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Offline Bank Cheque Signature Verification: Review

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Abstract - In today's era, signatures are the most widely accepted form of biometric identity verification. Signature verification is a widely and commonly accepted tradition for authentication of an individual. Intensive research has been done on offline bank cheque signature verification. Recently, the signature recognition schemes are growing in the world of security technology. Hand written Signature of an individual is also unique and for identification of humans are being used and accepted specially in the banking and other financial transactions. Signatures provide a safe means of verification and authorization in authorized documents. The extraordinary dispersion of the internet in our daily life as well as growing need of personal verification in many daily applications, signature verification systems for authorization and authentication have become enormously important in every sector due to increasing concerns for security. This paper presents some of the most relevant advances in the field of offline signature verification and highlights some directions for further research.

Index Terms—Image Acquisition; Preprocessing; Signature Verification; FAR(false acceptence rate); FRR(false rejection rate); Forgery .

I. INTRODUCTION

Handwritten Signatures are one of the most commonly used behavioral biometrics for personal identification and Verification. Even with the introduction of new technologies handwritten signature is continuously used as a means of communication in day to day life like, in a formal agreements, financial systems, government use, marketing documents or paintings etc. The signature is a behavioural biometrics, and is therefore inherently reliant on the changing activity pattern of the signer and the signing process [1]. Offline bank cheque verification system is developed for make easy transaction in banks. Signatures are a special case of hand writing in which special characters and flourishes are available. In many cases, the signature is not readable even by a human. Signature is a behavioural biometric. It is not based on physiological properties of the human being, such as fingerprint or face, but behavioural ones. As such one's signature may change over time and it is not nearly as unique or difficult to forge as iris patterns or fingerprints. However signature's pervasive acceptance by the public makes it more appropriate for certain lower-security authentication needs. Signature has a fundamental advantage in that it is the customary way of identifying an individual in daily operations such as automated banking transactions and electronic fund transfers. Signature analysis can only be applied when the person is/was conscious and disposed to write in the usual manner. To give a counter example, a person's fingerprint may also be used when the person is in an unconscious state of mind. Signatures are a behavioural biometric that change over a period of time and are influenced by physical and emotional conditions of the signatories [2].

Signature of a individual may vary according to his mood, health etc. Even the genuine signer may not imitate his own signature as it is, some minor change will be there. Hence, it is difficult to make a distinction that whether signature is genuine or forged one. A person's signature often changes depending on some rudiments such as mood, fatigue, time etc. as an image because a person may use any symbol, line, curve & letter or group of letters. So to make ensure that the signature is real or forged we make signature verification system.

Signature verification is classify into two categories:
1. Offline signature verification: Offline properties of signature is deal with only structural characteristics. The off-line mode allows generating a handwriting static image from a scanning document and used for analysis.

Fig. 1 Offline Signature

Fig. 2 Online Signature

2. Online signature verification: Online features represent the structural as well as behavioral characteristics of a signature such as total time taken by the signer to sign, the pressure applied on the pen tip, the acceleration, the pen

tip angle etc. Signature system acquiring data directly from user through stylus, touch screen, or a digitizer that can generate dynamic values, such as coordinate values, time, or speed of signature.

Table 1 Online and Offline verification

No.	Offline verification	Online verification
1	Input data from scanned the signature	Input data obtain through stylus, digitizer or touch screen
2	Having a lot of noise	Zero noise
3	Information obtained slightly	Information obtained by varying
4	The verification process is fast	The verification process is very fast
5	Fairly high degree of accuracy	Very high degree of accuracy

II. BASIC TERMS

A.) Forgery: A signature forgery means an attempt to copy someone else's signature and use them against him to steal his identity there can be basically three types of forgeries:

1. Random Forgery:

The forger doesn't have the shape of the writer signature but comes up with a draw of his own. He may derive this from the writer's name. This forgery accounts for majority of forgery cases though it's easy to detect with naked eyes.

2. Simple Forgery:

The forger knows the writers signature shape and tries to imitate it without much practice.

3. Skilled Forgery:

This is where the forger has unrestricted access to genuine signature model and comes up with a forged sample.

B.) Error rate: A signature verification system can be checked for accuracy using the following two parameters:

1. False Acceptance Rate:

The false acceptance rate (FAR), is the measure of how many times a forged signature sample is accepted by the biometric system as genuine. A system's FAR can be typically calculated as the ratio of the number of false acceptances and the number of total attempts. FAR is known type 2 error.

2. False Rejection Rate:

The false rejection rate (FRR), is the measure of how many times a genuine signature sample is rejected by a biometric system as forged. A system's FRR can be calculated as the ratio of the number of false rejections and the number of total attempts. FRR is known as type 1 error.

Average Error Rate:

The Average Error Rate (AER) is the average of type 1 and type 2 errors.

Equal Error Rate:

The EER is the location on a ROC or Detection Error Trade-off curve where the FAR and FRR are equal. Smaller the value of EER, better is the performance of the system.

III. RELATED WORK

A lot of of research work has been done on offline signature verification system. A large number of articles and papers have been published on this topic during the last few decades. Some of papers are discussed below to understand the topic.

Shih-Yin Ooi, Andrew Beng-Jin Teoh and Thian-Song Ong [3] proposed a novel method to increase the accuracy in biometric matching which we term biometric strengthening. They reported 1.1% equal error rate (EER) over the independent database on random forgery, while casual forgery on EER 1.2% and lastly skilled forgery on EER 2.1% along the paper. This experiments show that biometric strengthening reduces the false acceptance rate (FAR) and false rejection rate (FRR) by increasing the disparity between the features of the two persons, which tends to tolerate more intrapersonal variance which can reduce the FRR without increasing the probability of false accepts.

Abhay Bansal, Divye garg and Anand Gupta [4] proposed a contour matching algorithm that tracks the basic characteristic patterns in a sample signature and verifies it. It capitalizes on the geometrical properties of the signature and takes into account the inevitable intrapersonal variations for the user set A. The system is trained with 8 original signatures and given a test sample; verification is done by a triangle matching algorithm that validates a signature on the basis of the relative position of the critical points. FAR in case of Random Forgery was found to be 0.08% and in case of Simple and Skilled forgery it was 13.02%. FRR was 2.64%.

Ioana Barbantan, Camelia Vidrighin and Raluca Borca [5] presents a new offline signature verification system, which considers a new combination of previously used features and introduces two new distance-based ones. A new feature grouping is presented. They experimented with two classification methods and two feature selection techniques. The best performance so far was obtained with the Naive Bayes classifier on the reduced feature set. The best classification accuracy is obtained when using Naive Bayes as classifier, 91.40%. A mean classification accuracy of 84.79% is obtained.

Muhammad Reza Pourshahabi, Mohammad Hoseyn Sigari and Hamid Reza Pourreza [6] proposed contourlet transform method. Contourlet transform (CT) is used as feature extractor in proposed system. Signature image is enhanced by removing noise and then it is normalized by size. After preprocessing stage, by applying a special type of Contourlet transform on signature image, related Contourlet coefficients are computed and feature vector is created. Euclidean distance is used as classifier.

Mustufa Berkay Yilmaz, Berrin Yanikoglu, Caglar Tirkaz and Alisher Kholmatov [7] present an offline signature verification system based on a signature's local histogram features. The signature is divided into zones using both the Cartesian and polar coordinate systems and two different histogram features are calculated for each zone: histogram of oriented gradients (HOG) and histogram of local binary patterns (LBP) . The classification is peiformed using Support Vector Machines (SVMs), where two different approaches for training are investigated, namely global and user-dependent SVMs. The fusion of all classifiers (global and user-dependent classifiers trained with each feature type), achieves a 15.41% equal error rate in skilled forgery test, in the GPDS-160 signature database without using any skilled forgeries in training.

Srikanta Pal, Alaei Alireza, Umapada Pal and Micheal Blumenstien [8] proposed a technique for a bi-script off-line signature identification system is proposed. In the proposed signature identification system, the signatures of English and Bengali (Bangla) are considered for the identification process. Different features such as undersampled bitmaps, modified chain-code direction features and gradient features computed from both background and foreground components are employed for this purpose. Support Vector Machines and Nearest Neighbour techniques are considered as classifiers for signature identification in the proposed system.

Vu Nguyen and Micheal Blumenstien [9] investigate the performance of a small feature set consisting of 33 feature values. In the experiments using Support Vector Machines (SVMs), an average error rate (AER) of 16.80% was obtained together with a low false acceptance rate (FAR) for random forgeries of 0.19%.

M.K. Sharma and V.S. Dhaka [10] have proposed a segmentation technique for words and characters. The proposed Pixel Plot and Trace and Re-plot and Retrace (PPTRPRT) technique extracts text region from text scripts and lead iterative processes for segmentation of text lines along with skew and de-skew operations. The outcomes of iterations are used in pixel-space-based word segmentation, and the segmented words are used in segmentation of characters. Investigational outcome shows that the proposed techniqueis competent to segment characters from text scripts, and accuracy of outcomes is up to 99.578 %.

M.K. Sharma and V.S. Dhaka [11] have proposed a recognition technique for words and characters. In this three classifiers namely GADNT, GANNT and GNDT, with the storage constraints are proposed for image classification. The proposed GADNT is able to design the proper number of child nodes of each decision node in the GDT according to the classification error rate and computing complexity of GDT. In GNT, the GANNT is proposed to search for the proper number of hidden and output nodes in the neural network according to the classification error rate and computing complexity of GNT.

M.K. Sharma and V.S. Dhaka [12] have proposed a segmentation technique for words and characters. The PPTRPRT is a new technique for reconstructing the bilingual offline handwritten cursive scripts and will give a concrete base to design an OCR with optimum correctness and bottommost cost. The proposed PPTRPRT framework gives best segmentation outcomes up to 99.78 % using FFNN as a classifier, and the size of dataset was 68,000.

M.K. Sharma and V.S. Dhaka [13] have proposed a segmentation technique for cursive script. That research work presents a realistic technique for character segmentation of English offline handwritten cursive scripts using a FFNN. The PPTRPRT technique is a new technique for reconstructing English offline handwritten cursive and is driving the results by keeping an approach between under-segmentation and over-segmentation. The technique will provide a concrete basis by which design of an optical character reader with fine accuracy and low cost will be achieved.

Douglas J. Kennard, William A. Barrett and Thomas W. Sederberg [14] present a method of discriminating between authentic and forged signatures using 2-D geometric warping. After an initial coarse-alignment step, they use an automatic morphing correspondence algorithm to compute

2-D geometric warps that align the strokes of a questioned signature with those of known reference examples. They use distance maps to compute a difference metric, and then either accept the signature as genuine or reject it as a forgery depending on how different it is from the reference examples.

This method achieves equal error rate (EER) accuracies of about 94%–96% on our English dataset of blind forgeries and 87%–91% on casual forgeries.

IV. METHODOLOGY

In Offline signature verification a general methodology is follows. These are the general steps involved in signature verification system [15].

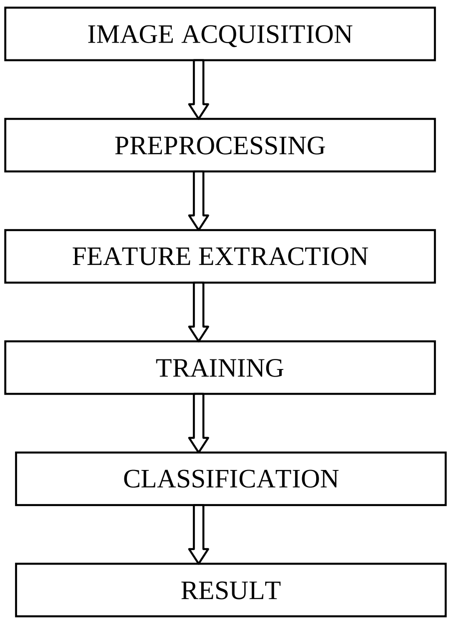

Fig.3. General streps in offline signature verification

1. Image Acquisition: The process of selecting the image and giving to the system as input is called image acquisition. Signatures can be captured by a camera or it can be scanned by a scanner. Camera uses MegaPixels (MP) format and scanner uses Dots per inches (DPI) format and so scanning the signature by using a scanner will give more accurate results [16]. The scanner helps to digitize, analyze and process an image. The output of a scanner is an uncompressed image. The scanner has to be placed in a suitable environment with computer connectivity. The Scanned signature is treated

as a pixel distribution of a particular person. It is considered as a single digital image as one cannot split individual characters in a signature. Image scanned should have a good quality resolution. The background of the signature will be different for each bank cheque and also there should not be any fold marks on the signature. The use of rubber stamps should not overshadow the clear appearance of the signature. The scanned image should have all the portions of the cheque.

2. Image Pre-processing: The purpose of pre-processing phase is to make signatures standard and ready for feature extraction. The pre-processing stage primarily involves some of the following steps:

1) Noise reduction: A noise filter is a normalization that applied to remove the noise caused during scanning and improves the quality of document.

2) Resizing: The image is cropped. Then zoom in or zoom out, to the bounding rectangle of the signature

3) Binarization: it is the process of transformation from color to grayscale and then converts to binary image.

4) Thinning: The goal of thinning is to eliminate the thickness differences of pen by making the image one pixel thick. The aim of this is to reduce the character features to help in feature extraction and classification.

5) Clutter Removal: Any unconnected black dots are removed before processing and this is done by masking.

6) Skeletonization: Skeletonization is used to remove selected foreground pixels from the binary image. So the outcome is a representation of a signature pattern by a collection of thin arcs and curves.

3. Feature Extraction: After the pre-processing steps, feature extraction is performed to collect similar unique properties of a signature. Various methods are available for creating features from the signature image. Features extracted for off-line handwritten signature verification can be broadly divided into three main categories:

1) Global features– The signature is viewed as a whole and features are extracted from all the pixels confining the signature image. Based on the style of the signature, different types of Global features are extracted. Signature area (Signature Occupancy Ratio), Signature height-to-width ratio, Maximum horizontal histogram and maximum vertical histogram, Image area, Edge point numbers of the signature, Signature height, Horizontal and vertical center of the signature Image area, Pure width, Pure height, Vertical projection peaks, Horizontal projection peaks Number of closed loops Local slant angle Number of edge points Number of cross points Global slant angle Baseline shift.

2) Local features – Local features are extracted from a portion or a limited area of the signature image. It applied to the cells of a grid virtually super imposed on a signature image or to particular elements obtained after signature

segmentation. These features are calculated to describe the geometrical and topological characteristics of local segments. These features are generally derived from the distribution of pixels of a signature, like local pixel density or slant.

3) Geometric features– These features describe the characteristic geometry and topology of a signature and preserve their global as well as local properties. Geometrical features have the ability to tolerate with distortion, style variations, rotation variations and certain degree of translation.

4. Classification: The classification stage is the decision making part of the recognition system. The performance of a classifier relies on the quality of the features. There are many existing Classical and soft computing techniques for handwriting identification. They are given as:

1) Classical Techniques:

i) Template matching

ii) Statistical techniques

iii) Structural techniques

2) Soft Computing Techniques:

i) Neural networks (NNs)

ii) Fuzzy- logic technique

iii) Evolutionary computing techniques

V. COMPARATIVE ANALYSIS

In this section we studied various techniques used in offline signature verification.

Javed Ahmad Mahar, Mohammad Khalid Khan, Mumtaz Hussain Mahar [17] proposed a mechanism that automates the offline signature verification for bank cheques even with different background colors. Work present in this paper is focused, to examine whether an input signature of colored bank cheque is a genuine signature or a forged. This task is performed by comparing the collected signature samples (white background) with input signatures (colored background). The Signature Verification of Colored Cheques (SVCC) system of verifying the signatures having different background colors in spite of white paper specimens through variation of color intensity is discussed andpresented. In this paper a powerful mechanism has been proposed in which a complete automatic offline signature verification system has been design. This system is capable of verifying the image of handwritten signature that is captured from the bank cheques that are often in colored paper. The SVCC system has been discussed and presented for the above purpose. The simple features were compared and implemented to confirm the performance of feature extraction methods; K-NN classifier is also used. The test accuracies achieved through grid feature method were 92.7%, the test accuracies got through global feature method are 89.8% and the test accuracies achieved through texture feature method are 96.9%.

RamachandraA C, Jyoti Srinivasa Rao, K B Raja, K R Venugopala, L M Patnaik [18] propose a Robust Off-line Signature Verification Based on Global Features (ROSVGF) for skilled and random forgeries. In this model prior to extracting the features, they pre-processed the signatures in the database. Pre-processing consists of i) Normalization ii) Noise reduction iii) Thinning and Skeletisation, for feature set extraction which consists of global features such as signature height-to-width ratio (Aspect ratio), Maximum Horizontal Histogram and Maximum Vertical Histogram, Horizontal center and Vertical canter of the signature, End points of the signature, Signature area. It is observed that their proposed model gives the better Type I and Type II errors compared to existing models. For experiment 21 persons are considered, and for each person 15 genuine signatures are taken at different timing and 10 skilled forgery samples are taken for each person. The data base has 315 genuine samples and 210 skilled forgery samples. For each sample features are extracted and based on Euclidian-distance validation done.

Vu Nguaen, Yumiko Kawazoey, Tetsushi Wakabayashiy, Umapada Palz, and Michael Blumenstein [19] proposed the performance of two feature extraction techniques, the Modified Direction Feature (MDF) and the gradient feature are compared on the basis of similar experimental settings. In addition, the performance of Support Vector Machines (SVMs) and the squared Mahalanobis distance classifier employing the Gradient Feature are also compared and reported. Without using forgeries for training, experimental results indicated that an average error rate as low as 15.03% could be obtained using the gradient feature and SVMs. In this work, two comparisons have been made. The first one is the performance of two feature extraction techniques, the gradient feature and the Modified Direction Feature. The second one is the performance of the Support Vector Machine and the squared Mahalanobis distance classifiers in conjunction with the gradient feature. Working together, the gradient feature and the SVM produced the best AER of 15.03% which is 2.22% better than the AER of the MDF.

K V Laxmi, Seema nayak [20] proposes a signature verification system that can authenticate a signature to avoid forgery cases. In the real world environment, it is often very difficult for any verification system to handle a huge collection of data, and to detect the genuine signatures with relatively good accuracy. Consequently, some artificial intelligence technique are used that can learn from the huge data set, in its training phase and can respond accurately, in its application phase without consuming much storage memory space and computational time. In addition, it should also have the ability to continuously update its knowledge from real time experiences. One such adaptive machine learning technique called a Multi-Layered Neural Network Model (NN Model) is implemented for the purpose of this work. Initially, a huge set of data is generated by collecting the images of several genuine and forgery signatures. The quality of the images is improved by using image processing followed by further extracting certain unique standard statistical features in its feature extraction phase. This output is given as the input to the above proposed NN Model to further improve its decision making capabilities. The performance of the proposed model is evaluated by calculating the fault acceptance and rejection rates for a small set of data.

TABLE 2 COMPARATIVE ANALYSIS OF DIFFERENT TECHNIQUES

S. No.	Author	Method	Classifier	FRR(%)	FAR(%)
1.	Javed Ahmad Mahar, Mohammad Khalid Khan, Mumtaz Hussain Mahar[17]	Different Background color	K-Nearest neighbour	3.73	2.83
2.	RamachandraA C, Jyoti Srinivasa Rao, K B Raja, K R Venugopala, L M Patnaik [18]	ROSVGF	K-Nearest neighbour	5.4	4.6
3.	Vu Nguaen, Yumiko Kawazoey, Tetsushi Wakabayashiy, Umapada Palz, and Michael Blumenstein [19]	Gradient feature	Squared Mahalanobis distance	18.63	14.80
			SVM	16.54	13.51
4.	K V Laxmi, Seema nayak[20]	Machine Learning	Multilayer NN	8.0	12.0
5.	K. N. Pushpalatha, A K Gautam [21]	Direction and Textural	Feed Forward Back Propagation ANN	4.90	9.34
6..	Vahid Malekian, Alireza Aghaei, Mahdie Rezaeian, Mahmood Alian [22]	Signature envelop and adaptive density partioning	ANN	4.0	5.3
7.	M. D. Iqbal Quraishi, Arindam Das, Saikat Roy [23]	Image Transformation	FFNN	2.56	5.28
8.	Yasmin serdouk, Hassiba Nemmour and Youcef Chibani [24]	Textural and Topological features	AIRS	3.18	2.04

K. N. Pushpalatha, A K Gautam [21] propose offline signature verification based on Transform domain feature such as gradient, coherence and dominant local orientation. The acquired image is resized to bring all the signatures into a uniform size. The images are thinned using morphological process. The DWT technique is applied on signature images to get LL, LH, HL and HH subbands. The directional information feature is computed from the subbands. The directional features and textural features are concatenated to form the feature vector. The Feed Forward ANN tool in MA TLAB is used for classification and verification. The results of False Rejection Rate (FAR), False Acceptance Rate (FAR) and Total Success Rate (TSR) are obtained for GPDS-960 database. A total of 360 images are used for training and testing. It is observed that the values of FRR, FAR and TSR are improved compared to the existing algorithms. In this paper offline signature verification based on Transform domain feature such as gradient, coherence and dominant local orientation and Textural features like correlation, energy, homogeneity and contrast is presented. The necessary pre-processing techniques such as resizing, filtering and thinning using morphological process are applied on the signatures. The Feed Forward Back Propagation Neural Network is used for classification and tested for 360 samples with accuracy 88.34%. The results of False Rejection Rate (FAR) and False Acceptance Rate (FAR) are obtained for GPDS-960 database.

Vahid Malekian, Alireza Aghaei, Mahdie Rezaeian, Mahmood Alian [22] purposed a novel method for extracting easily computed rotation and scale invariant features for offline signature verification. These features are extracted using the signature envelope and adaptive density partitioning. The effectiveness of the proposed features has been investigated over 900 signatures using a neural network classifier. The experimental results show the verification accuracy rate of 90.7%. Among 150 genuine signatures, from 45 different persons, presented to the network 144 signatures were classified as genuine and 6 signatures as forgeries. Thus FRR of the system is 4.0%. Out of the 150 forged signatures tested with the network, 8 signatures were classified as genuine and142 as forgeries. Thus FAR of the system is 5.3%.

M. D. Iqbal Quraishi, Arindam Das, Saikat Roy [23] proposed an Artificial Neural Network based approach for implementing Automatic Signature verification and authentication system. In this era, with the rapid growth of Internet and the necessity of localized verification systems, handwritten signature has become an important biometric feature for the purpose of verification and authentication. The proposed method comprises spatial and frequency domain techniques for transformation. After extracting the Region of Interest Ripplet-II Transformation, Fractal Dimension and Log Polar Transformation are carried out to extract descriptors of the concerned signature to be verified as well as authenticated. In decision making stage Feed Forward Back Propagation Neural Network is used for verification and authentication purpose. This system has been tested with large sample of signatures to show its verification accuracy and the results have been found around 96.15%. Also forgery detection rate has been found 92% which is very encouraging. False Acceptance Rate and False Rejection rate of our system has been determined 5.28% and 2.56% respectively. This approach has been compared with some existing system and it has been observed that this system shows better performance. The proposed method to automatic verify and authenticate handwritten signature using multiple image transformations like power law transformation, ripplet-II transformation, fractal dimension and log polar transformation proves to be an effective and efficient approach. Also our system shows better performance than the systems already exist.

Yasmin serdouk, Hassiba Nemmour and Youcef Chibani [24] presents a new system for off-line handwritten signature verification. Specifically, Artificial Immune Recognition System (AIRS) is employed to achieve the verification task. Also, to provide a robust signature characterization, two new features are used. The first data feature is the Orthogonal Combination of Local Binary Patterns (OC-LBP), which aims to reduce the size of LBP histogram while keeping the same efficiency. In addition, they propose a topological feature that is based on the image Longest-Run-Features (LRF). The proposed features are evaluated comparatively to the state of the art methods. The results obtained for CEDAR dataset, highlight the efficiency of the proposed system. Specifically, two new features that take advantages from the textural characterization of LBP and the topological information are used. In addition, the verification task is based on a new classifier called AIRS and performance assessment of the proposed system is carried out using CEDAR dataset. Experimental results reveal the usefulness of the AIRS signature verification, especially when it is used with topological features. Precisely, the LRF-AIRS based verification provides an AER improvement that is about 3.56% over the state of the art.

VI. CONCLUSION

Bank cheque signature verification is most important process now a days. This paper presents a brief review of the recent works on off-line signature recognition & verification. Different existing approaches are discussed . In this paper we explain various techniques of offline signature verification in tabular form. There are still many challenges in this domain which includes the signatures from the same person are similar but not identical. Person's signature often changes because of age, illness, geographic location and up to some extent the emotional state of the person. Thus there is a need to combine different classifiers with different feature vectors in future work to enhance performance.

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