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RESEARCH ARTICLE

Modified Shape Context for Signature Verification of Automated Cheque Authentication System

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Abstract— Every person has a unique signature hence it is considered as one of the biometrics for the purpose of authentication. Signature is an indivisible part of any bank cheque but it can be copied by skill or by mere observation. To avoid such frauds many techniques have been found till date. Research here includes shape contexts for authentication of signature on bank cheque. Shape Contexts are mostly used to verify whether 2 shapes are similar or not. Existing work on shape context requires transformation for shape alignment but this research eliminates this extra work. This paper presents a modified version of shape context for signature verification on bank cheque using K-Nearest Neighbour classifier. Proposed system also demonstrates effective performance when compared with other pattern matching technique Local Binary Pattern.

Keywords— Bank Cheque Authentication, K-NN Classifier, Offline Signature Verification, Signature Verification, Shape Contexts

I. INTRODUCTION

Signatures are critically important in society. Signatures authorize credit, debit cards, cheque transactions. Signatures also validate documents such as applications, contracts, tax etc. A Signature Verification is a biometric identification method using a person's signature characteristics (writing speed, pen pressure, shape of loops, etc.) to identify that person. Since there is an increasing number of transactions, especially related to financial and business are being authorized via signatures. Hence the need to have methods of automatic signature verification must be developed if authenticity is to be verified and guaranteed successfully on a regular basis.

Approaches to signature verification fall into two categories according to the acquisition of the data: On-line and Off-line. In online signature verification signature is written on to the hand-held device such as tablet, which is to be read and verified at the run time. In case of offline signature verification signature is written and is available on the paper it is then scanned using optical scanner to be digitally available on the computer for verification. In case of online signature verification static as well as

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dynamic features are considered but in case of offline signature verification only static features are available. Research here includes offline signature verification based on shape contexts.

Signatures on check or any other confidential document can be easily copied by observation, by practice or by skill. There are huge techniques applied by forgers to copy the original signature, thereby they can create frauds and this could be biggest financial loss to the owner of the account as well as bank. To prevent such loss an automated system is must which can keep the record of account owner's signatures at the start of opening an account and verify the signature at the time of every cheque transaction with great accuracy. Proposed system addresses this need.

II. SHAPE CONTEXTS IN SHAPE MATCHING

A. SHAPE CONTEXTS

Shape contexts were first introduced by Belongie et al. in [1]. Shape context is a feature descriptor used in object recognition. Shape context descriptor describes the coarse distribution the rest of the shape with respect to the given point on the shape. Where shape descriptor of a given point on the shape is the histogram of polar coordinates relative to all other points. For a point p_i on the shape, a coarse histogram h_i of the relative coordinates of the remaining $n - 1$ points is computed.

$$h_i(k) = \#\{q \neq p_i : (q - p_i) \in bin(k)\}$$

The figure 1 shows the shape context histogram for a point on the contour of a shape. The shape context histogram of a point p_i thus represents the distribution of relative coordinates that are distributed over a log-polar space.

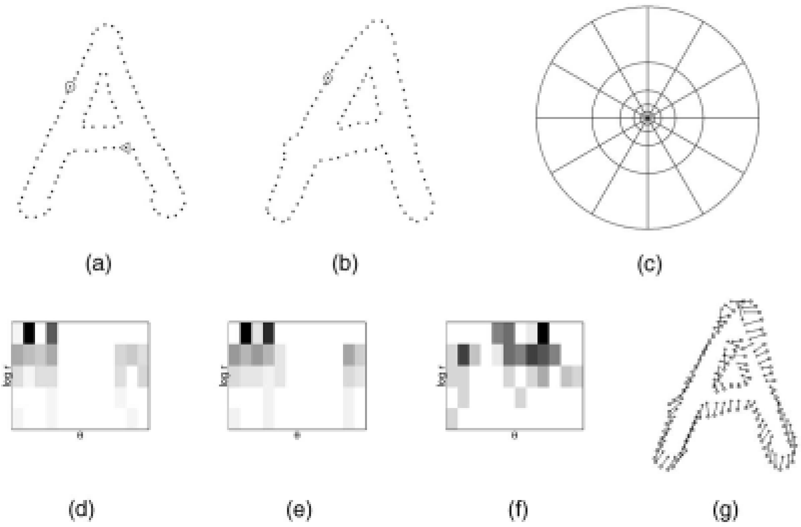

Fig1. Shape context computations and matching

(a) and (b) Sampled edge points of two shapes. (c) Diagram of log-polar histogram bins used in computing the shape contexts. Five bins used for log r and 12 bins for θ (d),(e) and (f). Each shape context is a log-polar histogram of the coordinates of the rest of the point set measured using the reference point as the origin. (g) Correspondences found using bipartite matching, with costs defined by the distance between histograms.

The shape context descriptor has the following invariance properties as mentioned in [2]

- Translation: It is inherently translation invariant because it is calculated with the help of relative point locations.
- Scaling: Normalizing the radial distances by mean distance between all point pairs helps in making scale invariant.
- Rotation: Rotation invariance is accomplished by rotation of the coordinate system at each point in such that the positive x-axis is aligned with the tangent vector.
- Shape variation: It is robust against slight shape variations.

B. EXISTING SYSTEM FOR SHAPE MATCHING WITH BASIC SHAPE CONTEXTS

Shape contexts are used to find out whether two shapes are similar or not and to recover the point of correspondences.

<u>Method Used in Shape Matching</u>

1. It is assumed that any shape contains infinite set of points on its internal or external contour. Considering this the given two shapes (known and unknown shapes) are sampled into N sample points. (possibly 100 points)

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2. For each point p_i on the shape, consider the $n - 1$ vectors obtained by connecting p_i to all other points. This set of all these vectors at this point is a shape context of p_i relative to all other co-ordinates on the shape.
3. Match each point from the known shape to a point on an unknown shape. To minimize the cost of matching, first choose a transformation (e.g. affine, thin plate spline, etc.) that warps the edges of the known shape to the unknown (essentially aligning the two shapes). Then select the point on the unknown shape that most closely corresponds to each warped point on the known shape.
4. Calculate the "shape distance" between each pair of points on the two shapes. Use a weighted sum of the shape context distance, the image appearance distance, and the bending energy (a measure of how much transformation is required to bring the two shapes into alignment).
5. To identify the unknown shape, use a nearest-neighbour classifier to compare its shape distance to shape distances of known objects.

C. LIMITATIONS OF EXISTING SYSTEM

Existing work containing basic shape context for object recognition computes the radial and angular distances with respect to all points on the shape considering one sample point randomly at a time as a reference point from the set of n sample points and the overall work has time complexity O (N^3). If this implementation would have to be used for signature verification it would also be a time consuming task. The iterative approach of fitting a thin-plate-spline (TPS) model with the matched features takes considerable amount of time to converge to the desired shape for matching purposes. That is transformation for shape matching is must in order that the shape contexts computation become useful. All these factors motivate an improved system with reduced processing time.

III.RELATED WORK

In [1] shape contexts matching approach consist of 3 stages:

1. Solving the correspondence problem between 2 shapes by shape contexts descriptor and bipartite matching method.
2. Applying the correspondences to estimate an aligning transform use thin plate spline (TPS)modeling transformation and
3. Computing the distance between the two shapes as a sum of matching errors. The distance will be estimated as weighted sum of three terms: shape context distance, image appearance distance, and bending energy. It is defined as: $D=1.6D_{ac}+D_{sc}+0.3D_{be}$

Where shape context distance is the symmetric sum of shape context matching costs over best matching points. Appearance cost is the sum of squared brightness differences in gaussian windows around corresponding image points. And bending energy is a measure of how much transformation is required to bring two shapes into alignment. This shape method had been applied to Digit recognition, Silhouette similarity-based retrieval

Two algorithms for rapid shape retrieval presented as in [3] by Greg Mori et al. as: representative shape contexts, performing comparisons based on a small number of shape contexts, and shapemes, using vector quantization in the space of shape contexts to obtain prototypical shape pieces. Authors have shown that how a shape context-based pruning approach can assist by constructing an accurate short list in order to reduce the computational expense which was greater if shape contexts were used via deformable template based framework. For this they proposed two methods of matching—one using a small number of representative shape contexts and the other based on vector quantization of shape contexts into shapemes. They also presented generalized shape contexts (GSCs), an extension to shape contexts which makes use of local tangent information at point locations.

A system for offline signature verification based on shape context descriptors using shared and user specific thresholds as in [4] presented by Marcin Adamski and Khalid Saeed. Authors have presented a system for offline signature verification based on Shape Context Descriptors. The system input is binarized images of handwritten signatures from GPDS database available for non-commercial research. During preprocessing each signature image is thinned using KMM algorithm in order to obtain 1-pixel wide skeleton. The feature vector is built from Shape Context Descriptors computed for selected points on skeletonized signature line. The verification process is based on the distance measure that uses Shape Context Descriptors.

Offline signature identification and verification using noniterative shape context algorithm had been presented in [5] by Adamski M., Saeed K. The system had an aim to recognize offline handwritten signatures using only one reference sample per person. Authors presented experimental results on offline signature identification and verification. At the first stage of the presented system, the binary image of the signature undergoes skeletonization process using KMM algorithm to have a thinned, one pixel-wide line, to which a further reduction is applied. For each thinned signature image a fixed number of points comprising the skeleton line are selected. The recognition process is based on comparing the reference signatures with the questioned samples using distance measure computed by means of Shape Context algorithm.

A method for fast shape context matching using indexing proposed in [6] by Chien_Chou Lin and Chun-Ting Chang. Authors have presented an efficient 2D shape matching algorithm. This algorithm uses the mean distances and standard deviations of shape contexts as the index of shapes to reduce the search space of the previous work on shape matching with

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shape context descriptor. The best-fit ellipse modelling is adopted as the preprocessing for normalizing its scale. The simulation databases include human body postures and shapes of 3D objects from MPEG-7 silhouettes, and the COIL data set, respectively. Experimental results show that the recognition rates are 98% for human body postures and 100% for shapes of 3D objects.

Ling, Haibin, and David W. Jacobs [7] proposed a method using the inner-distance to build shape descriptors that are robust to articulation and capture part structure. They proposed three approaches to using the inner-distance. The first method combines the inner-distance and multidimensional scaling (MDS) to build articulation invariant signatures for articulated shapes. The second method uses the inner-distance to build a new shape descriptor based on shape contexts. The third one extends the second one by considering the texture information along shortest paths. These approaches have been tested on a variety of shape databases including articulated shape dataset, MPEG7 CE-Shape-1, Kimia silhouettes, the ETH-80 data set, two leaf data sets, and a human motion silhouette dataset.

IV. PROPOSED SYSTEM

A. OBJECTIVE

In this work a feature-based method using shape context descriptor is proposed. A shape context is calculated for each sample point with respect to centroid of the signature relative to n (possibly 100) sample points on the contour of the signature considering centroid as a reference point. This method will be applied to both test signature and template signatures from the database and then compute shape context distance between test signature and template signatures. This method will reduce the number of matching candidates and processing time. The main objective is to apply this method for signature verification on cheque and analyse its accuracy of classification with one of the existing methods used for signature verification as Local Binary Pattern.

B. SYSTEM REQUIREMENTS

Hardware Requirements

- **System:** intel core i_5-i_7 processor
- **OS:** Windows 7 Home Basic
- **Ram:** 4 GB
- **Disk space:** 40 GB

Software Requirements

- **Software:** MATLAB

Database Requirement

To run the system for cheque authentication, a signature database is must which contain original signatures of account owner at the time of account opening. Few real cheques are used as an input to test the proposed method. Original signatures from an account owner are kept in signature database. Cheques signed by account owners are kept in cheque database and are used as an input to the system to verify against signature database.

V. SYSTEM IMPLEMENTATION

System implementation is done for proposed method Modified Shape Context for signature verification on bank cheques. An existing method LBP is also implemented to compare the performance of proposed method. Figure 2 gives complete GUI for project. Figure 3 gives scanned cheque available in cheque dataset selected as input. Signature cropped from cheque for further verification is as in figure 4.

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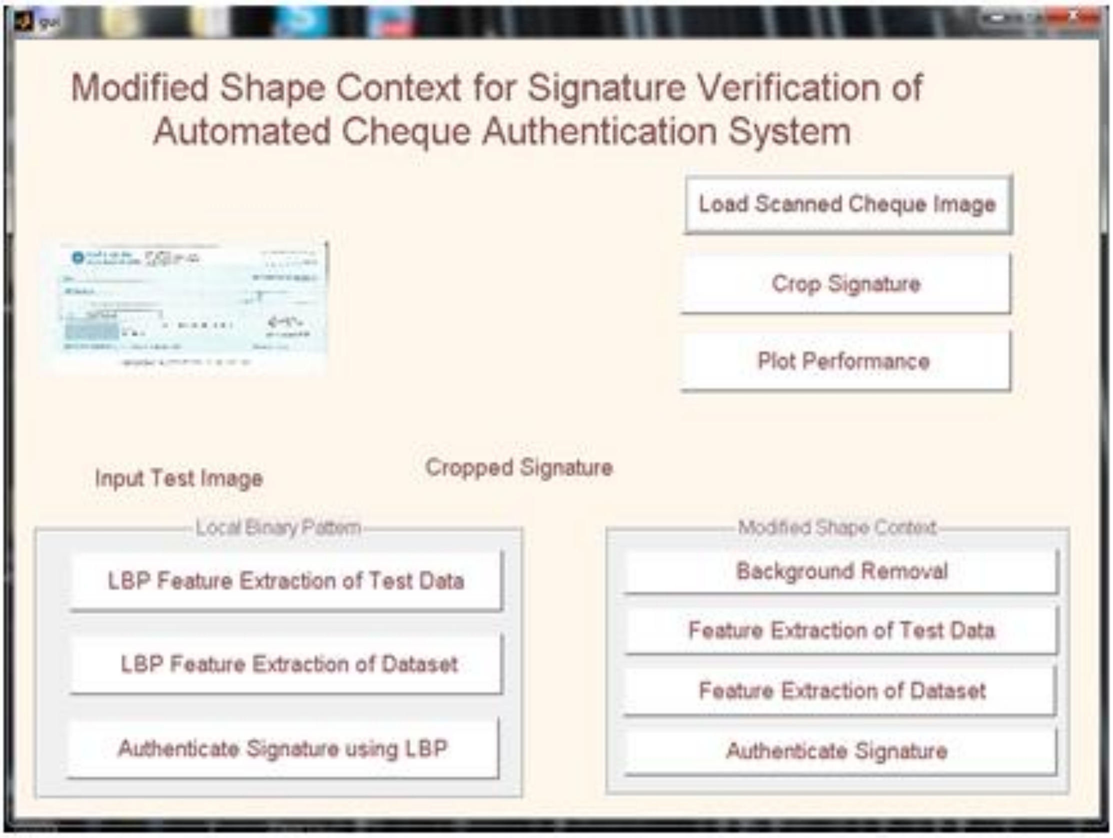

Fig. 2 Load Scanned Cheque Image

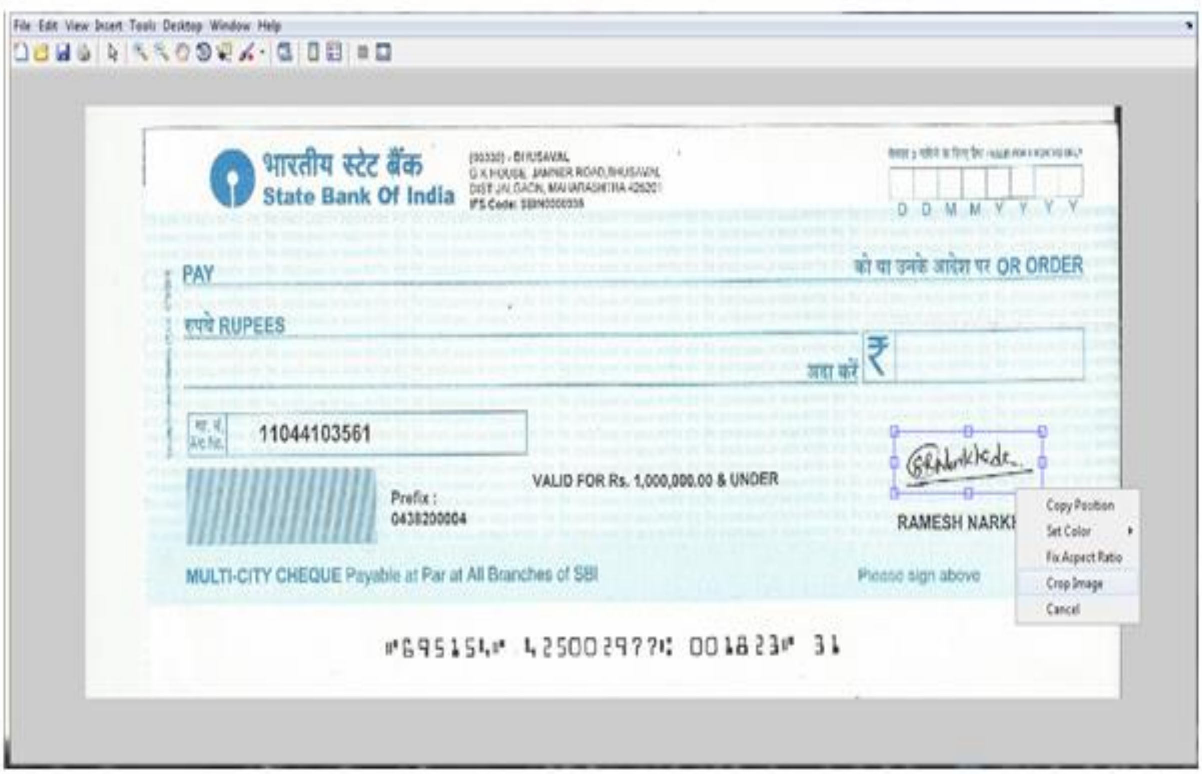

Fig. 3 Scanned Cheque from Cheque Dataset Selected as Input

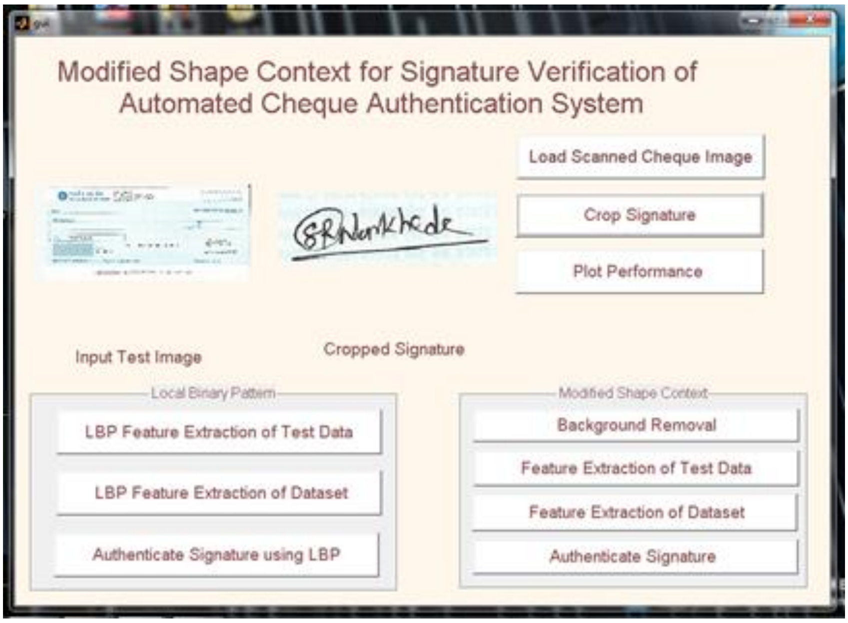

Fig. 4 Cropped Signature from Scanned Cheque

A. *LOCAL BINARY PATTERN FOR CHEQUE AUTHENTICATION*

A local binary pattern (LBP) is a type of feature used for classification in computer vision. In the basic LBP method, a gray scale image is processed such that a binary code is generated for each pixel in the image. This code encodes whether the intensities of the neighboring pixels are greater or less than the current pixel's intensity. So, for instance in a 3x3 neighborhood with the current pixel being center, a binary code of length 8 is generated consisting of 0s and 1s, according to the relative intensities of the neighbors. A histogram is then computed to count the number of occurrences of each binary code, describing the proportion of common textual patterns. LBP feature extraction gives local binary patterns from cropped signature and reference signatures. Verification is done using chi-square distance method. Figure 5 gives result of verification of cropped signature from sample cheque as in figure 4 using LBP.

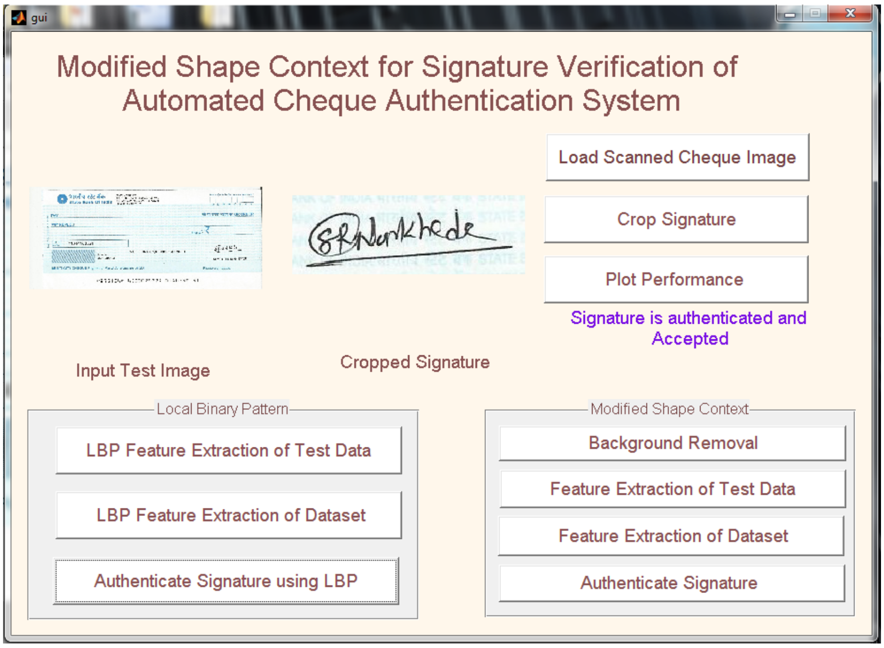

Fig. 5 Authentication Result Using LBP

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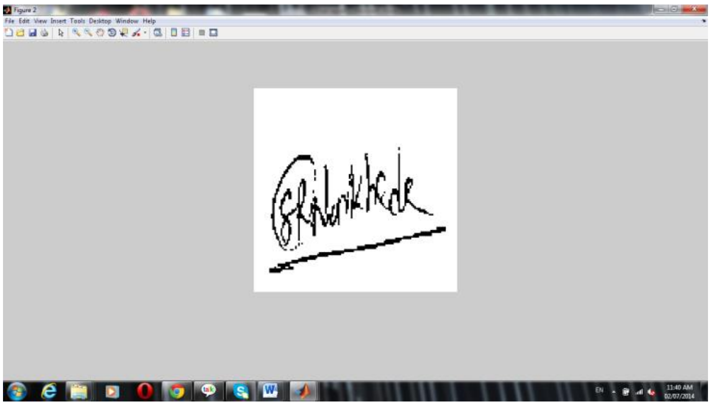
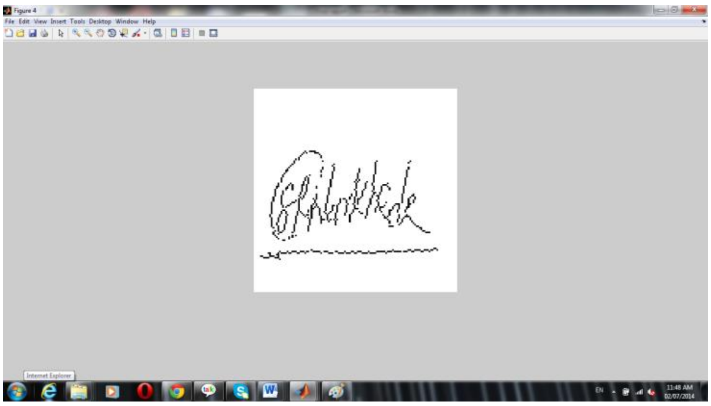
B. MODIFIED SHAPE CONTEXT FOR CHEQUE AUTHENTICATION:

1. Select Background Removal that is normalization is done to the cropped signature as resizing, thinning, rotating as in fig.6 a), b), c) respectively.



a) Resising

b) Thinning



c) Rotating

Fig. 6 Background Removal a)Resizing, b)Thining, c)Rotating

2. Apply feature extraction for cropped signature. Here, that is calculating centroid of the signature. That is x and y coordinates of the centroid of input signature image is calculated as in figure 7. Shape context is also calculated for each sample boundary point considering centroid as a reference point.

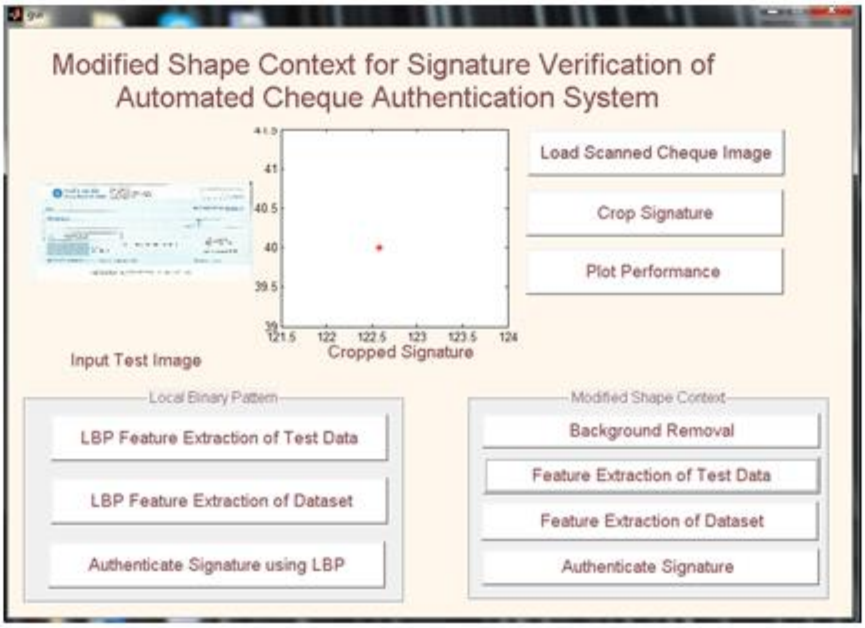


Fig. 7 Feature Extraction of Cropped Signature

3. In feature extraction of dataset first same normalization operations are performed as with cropped signature. Centroid of each reference signature in dataset is calculated. Shape context calculated for each sample point with respect to centroid.

4. Shape distance between each pair of points on two shapes (test signature and template signature) is calculated as a weighted sum of shape context distance and image appearance distance. To identify the test signature, K-Nearest-Neighbours classifier is used to compare its shape distance to shape distances of template signatures. If the shape distance difference <= threshold, the cost matrix for computing shape contexts is calculated in MATLAB and minimum cost is found out as a similarity measure. The output will be either test signature is authenticated and accepted or test signature is not authenticated and accepted depending on the input as in figure 8.

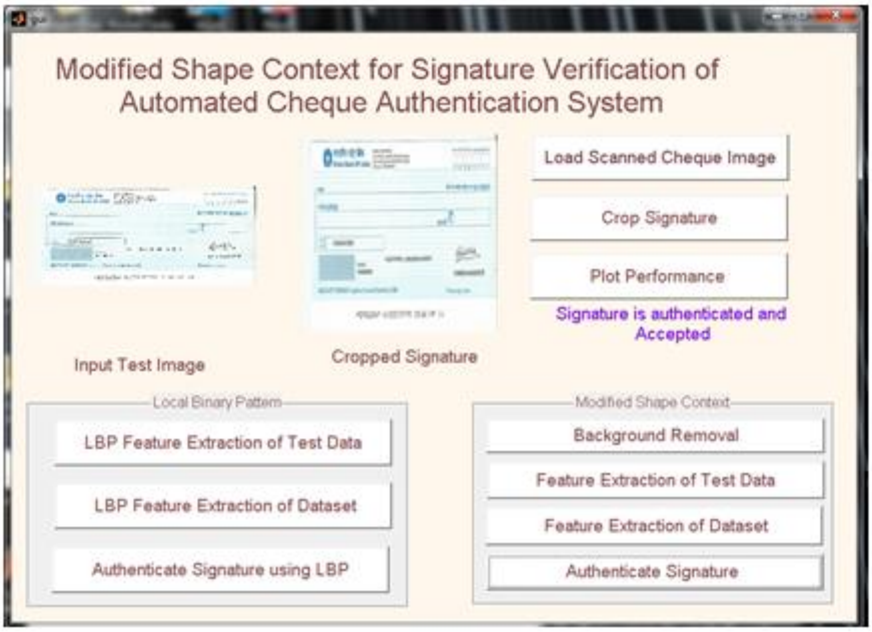


Fig. 8 Authentication Result Using Modified Shape Context

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VI. Performance Analysis

Sample dataset containing scanned cheques were passed as input to the system. For authentication of cropped signature on cheque dataset containing reference signatures used. Table I gives details of verification result for LBP and Modified Shape Context. Out of 5 sample cheques 2 cheques were authenticated by LBP and 3 cheques were authenticated by Modified shape context. Overall accuracy of LBP as per these readings is 60% and overall accuracy of Modified Shape Context is 80% as plotted in bar chart of figure 9.

Table I
Performance Analysis Results

Sample cheques from cheque dataset	Reference signature availability in signature dataset	Verification Result Using LBP	Verification Result Using Modified SC
1	YES	Authenticated	Authenticated
2	NO	Not Authenticated	Not Authenticated
3	YES	Authenticated	Authenticated
4	YES	Not Authenticated	Not Authenticated
5	YES	Not Authenticated	Authenticated

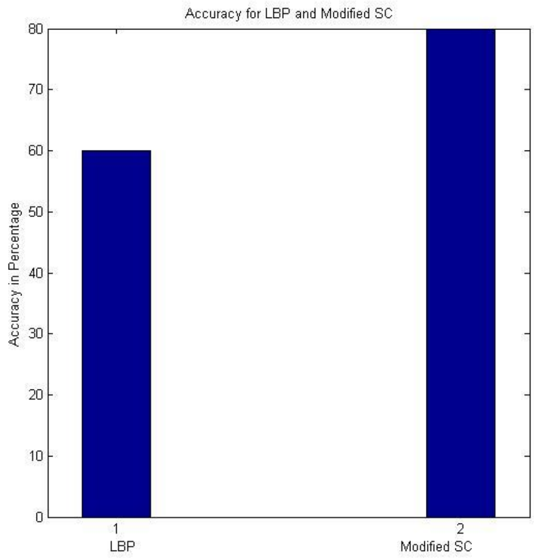

Fig. 9 Performance Plot of Modified Shape Context and LBP

VII. Conclusion and Future Work

A robust offline signature verification system based on modified shape context is proposed. Performance analysis results show that proposed system performance is greater than one of the existing systems for signature verification on bank cheque as Local Binary Pattern. Modified version of shape context proposed here does not need transformation for shape alignment since all the calculations are done with respect to centroid. This eliminates the extra work required in transformation. Therefore total processing time is reduced as compared to basic shape contexts used for object recognition. This system will prove to be very useful in banking for cheque authentication. Future work includes collection of larger database. Some other geometric features can also be extracted to increase accuracy of the system.

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