in Fig.7.

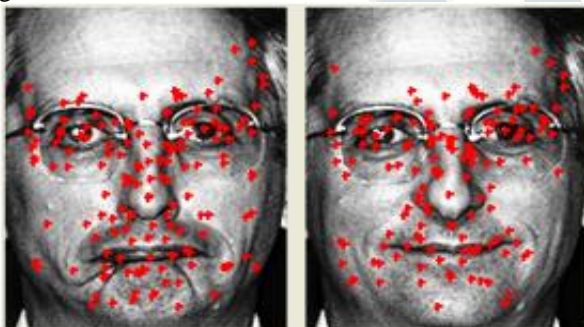


Fig. 7. Interest points in face image [12]

The SURF feature vectors of the set of interest points are then computed to describe the image and these feature vectors are normalized to 1. These features are person-specific, since the number and the positions of points selected by SURF detector as well as the features around these points computed by SURF descriptor are different in each person's image. In face recognition, matching points in two images must have the similar locations on the two faces. Thus for an interest point (x,y) in the test image the search area for its mate is limited within a rectangular window centred at (x,y) of the gallery image. The point-pair with the minimum distance between descriptors will be considered as a candidate matching pair. To verify the validity of the candidate point-pair, the next minimal distance of point-pair, which contains the same point of the test image, is then searched over the whole area of the gallery image. If the ratio of these two distances is smaller

than a pre-defined threshold, the point-pair with the minimum distance is confirmed as a matched pair. Since location information is introduced in search of the minimum-distance point-pair, and the ratio of the minimum distance and next to minimum distance measures the matching reliability of two interest points in some degree, the above method can avoid mismatching effectively. Finally, based on the result of the point-matching, it defines a similarity measure which contains the number of matched points, the average value of the Euclidean distance, and the average distance ratio of all matched points, for face recognition. When the number of the matched points of two images is smaller than the predefined threshold, it is thought that the matching result is not reliable. Fig.6 shows an example of the point matching result.

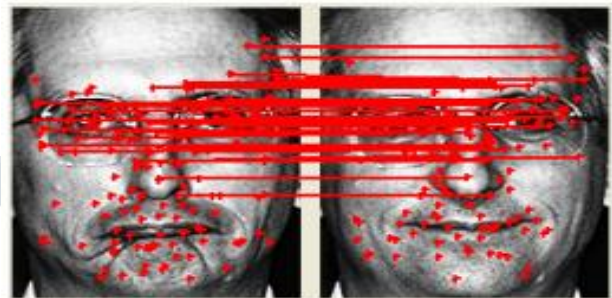


Fig. 8. Example of point matching result.[12]

The red lines indicate the corresponding matched interest points. Thus the SURF technique extracts features from LTP or LDP of query image and compares it with stored features of training set one by one and finally gives the matched face with query image.

III. PROPOSED SYSTEM

Proposed system does experiments on single face images in FACE94 database, so the face detection steps and multiple faces in input image conditions are not taken into consider while doing experiment. But for such situation Viola-John algorithm can be used to detect the image with no face image as well as image with multiple faces.

A. Face Alignment

In proposed system there is no substantial pose variation as it restrict with frontal poses of face images. There is some variation due to slight rotation of camera during image acquisition. So there is a need for face alignment before extracting features to make the correspondence of eyes, nose and mouth of test face to the training face. For experiment proposed system uses 20 subjects. Each subject has 20 variations from which 14 variations are taken for training and 6 variations of each subject are taken to form testing dataset. The data flow diagram of system is as shown in fig.8

B. Feature vector Generation Process

For Training Dataset:-

Convert test image into grey scale and resize it to $m \times n$ (512 x 512).

Apply Weber’s Law as describer in section II and calculate the Weber Face.

Apply LDP code and LTP code on weber face as explained in Section II and form LDP, LTP Upper and LTP Lower feature set of test image.

C. Face Recognition:-

Do steps from 1 to 4 for test image and extract LDP , LTP Upper and LTP Lower features.

Apply SURF technique for matching the test image with training data set and find the best match.

Proposed system will give name of person form training dataset who has maximum matching features with testing image. The data flow diagram of proposed system is as shown in figure 8.

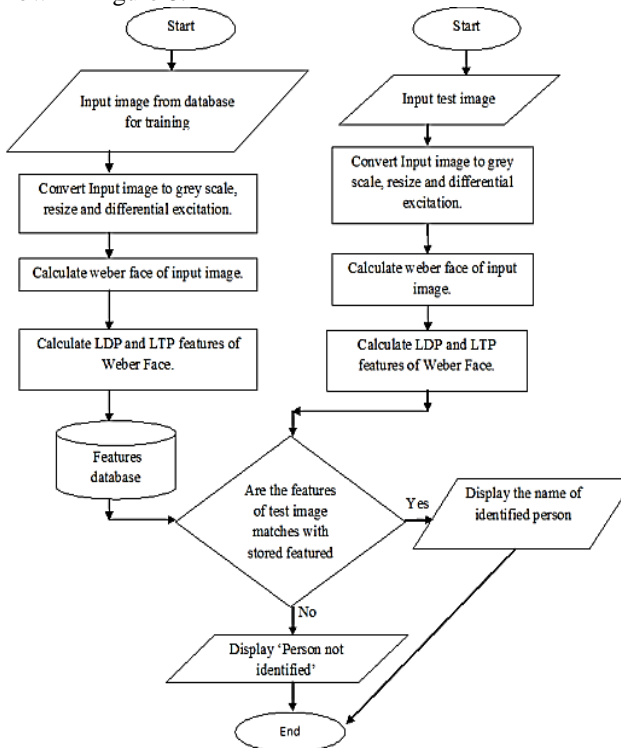


Fig. 8 Data Flow Diagram of Proposed System

IV. IMPLEMENTATION DETAILS

Proposed system implementation is done on FACE94 databases; a brief description of it is as given bellow.

A. FACE94 Database [2]

In FACE94 database subjects are positioned at a fixed distance from a camera are asked to speak sentences while a sequence of images is taken. The speaking induces variation in facial expressions. The database contains 20 images of

each person and there are 153 individuals. The size of all images in database is (180 x 200). Proposed system used sub part of database where it is tested on 400 images in which 280 images used for training and 120 images used as test dataset. Some sample images of this database are shown in Fig. 9



Fig. 9 Sample images in FACE94 database

B. Processor specification

The proposed system is installed on machine having specification as- Dell Inspiron 15, 3000 series laptop with 500GB HDD, 4GB RAM. The processor is AMD E1 6010 APU with AMD Radeon R2 Graphics, 1.35 GHz.

V. RESULTS AND DISCUSSION

Fig.10 shows the output of different steps in proposed system.

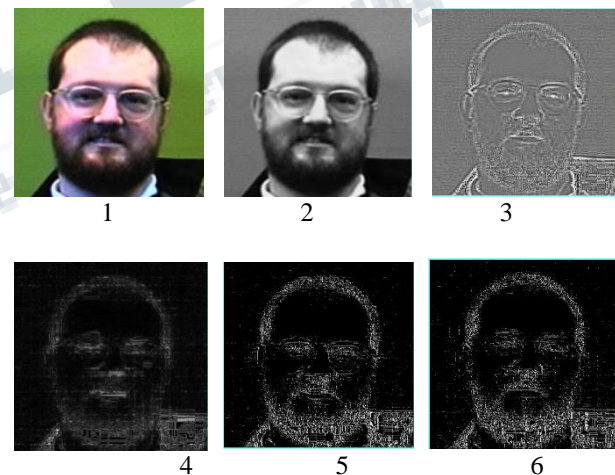


Fig.10. Result of methods implemented

1.Input colour image. 2. Grey Scale image. 3. Weber Face of input image. 4. LDP image. 5. LTP Upper image 6. LTP Lower image. As shown in Fig 10 the output of LTP Upper and LTP Lower motivates to test system with individual result of LTP Upper and LTP Lower. While during experiment system set the Alpha=3 and beta = 5 to avoid centre pixel is equal to zero while calculating Weber face of input image.

These are user defined values and gives better result in this experiment.

To form the LDP image as described in section III, system takes $k=1$ which is maximum out of $m1$ to $m7$.

During calculation of LTP Upper and LTP Lower as explained in section IV, threshold t is taken as 0.1

Table1 gives the result of testing of proposed system.

Table 1. Recognition accuracy of proposed methods.

	LDP	LTPU	LTPL
Single Image of each subject as training dataset	60%	30%	30%
14 variations of each subject in Training dataset	70%	65%	80%

VI. CONCLUSIONS

This paper has studied new way to extract the features in illumination in variation condition. It uses Weber Local Descriptor with only differential excitation and pre-processing of input image. The main contributions of this study are:

1. WLD produces better result with differential excitation than by using Gaussian Filter.
2. Without feature reduction technique, the face recognition process is time consuming. So it is necessary that either to keep input image small in size or to use feature reduction technique to produce the result in minimum time.
3. LTP with minimum threshold creates more similar outputs of LTP Upper and LTP Lower but have different performance at recognition level.
4. LTP Lower gives better performance than LTP Upper and LDP. The future scope of proposed system is to do the same experiment by concatenating the LTP Upper and LTP Lower result and use the feature reduction technique or parallel processing to speed up the recognition process.

REFERENCES

[1] Biao Wang, Weifeng Li, Wenming Yang, and Qingmin Liao, "Illumination Normalization Based on Weber's Law With Application to Face Recognition", IEEE Signal Processing Letters, Vol. 18, No. 8, August 2011.

[2] Bharat Lal Jangid, K.K. Biswas, M. Hanmandlu, Girija Chetty, "Illumination Invariant Efficient Face Recognition Using a Single Training Image", 978-1-4673-6795-0/15/\$31.00 ©2015 IEEE

[3] S. Anitha, A. Jeeva, Niveditha. R. Das, K. Yoheswari & P. Devi "Content Based Image Retrieval Using Local Tetra Pattern" International Journal of Electronics, Communication & Instrumentation Engineering Research and Development (IJEIERD) ISSN 2249-684X Vol. 3, Issue 1, Mar 2013, 219-228 © TJPRC Pvt. Ltd.

[4] Adin Ramirez Rivera, Jorge Rojas Castillo, Oksam Chae "Local Directional Number Pattern for Face Analysis: Face and Expression Recognition" IEEE Transactions on Image Processing 2012

[5] Xiaoyang Tan and Bill Triggs, "Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions", IEEE Transactions On Image Processing, Vol. 19, No. 6, June 2010,

[6] Abdullah Gubbi, Mohammad Fazle Azeem, Nishatbanu Z H Nayakwadi "Face recognition using Local Ternary Pattern and Booth's Algorithm", 2014, 3rd International Conference on Eco-friendly Computing and Communication Systems, 978-1-4799-7002-5/14 \$31.00 © 2014 IEEE

[7] Vinit.B, Akhila.M.K, Narmada Naik, Dr.Rathna.G.N, "GPU Accelerated Face Recognition system with Enhanced Local Ternary Patterns using OpenCL" 978-1-4673-6795-0/15/\$31.00 ©2015 IEEE

[8] Zhenyu, Wang, Huang Rong, Yang Wankou, and Sun Service, "An enhanced Local Ternary Patterns method for face recognition." 33rd Chinese, pp. 4636-4640. IEEE,2014.

[9] Shutao Li, Dayi Gong, Yuan Yuan "Face recognition using Weber local descriptors" S. Li et al. / Neurocomputing 122 (2013) 272–283 ,0925-2312/\$ - see front matter & 2013 Elsevier B.V. All rights reserved.

[10] Shilpa Sharma, Kumud Sachdeva, "Face Recognition using PCA and SVM with Surf Technique", International Journal of Computer Applications (0975 – 8887) Volume 129 – No.4, November2015

[11] Devani, Urvesh, Valmik B. Nikam, and B. B. Meshram. "Super-fast parallel eigenface implementation on GPU for face recognition." Parallel, Distributed and Grid face recognition increased the recognition performance of the Computing (PDGC), 2014

[12] Naik, Narmada, and G. N. Rathna. "Robust real time face recognition and tracking on gpu using fusion of rgb and depth image." arXiv preprint arXiv: 1504.01883 (2015).

[13] T. Jabid, M.H. Kabir, and O. Chae, "Facial Expression Recognition Using Local Directional Patterns", Proc. of 17th IEEE Int. Conf. on Image Processing (ICIP), 1605-1608, 2010.

[14] Jie Chen, Shiguang Shan, Chu He, Guoying Zhao, Matti Pietikainen, Xilin Chen, Wen Gao "WLD:A Robust Local Image Descriptor", IEEE transactions on pattern analysis and machine intelligence, vol. 32, no. 9, September 2010