Face Recognition Based on Hybridization of PPCA and SIFT Algorithm

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***Abstract*- In recent years, Face recognition has received substantial attention from both research communities and the market, but still remaining as a challenging in applications. Many face recognition algorithms, along with their medications, have been developed during the past decades. Their performances also suffer a severe degradation under variations in expressions or poses, especially when there is one gallery per subject only. The high resolution (HR) face images nowadays, some HR face database has currently been developed. In this work, a pose invariant face recognition method is presented for high resolution face verification test. A new key point descriptor, namely Pore-PCASIFT is used for extraction features from HR images. According to experimental analysis the proposed method is which is robust to alignment errors, using the HR information based on pore-scale facial features are the better then results.**

Keywords- Gabor wavelet, porescale PCA-SIFT, Eigen Faces, Eigenfaces Recognition, Eigenfaces Initialization, Feature Extraction

2. INTRODUCTION

Digital image processing technology for medical applications was inducted into the Space Foundation Space Technology Hall of Fame in 1994(Anil K. Jain, Robert P.W. Duin, and Jianchang Mao (2000)). In particular, digital image processing is the only practical technology for:

- Classification
- Feature extraction
- Multi-scale signal analysis
- Pattern recognition
- Projection

Image Processing Techniques

- Image Acquisition
- Image enhancement
- Image restoration
- Morphological Processing
- Segmentation
- Object Recognition
- Representation and description
- Image compression
- Color image processing

1.1. Eigenfaces Initialization

Step 1: Acquire an initial set of face images (the training set)

Step 2: Calculate the eigenfaces from the training set, keeping only the M images that correspond to the highest eigenvalues. These M images define the face space. As new faces are experienced, the eigenfaces can be updated or recalculated

Step 3: Calculate the corresponding distribution in M-dimensional weight space for each known individual, by projecting their face images onto the "face space."

1.2. Eigenfaces Recognition

Step 1: Calculate a set of weights based on the input image and the M eigenfaces by projecting the input image onto each of the eigenfaces. Step 2: Determine if the image is a face at all by checking to see if the image is sufficiently close to "face space."
Step 3: If it is a face, classify the weight pattern as either a known person or as unknown.
Step 4: (Optional) Update the eigenfaces and/or weight patterns.

3. METHODOLOGY

3.1. Introduction

In imaging science, image processing is processing of images using mathematical operations by using any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

3.2. System Follow Diagram

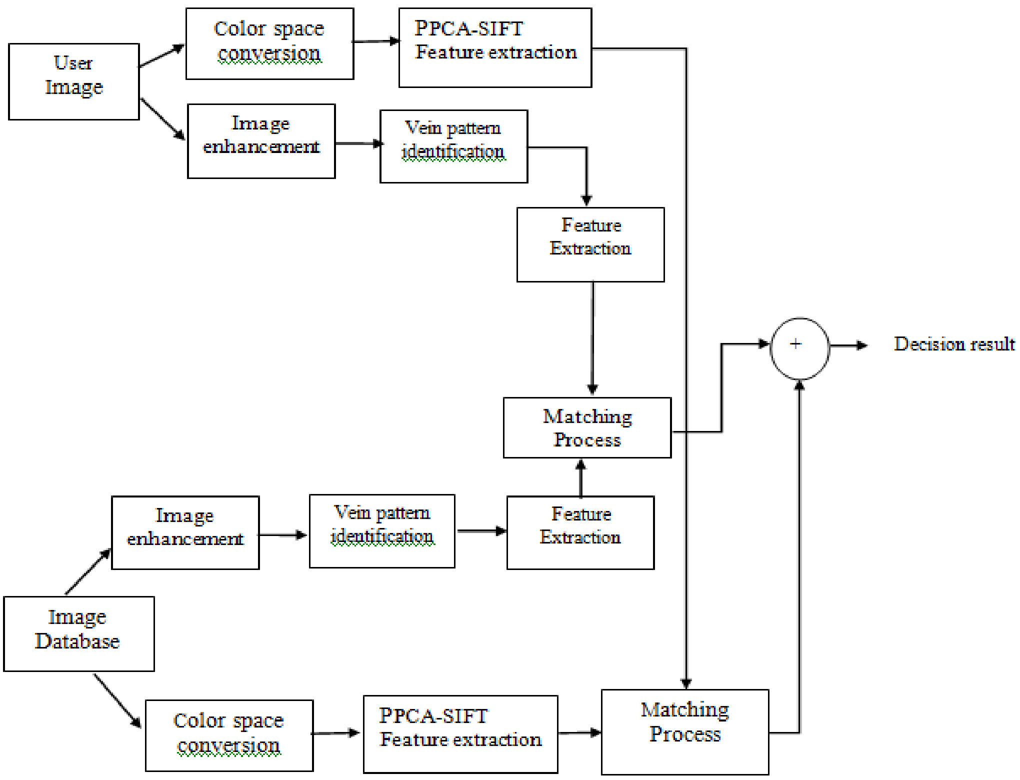

Figure 1. System follow diagram

3.3. Feature Extraction

In the result of application of the PCA algorithm an original data of image is projected into a new coordinate space. Each coordinate axis in the new coordinate space will represent a principal component vector. The first principal component vector is the direction along which the variance is a maximum; the second principal component vector is defined by the direction which maximizes the variance among all directions orthogonal to the first vector and so on. PCA algorithm includes the following steps (Prof. Y. Vijaya Lata , Chandra Kiran Bharadwaj Tungathurthi , H. Ram Mohan Rao , Dr. A. Govardhan , Dr. L. P. Reddy). The first step is the reading of the face images from the database and converting them into gray scale values. After these operations obtained 2D face images are converted into 1D image vector. The images are converted to represent each face image of dimensions NxN to single beam of dimensions N×N to single beam of dimensions N2 x1. The data are stored in the T = [T α] vector. Here α is the converted image represented in 1D, T is the vector that contains all converted images. In the second step the mean of images of T vector is calculated Equation 1:

$$m = \frac{1}{x}\sum_{i=1}^{x} T_i,\ i = 1,2,\dots\dots,X \qquad (1)$$

Where, m is a mean, X is a number of images in the database. In the third step the deviation Φi of each image from the mean image are determined Equation 2

$$\phi_i = T_i - m, i = 1,2,\dots\dots\dots,X \qquad (2)$$

In the fourth step the eigenvectors of the covariance matrix C = A×A T are calculated. Here A = [ϕ_1, ϕ_2,……,ϕ_i]. In this step it is necessary to solve the eigenvalue problem (Turk and Pentland, 1991) Equation 3

$$CU = UA \qquad (3)$$

Here Λ is a diagonal matrix that represents the eigenvalues of the matrix C and Λ = diag [λ_1, λ_2, …,λ_{NN}]. U is the associated eigenvectors of λ. These eigenvectors represent the new face space. In the fifth step a centred image vector is projected into face space Equation 4

$$\text{Temp} = U^T A\ , \quad P = [P\ \text{temp}] \qquad (4)$$

Where, P is a vector that contains all projected images. The original image vector A may be reconstructed from the projections: In the sixth step PCA features are extracted from the test images In the seventh step Euclidean distances are calculated Equation 5:

where, E is the Euclidean distance vector. In the eighth step the minimum Euclidean distance using min (x) function is computed. The corresponding index with the minimum distance is the recognized image.

$$\text{Temp} = [\text{norm}\ (\bar{P} - P(I))]^2 \qquad (5)$$

3.4. Principal Component Analysis (PCA)

The first notable and accepted descriptions of Principal Component Analysis were given in the early 20th century by Pearson and Hotelling. Originally, the purpose of deriving principal components was to reduce the number of variables while still retaining pertinent information. This is particularly useful when the number of variables can be reduced significantly to a few principal components, even if the principal components have no clear meaning. The principal components provide vectors that describe the major variation of a sample. Oftentimes, severe reduction in dimensionality alone is justification for use of principal components, and can greatly enhance computational efficiency (Chellappa R., Wilson C., and Sirohey S,1995).

One practical example of principal components is the interpretation of anatomical measurements of an animal species. Within a species, typically anatomical measurements of a large number of animals are taken and principal components are computed. Usually, the first principal component reflects the general size of the individual animal. Subsequent components could correspond to different shapes. By interpreting the first few, high variance principal components, it is hoped that major sources in variations of anatomical measurements within a species can be identified. In 1902, Macdonell conducted a study using seven anatomical measurements of 3000 criminals (Robert J. Baron 1981). The first principal component was overall size, the second contrasted the head to limb measurements, while the last related the roundness vs. thinness of the head.

Another widely used application of principal component analysis is with regard to atmospheric science.

The Principal Component Analysis is a method of projection to a subspace and is widely used in pattern recognition. An objective of PCA is the replacement of correlated vectors of large dimensions with the uncorrelated vectors of smaller dimensions. Another objective is to calculate a basis for the data set. Main advantages of the PCA are its low sensitivity to noise, the reduction of the requirements of the memory and the capacity, and the increase in the efficiency due to the operation in a space of smaller dimensions. The basis of the eigenfaces method is the Principal Component Analysis (PCA). Eigenfaces and PCA have been used by Sirovich and Kirby to represent the face images efficiently. They have started with a group of original face images, and calculated the best vector system for image compression. Then Turk and Pentland applied the Eigenfaces to face recognition problem.

In fact, principal component analysis was the leading statistical technique used between 1999 and 2000 in the International Journal of Climatology. Principal components are used in this capacity to describe trends and patterns in pressure, temperature and other atmospheric measurements. In some examples, large areas of land are mapped out in a grid, and pressure or atmospheric measurements are taken at each grid point. These observations are then analyzed with principal component analysis, whereby a few vectors describe the largest variance in atmospheric measurements. Each loading or weight of each principal component at a particular grid point can be mapped geographically, and contours can be subsequently drawn. In the field of atmospheric science, almost always the reduction in variables is significant while a large proportion of the original data variance is maintained (R. Brunelli and T. Poggio, 1993).

3.5. Scale Invariant Feature Transform (SIFT)

SIFT is a well-known method for object recognition devolved by David Lowe S. SIFT discriminate that it invariant to image scaling and rotation, and robustness for illumination and 2D camera view point. It used in many applications mainly for object recognition. Mohammad Ali apply sift method for face recognition and in 2009 Cong and Jiang apply two improvement on sift for face recognition. Sift has four step to identify the feature in the image which is a vector of 128 dimension, first step search about all scale and location using difference of Gaussian function after make blurring by Gaussian filter in image this step called scale space extreme detection and in it decide if the key point is interest or not by search for a minimum or maximum value with 26 neighbour related for any pixel (key point). Finally find key point descriptor that created from local image gradients and this feature based on orientation histogram (David G Lowe 2004).

3.6. PPCA-SIFT (PORESCALE PCA-SIFT)

When PCA-SIFT technique is combining it is used for extract the feature and reduces the dimensionality of data. PCA is a standard technique for dimensionality reduction, which is well-suited to represent the key point patches and enables us to linearly-project high-dimensional samples into a low-dimensional feature space. In other words, PCA-SIFT use PCA instead of histogram to normalize patch gradient. The feature vector will significantly smaller than the standards SIFT feature vector, and it will be used with a same matching algorithms. PCA-SIFT, like SIFT, also used Euclidean distance to determine whether the two vectors correspond to the same key point in different images. In PCA-SIFT, a input vector is created by concatenation of the horizontal and vertical gradient maps for the 41x41 patch centered to the key point(Matthew Turk and Alex Paul Pentland, 1991), which has 2x39x39=3042 elements. According to PCA-SIFT, fewer components requires less storage and will be resulting to a faster matching, and choose the dimensionality of the feature space, n = 20, which results to significant space benefits.

3.6.1.Eigen Values and Eigen Vectors

In linear algebra, the eigenvectors of a linear operator are non-zero vectors which, when operated by the operator, result in a scalar multiple of them. Scalar is then called Eigen value ( ) associated with the eigenvector (X). Eigen vector is a vector[33] that is scaled by linear transformation. It is a property of matrix. When a matrix acts on it, only the vector magnitude is changed not the direction.

AX = X, where A is a vector function.

(A   I)X = 0, where I is the identity matrix.

This is a homogeneous system of equations and form fundamental linear algebra. We know a non-trivial solution exists if and only if Det (A   I) = 0, where det denotes determinant.

When evaluated becomes a polynomial of degree n. This is called characteristic polynomial of A. If A is N by N then there are n solutions or n roots of the characteristic polynomial. Thus there are n Eigen values of A satisfying the equation. AXi = iXi , where i = 1,2, 3,.....n

If the Eigen values are all distinct, there are n associated linearly independent eigenvectors, whose directions are unique, which span an n dimensional Euclidean space.

3.6.2.Face Image Representation

Training set of m images of size N x N are represented by vectors of size N^2.

Each face is represented by 1; 2; 3;   M

Feature vector of a face is stored in a NxN matrix. Now, this two dimensional vector is changed to one dimensional vector.

3.6.3.Eigen Face Space

The Eigen vectors of the covariance matrix AA^T are AX^i which is denoted by U^i. U^i resembles facial images which look ghostly and are called Eigen faces. Eigen vectors correspond to each Eigen face in the face space and discard the faces for which Eigen values are zero thus reducing the Eigen face space to an extent. The Eigen faces are ranked according to their usefulness in characterizing the variation among the images.

A face image can be projected into this face space by $_k = U^T (_k)$; k=1,....,M, where ($_k$) is the mean centered image..

Hence projection of each image can be obtained as 1 for projection of image1 and 2 for projection of image2 and hence forth.

3.7. Recognition Step

The whole recognition process involves two steps:

a. Initialization process

b. Recognition process The Initialization process involves the following operations:

- Acquire the initial set of face images called as training set.
- Calculate the Eigenfaces from the training set, keeping only the highest Eigenvalues. These M images define the face space. As new faces are experienced, the eigenfaces can be updated or recalculated.
- Calculate distribution in this M-dimensional space for each known person by projecting his or her face images onto this face-space.

These operations can be performed from time to time whenever there is a free excess operational capacity. This data can be cached which can be used in the further steps eliminating the overhead of re-initializing, decreasing execution time thereby increasing the performance of the entire system. Having initialized the system, the next process involves the steps:

- Calculate a set of weights based on the input image and the M eigenfaces by projecting the input image onto each of the Eigenfaces.
- Determine if the image is a face at all (known or unknown) by checking to see if the image is sufficiently close to a ―free space.
- If it is a face, then classify the weight pattern as either a known person or as unknown.

Update the eigenfaces or weights as either a known or unknown, if the same unknown person face is seen several times then calculate the characteristic weight pattern and incorporate into known faces. The last step is not usually a requirement of every system and hence the steps are left optional and can be implemented as when the there is a requirement.

4. PROPOSED PCA WITH SIFT

4. 1. Pore-Principal Component Analysis-SIFT Algorithm

Recognition of human faces using PCA was first done by Turk and Pentland and reconstruction of human faces was done by Kirby and Sirovich. The recognition method, known as eigenfaces method defines a feature space which reduces the dimensionality of the original data space. This reduced data space is used for recognition. Eigen faces are based on the dimensionality reduction approach of Principal Component Analysis (PCA) (David G. Lowe 2004). The basic idea is to treat each image as a vector in a high dimensional space. Then PCA is applied to the set of images to produce a new reduced subspace that captures most of the variability between the input images. The Principal Component Vector (eigenvectors of the sample covariance matrix) is called the Eigen face. Every input image can be represented as a linear combination of these eigenfaces by projecting the image onto the new eigenfaces space. Then we can perform the identification process by matching in this reduced space. An input image is transformed into the Eigen space and the nearest face is identified using a nearest neighbour approach. Euclidean distance is used to match the input image against all images in the database. It's a statistical method that objected to reduce the dimensionality space of variables without losing of the data. PCA used in many application and from these applicant it used in face recognition, the scenario of PCA working that we get a database of faces image, build the eigen space by putting all the image into a one large image, and the mean of every face and subtract it from large image, this step called the normalization stage. Then and the covariance matrix and calculate the eigenvalues and eigenvectors from the matrix, to choose best Eigen values we should sort them in descending according the eigenvectors. Finally we make projection to Eigen space.

The Eigenfaces problem is one that aims to provide a means of facial recognition. To begin, a collection of images of human faces (library or training set) is needed. Given an input image, we would like to determine whether the image is a face, as well as if the image matches one of the images in the library. Moreover, the Eigenfaces technique relies on information theory and utilizes PCA, the method of reducing dimensionality while preserving the variance of a data set, to recognize facial features. More specifically, the principal components used in the Eigen face technique are eigenvectors of the covariance of the matrix of face images, while each face is a point in n space where n is the number of pixels in each image.

The relevant information of a face image needs to be extracted and compared to a previously defined database of face images. One convenient measure of facial image information is in the variation of the data of face images. More importantly, this variation will avoid predisposition towards focusing on facial features. We will be seeking the principle components of the face image distribution in the library or training set of face images (recall that this was shown to be the eigenvectors of the covariance matrix of the set of data).The largest Eigen values and corresponding eigenvectors (Eigenfaces) will account for the most variation in the dataset. These vectors characterize the features that describe the variation between the face images, and each face image in the set can be represented as a linear combination of all the eigenvectors.

As previously explained, to implement PCA to facial recognition techniques, images need to be represented as random vectors. Suppose that the library of images (i.e.) set of face images to which an input image will be attempted to be matched consists of M images, and that each image is represented as an i x j matrix of pixels values. Now let n = ij. The first step is to transform the M images into column vectors of length n. Consider an arbitrary image from the total M-sized collection, call it I1:

$$I_1 = \begin{pmatrix} P_{11} & P_{12} & P_{Ij} \\ P_{21} & P_{22} & P_{2j} \\ P_{i1} & P_{i2} & P_{ij} \end{pmatrix} \text{ix}$$

Now we wish to transform I_1 into a column vector, call it I_1. This will be achieved by concatenating the columns of I_1:

$$SP_1 = \begin{pmatrix} P_{11} \\ P_{21} \\ \vdots \\ P_{i1} \\ P_{21} \\ P_{22} \\ \vdots \\ P_{i2} \\ P_{13} \\ \vdots \\ P_{ij} \end{pmatrix} nx1$$

After performing this transformation on all M images, we will obtain the following set S: S= {P1, P2,............PM}

Since we are not interested in the commonalities between our M images, we would like to subtract the mean image, call itψ from each P_x where $x \in N$, $1 \leq x \leq M$ we will computed ψ as: $\psi = \frac{1}{M}\sum_{i=0}^{M} P_i$

Now taking the difference of each P_x , $x \in N$, $1 \leq x \leq M$ and ψ we obtain a new set of vectors that we can represent as matrix A: $A=[\Phi_1,\Phi_2 \ldots\ldots \Phi_M]n \; X \; M$, Where $\phi = P_i - \psi$,$i \in N$, $1 \leq x \leq M$We now have a collection of data that will form our training setor library, and it defines the face space. This space is currently defined in n space, but we would like toreduce the dimensionality while preserving information of interest (the variance). To that end, we proceed by constructing the covariance matrix using a maximum-likelihood estimator for a population covariance matrix; call it C, of the random vectors P_x,$x \in N$, $1 \leq x \leq M$: $C=\frac{1}{M}\sum_{i=0}^{M} \Phi_1, \Phi_{2_i}$ an n x n matrix

Now we would like to show that $C= \frac{1}{M}AA^1$. We proceed directly and observe that:

$$C= \frac{1}{M}AA^1$$

$$\Leftrightarrow \; \frac{1}{M}\sum_{i=0}^{M} \Phi_1, \Phi_{2_i} = \frac{1}{M}AA^1$$

$$\Leftrightarrow C=\frac{1}{M}\sum_{i=0}^{M} \Phi_1, \Phi_{2_i} = AA^1$$

$$\Leftrightarrow C=\frac{1}{M}\sum_{i=0}^{M} \Phi_1, \Phi_{2_i} = A=[\Phi_1,\Phi_2 \ldots\ldots \Phi_M]nXM \begin{pmatrix} \Phi_1' \\ \Phi_2' \\ \vdots \\ \Phi_M \end{pmatrix} M\times n$$

$$\Leftrightarrow \; \sum_{i=0}^{M} \; {}_i \begin{pmatrix} \Phi_1' \\ \Phi_2' \\ \vdots \\ \Phi_{in} \end{pmatrix} n\times 1(\phi_{i1}\phi_{i1} \ldots\ldots \phi_{in})1xn = \begin{pmatrix} \phi_{11} & \phi_{12} & \cdots & \phi_{M1} \\ \phi_{12} & \ddots & & \vdots \\ \vdots & \ddots & & \vdots \\ \phi_{i1} & \cdots & \cdots & \phi_{mn} \end{pmatrix} nxm \begin{pmatrix} \phi_{11} & \phi_{12} & \cdots & \phi_{1n} \\ \phi_{21} & \ddots & & \vdots \\ \vdots & \ddots & & \vdots \\ \phi_{M1} & \cdots & \cdots & \phi_{mn} \end{pmatrix} Mxn$$

$$\begin{pmatrix} \phi_{11}^2 + & \phi_{21}^2 + & \ldots \phi_{M1}^2 & \phi_{11}\phi_{12} + \phi_{21}\phi_{22} \ldots\ldots + \phi_{M1}\phi_{M2} \ldots\ldots \phi_{11}\phi_{1n} + \phi_{21}\phi_{2n} + \cdots + \phi_{m1}\phi_{mn} \\ \phi_{11}\phi_{12} & + & & \vdots \\ \vdots & \ldots & & \vdots \\ & & & \ddots \end{pmatrix}$$

5. EXPERIMENTAL ANALYSIS AND RESULTS

A new approach is proposed for invariant faces and described as follows:- The input image is loaded into the system. The image is then converted into gray-scale image. The features will be extracted from that image using PPCA-SIFT algorithms respectively. And then there will be an image produced which consists of combined features using PPCA-SIFT. PCA will be then applied directly to that image and eigenvectors will be extracted from each face. The goal is to extract the important information from the face data to represent it as a set of new orthogonal variables called principal components. On the above basis, matching will take place between the input image and the image on which PCA is applied for invariant faces having different expressions, contrast and rotation.

UCI is considered as the input data for this study including 300 face images belonging to 30 different people taken from different angles as well as light intensity. For the first test, 90 images were randomly selected and 1 image of each person was considered as the training image (three persons were considered for training). As an example of the algorithm output, we assumed the three images in Figure 2 as training images. Then, a randomly selected image form the three target persons was tested. A function removing all unnecessary part of the image such as background was called. Then, employing improved PPCA-SIFT algorithms, key points in the training images using sift were extracted.

Table 1. Quality Measure

Quality Measure	**Accuracy**	**Time**
Gabor	84%	5.3
GPCA	87%	4.9
PCA-SIFT	95%	3

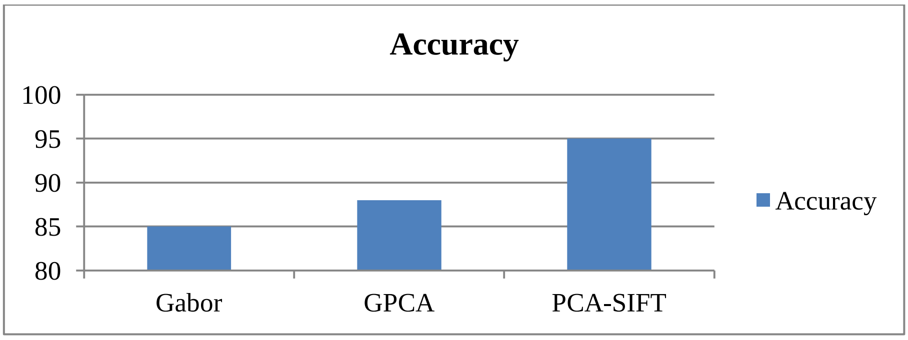

Figure 2. PCA-SIFT algorithm accuracy

6. CONCLUSION

People are usually identified by their faces. Developments in the past few decades has enabled human to automatically do the identification process. Early face recognition algorithm used simple geometric models. Now, face recognition process employs the advanced statistical science and matching methods. Improvements and innovations in face recognition technology during 10 to 15 past years have propelled it to the current status. Face recognition is applicable for both investigation and identification. This study provided a new face recognition method based on PCA SIFTS features. Improving PCA-SIFT algorithm, this study focused on face recognition. Results indicated the superiority of the proposed algorithm over the PCA-SIFT. To evaluate the proposed algorithm, it was applied on UCI database and then compared to other face detection algorithms including Gabor, GPCA, and PCA-SIFT. The results obtained from various tests showed that the proposed algorithm, with 95% accuracy and run time of 3.0 seconds, is more efficient and accurate than other algorithms yet the run time was less than others.

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