Engineering Science and Technology, an International Journal 20 (2017) 143–150

HOSTED BY

ELSEVIER

Contents lists available at ScienceDirect

Engineering Science and Technology, an International Journal

journal homepage: www.elsevier.com/locate/jestch

Full Length Article

A novel 3D approach to recognize Telugu palm leaf text

T.R. Vijaya Lakshmi [a,*], Panyam Narahari Sastry [b], T.V. Rajinikanth [c]

[a] Department of ECE, MGIT, Hyderabad, India
[b] Department of ECE, CBIT, Hyderabad, India
[c] Department of CSE, SNIST, Hyderabad, India

ARTICLE INFO

Article history:
Received 2 May 2016
Revised 19 June 2016
Accepted 19 June 2016
Available online 28 June 2016

Keywords:
Palm leaf manuscripts
Contact type 3D profiler
3D feature
Background elimination
Raster scanning
Character segmentation and recognition

ABSTRACT

Ancient wisdom and heritage of Southeast Asian countries were preserved in thousands of palm leaf manuscripts. Due to various factors like aging, insect bites, stains, etc., they are easily susceptible to deterioration. Hence preserving and digitizing such fragile documents is highly essential. Traditional scanning or camera-capturing of such documents suffer from multiple noise artifacts. A depth sensing approach is proposed to eliminate background noise for such manuscripts. The segmented characters extracted from Telugu palm scripts are further recognized using statistical approaches. The improved recognition accuracy is reported using the 3D feature (depth).

1. Introduction

This work deals with the recognition of Telugu Palm leaf characters by acquiring 3D data using a contact type profiler. For several centuries, a medium, palm leaf, was used for writing before the advent of paper. These scripts contain information about art, literature, science, technology, astronomy, medicine, music, etc. These are mostly preserved in museums, temples and universities in many countries. A sample palm leaf used in our experiments is shown in Fig. 1. A special stylus is used to engrave letters on the palm leaf. These manuscripts are rubbed with charcoal powder to make the script readable just before reading.

The palm leaf is easily susceptible to deterioration. The various deterioration factors for such manuscripts are stains, blackening of the surface, insect bites, fading of writing, cracks on the surface, climatic variations, etc. Hence, it is essential to preserve the information on these manuscripts by digitization.

India being a multilingual country has 22 official languages. The most popular ones in its southern part of India are Telugu, Malayalam, Tamil, and Tulu. Telugu has about 70 million speakers [1] and has 16 vowels and 36 consonants called basic characters. The combination of a consonant and a vowel modifier forms a compound character. Hence the possible number of consonant-vowel combinations become 576 (36×16). In the current work, 56 compound characters are considered in the dataset, which is formed when a subset of 14 consonants are combined with 4 vowel modifiers. Compound character recognition is a challenging task for the researchers. This is because more similarities are found in compound characters.

The printed versions of some similar compound Telugu characters- Li, Vi, Pi, Si, and Ni are shown in Fig. 2(a)–(e) respectively. These compound characters are formed when five Telugu consonants La, Va, Pa, Sa and Na combined with a vowel modifier (Gudi). The confusion was arising for the characters shown in Fig. 2(a)–(e) with high similarity index are shown in Fig. 2(f)–(k). The critical area that differentiates these characters is marked in ovals. If there are stains in these critical parts, on any pair of similar characters shown in Fig. 2(f)–(k), then it is tough to identify them. Traditional scanning or camera-capturing of the documents will not solve such problems. The stained characters/documents are very difficult for humans to annotate. The proposed data acquisition approach overcomes the problems like stains and discoloration; hence yields better recognition results for palm leaf manuscripts.

The main contributions in the proposed work are:

- Development of 3D dataset for Telugu palm leaf text (including compound characters).
- A novel background elimination using the 3D feature (depth) is proposed for Palm scripts even if there are stains on them.

* Corresponding author.
E-mail address: vijaya.chintala@gmail.com (T.R. Vijaya Lakshmi).
Peer review under responsibility of Karabuk University.

http://dx.doi.org/10.1016/j.jestch.2016.06.006
2215-0986/© 2016 Karabuk University. Publishing services by Elsevier B.V.

Fig. 1. Sample palm leaf (Text marked in rectangular box is used to explain the data acquisition procedure and the text marked in oval shape shows stains on the sample).

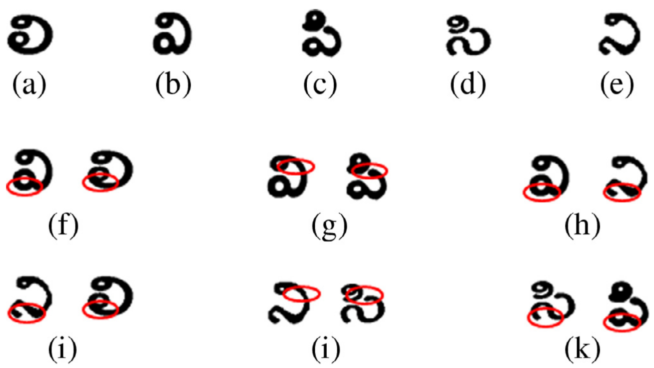

Fig. 2. Some similar printed Telugu compound characters formed when five different consonants combined with a vowel modifier (Gudi) (a) Li (b) Vi (c) Pi (d) Si (e) Ni; (f)–(k) Place where the pair of more similar compound characters differ marked in ovals.

Most of the Telugu characters are similar in 2D (XY) plane, which makes character recognition difficult. This problem can be overcome by acquiring 3D data from palm manuscripts. The varied depth of indentation also plays a major role in recognizing the characters [1]. Considering the depth information (a 3D feature), the patterns can be generated in other planes of projection. This helps in recognizing similar Telugu characters, which have dissimilar patterns in other planes of projection [1]. The rest of the paper is organized as follows. The related work is described in Section 2. The proposed 3D data acquisition for Palm leaf manuscripts is described in Section 3. In the same section, background elimination and character recognition are discussed. The experimental results are discussed in Section 4 and finally the paper is concluded in Section 5.

2. Related work

2.1. Existing 3D data acquisition system for historical palm manuscripts

Sastry et al. [1–5] contributed their work on palm leaf documents by extracting the 3D feature, depth of indentation which is proportional to the pressure applied by the scribe, for basic isolated Telugu characters. At manually selected points like bends, curves, start and end points of the character the three co-ordinates (X, Y, Z) were measured using "manually controlled mechanical instruments". The two co-ordinates (X, Y) were measured using a mechanical instrument called "measuroscope". The third co-ordinate Z, the depth of indentation, i.e., the pressure applied by the scribe, was measured using a "dial gauge indicator" having a least count of 0.01 microns. The "value of Z" varies from pixel to pixel for any character. Hence at every selected pixel point of a Telugu Palm leaf character, 3 co-ordinates (X, Y, Z) were measured. The number of pixel points selected on a character varies from 13 to 40. They developed patterns by considering two co-ordinates at a time, i.e., XY, YZ and XZ planes of projection. The similar patterns in XY plane have dissimilar patterns in YZ and XZ planes of projection. They reported the identification of similar characters in XY plane was confusing, and this can be resolved by their respective patterns in YZ or XZ plane of projection.

2.2. Existing preprocessing approaches for historical documents

Rapeeporn Chamchong and Chun Che Fung worked on ancient Thai palm manuscript images for background elimination and character segmentation. Linear filtering [6] was used to reduce noise and applied Support Vector Machine [7] to select appropriate binarisation techniques. Partial projection algorithm was used to segment the lines [8]. Further, they applied contour tracing and background skeleton tracing algorithms to segment the characters [8]. Segmentation is a crucial step followed by feature extraction and post processing [9,10].

Several contributions on historical documents were carried out to remove noise, subtract background, segment lines and characters in [11–13]. Tan et al. [14] contributed their work on handwritten character segmentation for Chinese database "KAIST Hanja" and presented kernel clustering approach based on "Conscience On-line Learning".

Historical Ottoman document retrieval system was presented by Ediz Saykal et al. [15] and Ismet Zeki Yalniz et al. [16]. The connected Ottoman characters were segmented by applying a threshold on the mean of the vertical histogram and by utilizing sliding window approach [16].

2.3. Existing character recognition approaches for palm manuscripts

Sastry et al. [1–5] used 2D correlation, 2D FFT, Radon transform and two-level recognition approaches to recognize basic isolated palm leaf characters by acquiring 3D data points. They generated patterns in three planes of projection (XY, YZ, and XZ). The number of characters considered in their work in each plane of projection was 140 from 28 different classes, i.e., 5 samples/class. The character samples were divided into five folds. Four folds were used as training to test one fold of characters. The results reported in [1–5] were not cross-validated.

3. Proposed methodology

The architecture of the proposed recognition scheme for palm leaf scribed text is shown in Fig. 3. It is divided into three major phases: 3D data acquisition, Preprocessing, and Character recognition. The detailed description of all the three phases is discussed in the following subsections.

3.1. 3D data acquisition

The existing work [1–5] was done only on "isolated basic Palm leaf Telugu characters" whereas the proposed work is carried out for not only basic characters but also compound characters. In

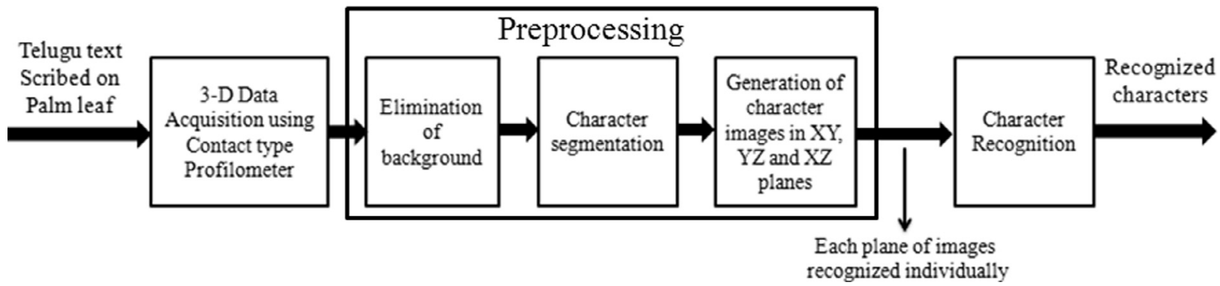

Fig. 3. Architecture of the proposed recognition scheme for palm leaf manuscripts.

the proposed approach, data has been acquired using a computer controlled XP-200 series profilometer manufactured by AMBiOS Technology. Contact type stylus profilometer is used to measure the depth of indentation (3D feature) or pressure applied by the scribe. A diamond point stylus of radius 2.5 microns is moved vertically and laterally in contact with the sample, for specified stylus force. Stylus Profiler used can measure surface variations up to 100nm (lateral resolution). The up/down movement of the stylus in Z direction generates an analog signal. The depth of indentation, Z, (a 3D feature) is recorded, converted into digital form and stored in the computer which is attached to the profilometer. This digital data is used for Palm leaf character recognition.

By raster scanning the text on palm leaf manuscript using the profiler, three co-ordinates X, Y, and Z are measured. The profiler can be programmed for vertical raster scanning by specifying the following parameters:

1. Scan distance (D) in Y direction.
2. Scan length (L) in X direction.
3. Step size (S) between two consecutive profiles/scans.

Scan distance (D) is the width of the text line or string, specified in millimeters as indicated in step 1 of Fig. 4. Scan length (L) is the length of the selected string on Palm leaf manuscript as described in step 2 of Fig. 4. Each vertical line in step 3 of Fig. 4 indicates a 2D scan profile. The difference between two consecutive profiles is the step size (S).

Each 2D scan profile contains recorded Y and Z values, where Y is measured in microns, and Z is measured in Angstrom units. The number of profiles (N) depends on the scan length (L) and the step size (S) between profiles and is given by L/S.

The left most profile is considered as reference for 'X' co-ordinate as shown in Fig. 4. For every profile, 'X' is incremented by the step size (S) as depicted in Eq. (1). Hence for each profile all the three co-ordinates (X, Y, Z) are generated.

$$X = S \times (P - 1) \tag{1}$$

where P is profile number.

3.2. Preprocessing

The background elimination, character segmentation and generation of patterns are the steps involved in preprocessing. These are explained below in detail.

3.2.1. Background elimination

A sample analog 2D scan profile generated using the profilometer is shown in Fig. 5. The x-axis in Fig. 5 indicates the points along Y direction (for the specified scan distance D) where the depth of indentation or pressure applied by the scribe is measured. The y-axis in Fig. 5 indicates the measured depth of indentation or pressure applied by the scribe along Z direction. As the palm leaves are very old, they exhibit waviness behavior (uneven background) and the same is recorded. The valley points indicate the depth of indentation, which enables us to separate the foreground and background.

The threshold (Th) applied is the 40% of the mean of all the minimum valley points found in the N profiles as expressed in Eq. (2). The minimum valley point V_{min} should be smaller than the predefined lateral height, to exclude the waviness behavior of the palm leaf scripts. The profile in Fig. 5 contain two minimum valley points. The number of minimum valley points varies from profile to profile. In any particular profile if none of the minimum valley points are not smaller than the predefined lateral height then it indicates the absence of the pressure applied by the scribe in that profile. In Fig. 5, the data points above the red line represent background or noise and the data points below the red line represent foreground or textual information.

$$Th = \frac{0.4}{n} \sum_{i=1}^{n} V_{min_i} \tag{2}$$

where n is the number of minimum valley points encountered from N profiles.

For every text line, the background free data points are extracted by applying the threshold computed from its N digital profiles. As the pressure applied by the scribe varies from line to line and from scribe to scribe, the threshold is separately computed for every text line. Hence, it is a novel depth sensing approach proposed in this paper for Palm manuscripts to eliminate background adaptively even for multiple scribes.

A sample of (X, Y) data points scattered before and after eliminating background for fourteen consecutive profiles is shown in Fig. 6, for the text line considered in Fig. 4. The (X, Y, Z) data points of the corresponding first three consecutive scan profiles is shown

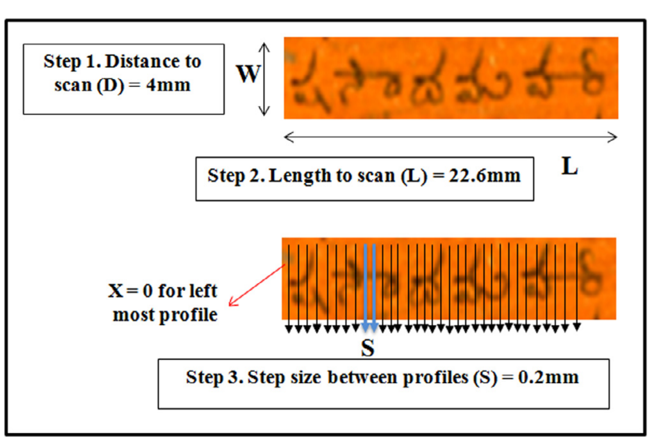

Fig. 4. Three steps involved for raster scanning (parameters D, L and S specified).

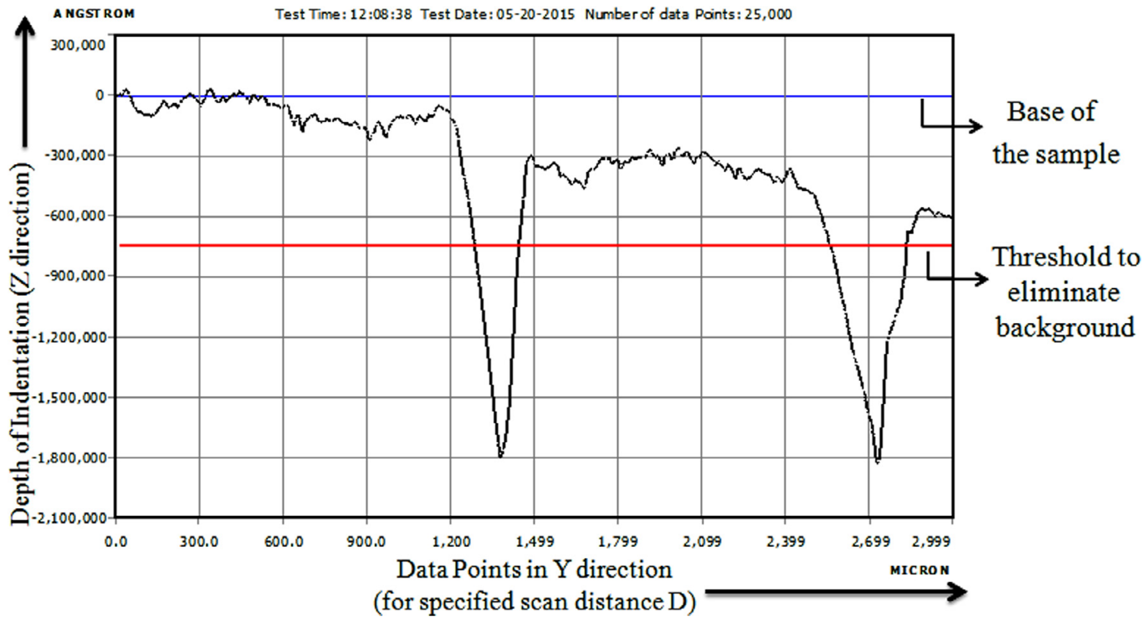

Fig. 5. Sample analog scan profile containing Y and Z data points.

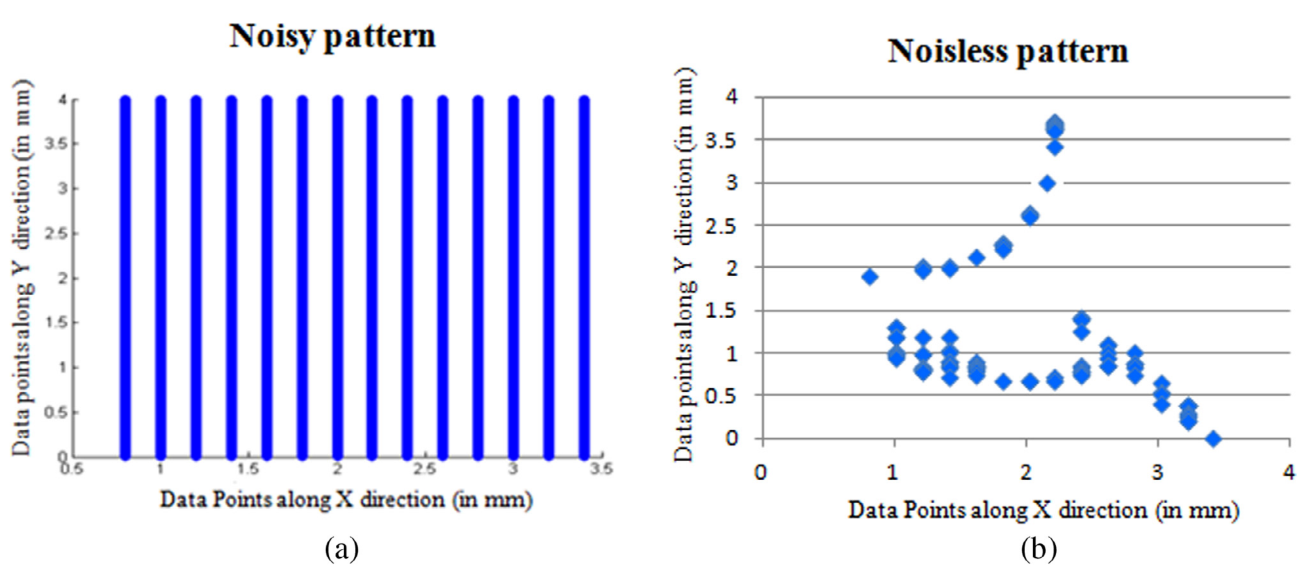

Fig. 6. Sample of (X,Y) data points scattered a)Before eliminating background b)After eliminating background using Eq. (2).

in Table 1. 'X' and 'Y' co-ordinates are denoted in millimeters (mm) and 'Z' co-ordinate is denoted in microns. For the first profile, 'X' is set to 0.8 and is incremented by the step size 'S' for the next profile, as depicted in Eq. (1).

Table 1
Sample data points after "Eliminating Background" for three consecutive profiles shown in Fig. 6.

S. No.	X in mm	Y in mm	-Z in microns
1	0.8	1.909672	44.29913
2	1	1.305766	48.91692
3	1	1.297935	48.34365
4	1	1.011192	111.6388
5	1	0.969326	132.645
6	1	0.954266	122.2135
7	1.2	2.023526	66.49148
8	1.2	1.193719	83.62815
9	1.2	0.983482	51.47387
10	1.2	0.8124	152.1339

3.2.2. Character segmentation

The (X, Y, Z) data points, after eliminating background, are used to segment the characters using vertical projection algorithm. The number of segmented points varies from character to character based on its size and shape. These data points are used to generate patterns in various planes.

3.2.3. Generation of patterns

Selecting 2 co-ordinates at a time, character patterns/images are generated in XY, YZ and XZ planes of projection. For every segmented character image/pattern, the minimum boundary of either the width or height of the character (whichever is greater) is normalized to a fixed value M ($M = 50$ in the current work). Preserving its aspect ratio further these images are resized to $M \times M$.

3.3. Character recognition

Feature extraction and classification are the steps involved in character recognition phase. The classifier employed is k-NN ($k = 1$). The two features extracted [17] for the normalized characters are as follows:

1. Distance profile 2. Histogram profile

3.3.1. Distance profile

Let the size of each character I (binary image) be $M \times M$. In this algorithm, the distance from one direction to the other is computed, to derive the boundaries of the character. The distances computed are from left to right, right to left, top to bottom and bottom to top directions.

To compute the boundaries from left to right direction, for every row of the character image, the background pixel count is computed until the first object pixel is found. Similarly, to compute the boundaries from right to left direction, the background pixel count is computed until the first object pixel is found while traversing from right to left direction. The distances computed while traversing from left to right (D^{LR})and right to left directions (D^{RL})for an i_{th}row of the character image are depicted in Eq. (3).

$$D_i^{LR} = \sum_{j=1}^{u} I(i,j), \qquad D_i^{RL} = \sum_{j=M}^{v} I(i,j) \tag{3}$$

where u and v are the column numbers at which the first object pixel is encountered when traversing from left to right and right to left directions, respectively. The procedure is repeated to compute the boundaries of the character while traversing from top to bottom and bottom to top directions. The distances computed while traversing from top to bottom (D^{TB}) and bottom to top (D^{BT}) directions for j_{th} column of the character image are depicted in Eq. (4).

$$D_j^{TB} = \sum_{i=1}^{q} I(i,j), \qquad D_j^{BT} = \sum_{i=M}^{r} I(i,j) \tag{4}$$

where q and r are the row numbers at which the first object pixel is encountered when traversing from top to bottom and bottom to top directions, respectively. The distances computed in all the four directions are concatenated to form a boundary feature vector which contains $4M$ features for each character. The boundaries extracted in all four directions for a Telugu Palm leaf compound character “Haa” is shown in Fig. 7.

3.3.2. Histogram profile

In histogram profile algorithm, the histogram of object pixels is computed in four directions. The four directions considered are horizontal, vertical, left-diagonal and right-diagonal. The row-wise and column-wise object pixels are counted, to derive the horizontal and vertical histogram features, respectively. The horizontal histogram (H_i) for i_{th} row and the vertical histogram (V_j) for j_{th}column are depicted in Eq. (5).

$$H_i = \sum_{j=1}^{M} I(i,j), \qquad V_j = \sum_{i=1}^{M} I(i,j) \tag{5}$$

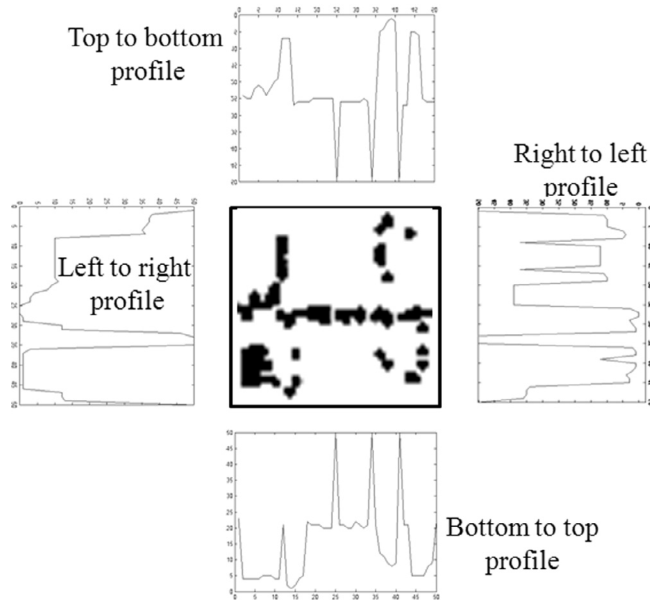

Fig. 7. Boundaries extracted along four directions for a Telugu Palm leaf character “Haa” using Distance profile algorithm.

The horizontal and vertical histograms are computed for $i = 1$ to M and $j = 1$ to M respectively.

The left (L_p) and right (R_p) diagonal-wise object pixels are counted to derive the p_{th}left and right diagonal histogram features, respectively, as depicted in Eq. (6).

$$L_p = \sum_i \sum_j diag((I(i,j),p)), \qquad R_p = \sum_i \sum_j diag(flip(I(i,j),p)) \tag{6}$$

For $p = -(M-1)$ to $(M-1)$ the number of diagonal-wise features computed is $2M-1$. All these four directions of histograms are concatenated to form the feature vector of the character. Hence a total of $2M + 2(2M-1)$ features form the feature vector for each character using histogram profile algorithm.

4. Evaluation results

Camera-captured and scanned documents are prone to several distortions like uneven illumination, perspective, motion blur, low resolution, etc. These distortions may elevate the noise levels in noisy documents. Preprocessing is the key step for any recognition system. While suppressing these distortions, the actual text information may also get distorted using the conventional noise removal approaches. With the proposed depth sensing approach, no additional noise is added. Using the 3D feature (depth of indentation) a novel background elimination approach is proposed. Though the contact type stylus is used for measurements, with the specified stylus force (10mg) applied on the sample document, no damage caused to it.

4.1. Preprocessing results

In all the documents, which are written by multiple scribes, the background is completely eliminated. The number of palm manuscripts considered for preprocessing is twenty-three. As pressure applied by the scribe is used as a feature in the current model, investigations are done on manuscripts written by a single scribe for character recognition. The sample results obtained after background elimination and character segmentation are shown in Fig. 8(b) and (c) respectively, for the palm leaf text strings considered in Fig. 8(a). Though there is a stain in the second input string considered in Fig. 8(a), the text/character is properly extracted after background elimination. The proposed approach is compared with the existing preprocessing approaches on historical documents from [8,14] and is tabulated in Table 2. Using the proposed approach the average segmentation accuracy achieved is 86.3%. The data acquired in [8,14] was using conventional scanning method. The segmentation algorithms presented in [8,14] were complex than the vertical projection profile algorithm used in the current work. Though the segmentation algorithm used is simple and conventional, it is observed from Table 2 that the segmentation accuracy is in line with the existing ones. This is due to the background subtraction approach used in the current work.

4.2. Character recognition results

The data points contain (X,Y,Z) co-ordinates for each segmented character. Selecting two co-ordinates at a time, patterns are generated in XY, YZ and XZ planes of projection. The generated patterns for similar Telugu characters considered in Fig. 2(a)–(e), in all the three planes of projection, are shown in Fig. 9(a)–(e). The characters shown in Fig. 8(a)–(e) are Li, Vi, Pi, Si, and Ni respectively. It is observed that the similar patterns in XY plane, have dissimilar patterns in YZ and XZ planes of projection. Hence, the 3D feature, depth of indentation (Z), solves recognizing similar Telugu characters.

A subset of 14 consonants when combined with 4 vowel modifiers, 56 different compound characters are formed. These compound characters are considered to create the dataset as discussed in the introduction section. All together $14 \times 4 = 56$ different classes are considered in the work. The number of characters considered for character recognition is 280 from 56 different classes, i.e., (5 samples/class). All together from three planes of projection, the number of character images generated are 840 (280×3). The character images generated in XY, YZ and XZ planes of projection are tested and trained separately, and the recognition accuracies are obtained for all the planes of projection. As there is no standard database for conducting tests, the system is 5-fold cross-validated. Each fold contains 56 characters from different classes. To test a fold of characters, the remaining 4 folds are used as training. Hence, with disjoint training and testing sets, all the characters are tested once. The average recognition accuracy of all the folds is considered as the recognition accuracy of the model in the current work.

Feature extraction and classification are the steps involved in character recognition. The two different features extracted from the character images are described in Section 3.3. For classification, Euclidean distance is calculated between the unknown test character and the training characters. The minimum distance between them is considered as the recognized one. The character recognition results obtained, using "Distance profile and Histogram profile" feature sets, are tabulated and compared with the existing work [1–5] in Table 3, for a normalized character image of size $M \times M$. The best recognition accuracy obtained is 83.2% in YZ plane of projection using "histogram profile" feature extraction method. Telugu characters have maximum variations in Y direction [1–5], which is an inherent characteristic of Telugu script. This attribute of Telugu script in combination with the 3D feature (depth of

Table 2
Comparison with existing preprocessing approaches on historical documents.

Description	Chamchong et al. [8]	Tan et al. [14]	Proposed approach
Script	Thai	Chinese	Telugu
Medium	Palm leaf	Written on paper	Palm leaf
Input system	Scanning, Thinning	Scanning, thinning	Profiler (3D)
Background	elimination	Linear filtering, SVM based binarization	Binarizing, eroding, dilating
Applying threshold on 3D feature (Z)			
Segmentation algorithm	Tracing background skeleton	Conscience on-line learning	Vertical projection
Segmentation accuracy %	82.57%	85.2%	86.3%

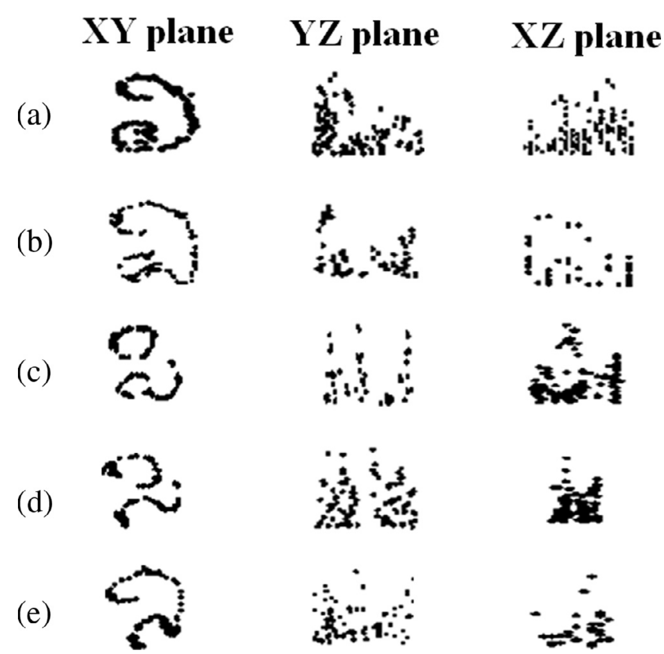

Fig. 9. Patterns generated in XY, YZ and XZ planes of projection for similar Telugu characters considered in Fig. 2(a)–(e).

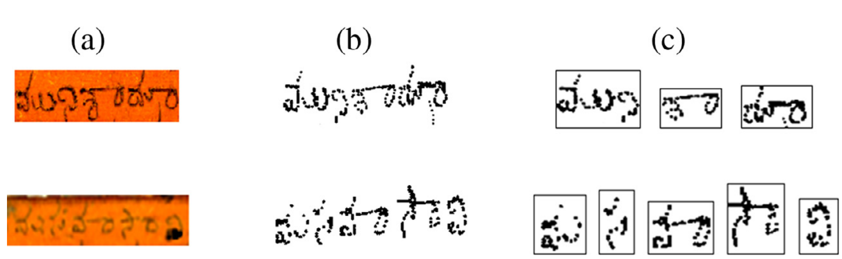

Fig. 8. Sample results (a) Input string images from palm leaf manuscript (b) Output images after background elimination (c) Output images after character segmentation.

Table 3
Comparison of character recognition accuracies.

Feature extraction	No. of features	Plane of projection		
		XY (%)	YZ (%)	XZ (%)
2D Correlation [1,2]	–	65	73	59
2D FFT [1,3]	M^2	25	71.4	50
Radon transform [5]	No. of angles $\times (M + \frac{M}{2})$	76	89	80
Two-level approach [4]	$2M^2$	32.2	92.8	67.9
Distance profile	$4M$	68.4	79.3	71.3
Histogram profile	$2M + 2(2M - 1)$	71.8	83.2	73.6

indentation), Z, yielded better recognition accuracies in YZ plane of projection compared to the other planes of projection.

The results reported in [1–5] were not cross-validated. They divided the character samples into five folds. Each fold contains 28 characters from 28 different classes. They tested only one fold of characters by training the classifier with four folds of characters. In 2D correlation method [1,2], the correlation coefficients between an unknown test character and all the training characters were computed. The maximum correlation coefficient value among them was used to classify the test character. This approach does not need a separate classifier. Hence, this approach is computationally less expensive compared to other approaches.

To classify characters, 2D FFT [1,3], Radon transform [5] and two-level recognition [4] approaches utilized Euclidean distance measure. In 2D FFT method [1,3], every pixel was transformed into the frequency domain, and their absolute magnitudes were considered as features. The number of features represents the character using 2D FFT method were equivalent to the size of the character image. In Radon transform method [5], along a radial line the pixel intensities projected at a particular angle were considered as features for a character. The number of features extracted in each projected angle was reported as $(M + \frac{M}{2})$. The number of angles considered in their work was 180 (0–179). Thereby the number of features used to describe a character is relatively very high and is greater than the size of the character image. They reported the best recognition accuracy of 89% in YZ plane of projection using Radon transform.

In the two-level recognition approach [4], the characters were tested on two levels. In the first level, 2D FFT features were extracted to classify the characters. The unrecognized characters from this level were again classified by extracting 2D DCT features in the second level. This approach is relatively expensive compared to all the approaches as the system is trained and tested for two times and the number of features needed is also high in number. The best recognition accuracy reported using this approach was 92.8%.

Compared to these existing approaches to recognize palm leaf basic characters, the number of features used to represent a character in the proposed approaches is very low. Hence, the memory required to store the features is relatively very low. If the number of features needed to describe a character is high, then the distance measure used to classify the characters, also needs a larger number of computations to undergo. So the number of computations needed for the proposed approaches are also low.

Even though the proposed dataset contain compound characters (which have high similarity index) the recognition accuracy of 83.2% is obtained in YZ plane of projection, using 'Histogram profile' method. Moreover, the results obtained are cross-validated in the proposed work, whereas the results reported in the existing work were not cross-validated (only one set of characters were tested).

The proposed data acquisition system for palm leaf manuscripts is compared with the existing one for such scripts [1–5] in Table 4.

Table 4
Comparison of 3D Data Acquisition systems for Palm leaf manuscripts.

Description	Sastry et al. [1–5]	Proposed Approach
Characters considered	Basic isolated characters	Basic and compound characters
Instrument used (3D data acquisition)	Measuroscope (X,Y), Dial gauge indicator (Z)	Profilometer
Data acquisition procedure	Manually selected points	Raster scanning
Background elimination	Not considered	Threshold on Z dimension
Character segmentation	Not considered	Vertical projection
No. of characters considered in all three planes	420	840
Robust against	–	Stains, discoloration

The depth sensing profiler is more sophisticated compared to the mechanical instruments used in the existing one. Background elimination and character segmentation were not considered in [1–5], as the measurements were taken only at selected points on the character. The existing system is completely controlled by human to select the data points on the character.

5. Conclusions and future scope

Preserving and digitizing thousands of fragile palm leaf manuscripts is highly essential as they contain important information related to science, technology, etc. and are easily susceptible to deterioration. Traditional camera-captured or scanned palm leaf documents suffer from several distortions. This paper proposed a novel 3D data acquisition system for such manuscripts. The contact type profilometer is used to measure the depth of incision (3D feature) on the palm leaves. The background noise is successfully eliminated by applying an appropriate threshold on the 3D feature. Compared to the conventional approaches, the proposed depth sensing approach for such manuscripts yielded better image quality results even for the stained ones. The best recognition accuracy obtained is 83.2% in YZ plane of projection using "histogram profile" feature extraction method. Telugu characters have maximum variations in Y direction which are an attribute of Telugu script. This attribute in combination with the 3D feature (Z) yielded better recognition accuracies in YZ plane of projection compared to the other planes of projection.

This work can be extended to enhance the recognition accuracy by exploring better feature extraction and classification approaches. It can also be extended for other consonant and vowel modifier combinations.

Acknowledgments

Sincere thanks to Dr. Ramakrishnan Krishnan, Former Director, ADRIN, Former Dean, IIST, Dept. of Space, ISRO, India, for his valuable guidance and support. Additional thanks to Prof. Rajaram and Ms. Sandhya, Hyderabad Central University, India, for permitting to utilize the profiler equipment in this research work. The authors also express their sincere thanks to Balaji Chilakuri and Varan Sreedevi for their extended support.

References

[1] P.N. Sastry, Modeling of palm leaf scribing – analysis using statistical pattern recognition (Ph.D. dissertation), JNTUH, Hyderabad, India, Sept 2010.
[2] P.N. Sastry, R. Krishnan, B.V.S. Ram, Classification and Identification of Telugu handwritten characters extracted from palm leaves using decision tree approach, J. Appl. Engn. Sci. 5 (3) (2010) 22–32.

[3] P.N. Sastry, T.R. Vijaya Lakshmi, R. Krishnan, N.V.K. Rao, Analysis of Telugu palm leaf characters using multi- level recognition approach, J. Appl. Eng. 10 (20) (2015) 9258–9264.
[4] P.N. Sastry, T.R. Vijaya Lakshmi, R. Krishnan, N. Rao, Analysis of Telugu palm leaf characters using multi-level recognition approach, J. Appl. Eng. Sci. 10 (20) (2015) 9258–9264.
[5] P.N. Sastry, R. Krishnan, A data acquisition and analysis system for palm leaf documents in Telugu, in: Proceeding of the Workshop on Document Analysis and Recognition, ACM, 2012, pp. 139–146.
[6] R. Chamchong, C.C. Fung, Comparing background elimination approaches for processing of ancient Thai manuscripts on palm leaves, International Conference on Machine Learning and Cybernetics, vol. 6, 2009, pp. 3436–3441.
[7] R. Chamchong, C. Jareanpon, C.C. Fung, Generation of optimal binarisation output from ancient Thai manuscripts on palm leaves, Adv. Decis. Sci. (2015) 1–7 925935.
[8] R. Chamchong, C.C. Fung, A combined method of segmentation for connected handwritten on palm leaf manuscripts, in: IEEE International Conference on Systems, Man and Cybernetics (SMC), 2014, pp. 4158–4161.
[9] Anu Bala, Tajinder Kaur, Local texton XOR patterns: a new feature descriptor for content based image retrieval, Int. J. Eng. Sci. Technol. 19 (2016) 101–112.
[10] Priyadarsan Parida, Nilamani Bhoi, Transition region based single and multiple object segmentation of gray scale images, Int. J. Eng. Sci. Technol. 19 (3) (2016) 1206–1215.
[11] U. Garain, T. Paquet, L. Heutte, On foreground background separation in low quality document images, Int. J. Doc. Anal. Recognit. (IJDAR) 8 (1) (2006) 47–63.
[12] J. Chen, D. Lopresti, Model-based ruling detection in noisy handwritten documents, Pattern Recognit. Lett. 35 (1) (2014) 34–45.
[13] M. Agrawal, D. Doermann, Clutter noise removal in binary document images, Int. J. Doc. Anal. Recognit. (IJDAR) 16 (4) (2013) 351–369.
[14] J. Tan, J.H. Lai, C.D. Wang, W.X. Wang, X.X. Zuo, A new handwritten character segmentation method based on nonlinear clustering, Neurocomputing 89 (2012) 213–219.
[15] Ediz Şaykol, Ali Kemal Sinop, Uĝur Güdükbay, Özgür Ulusoy, A. Enis Çetin, Content-based retrieval of historical Ottoman documents stored as textual images, IEEE Trans. Image Process. 13 (3) (2004) 314–325.
[16] Ismet Zeki Yalniz, Ismail Sengor Altingovde, Uĝur Güdükbay, Özgür Ulusoy, Ottoman archives explorer: a retrieval system for digital Ottoman archives, ACM J. Comput. Cult. Heritage 2 (3:8) (2009).
[17] T.R. Vijaya Lakshmi, P.N. Sastry, T.V. Rajinikanth, Hybrid approach for Telugu handwritten character recognition using k-NN and SVM classifiers, Int. Rev. Comput. Softw. 10 (9) (2015) 923–929.