International Journal of Advanced Trends in Computer Applications (IJATCA)
Volume 11, Number 1, Feb - 2026, pp. 1-28
ISSN: 2395-3519

Analysis 3D Trajectories towards Evaluation of Mid-Air-Writing Recognition Systems

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Abstract: *Writing a linguistic character or word in free space with a finger, marker, or handheld device is referred to as trajectory-based writing. It is widely used in situations where traditional pen-up and pen-down writing systems are inconvenient. It has a significant advantage over the gesture-based system due to its simple writing style. However, it is a difficult task due to the Characters that aren't all the same and writing styles that aren't all the same and the various systems used the nearest neighbor and root point interpretation were used to improve feature selection of trajectory. In this comparative study, mid air-writing recognition system using three-dimensional (3D) trajectories obtained by an image sensor that detects the fingertip works covered in detail. Moreover, the paper highlighted the different traditional works related to 3D trajectory based mid-air writing recognition systems and the algorithms used in those systems. An extensive comparative study was presented in this paper, revealed a dearth of information regarding mid air handwritten character recognition.*

Keywords: *3D, Trajectory, Gesture-based system, Mid air-writing*

I. INTRODUCTION

At the current time, one of the most fascinating and challenging applications of image processing and pattern recognition is mid air handwriting recognition. The ability to improve the man-machine interface makes the mid air handwriting recognition-based systems much popular in recent years. This field is contributing a lot to the advancement of automation of various processes. Also, the advancement in areas like artificial intelligence, speech recognition, computer vision, object recognition, deep learning, knowledge management, machine translation, and optical character recognition has boosted the interest of researchers in the field of mid air handwriting recognition. Recent researches are being focused on evolving robust and efficient strategies for developing efficient mid air handwriting recognition systems. The main objective is to provide higher recognition accuracy, low computation cost, high performance, and low processing time1.

1.1 Introduction to Mid-air Handwriting

The mid air hand writing recognition problems have been categorized in to two categories: offline and online. In an off-line system, the mid air handwritten page is digitized or scanned using a scanner or any other electronic device such as a digital camera, etc. On the other hand, in an online system, the writer's handwritten stroke information along with timestamp is recorded for processing. These handwritten strokes are the coordinates or sequence of points in the coordinate system. Thus, the temporal information available is used in the recognition process. Even though the online methods are superior as compared to their offline counterparts; the demand for an offline mid air handwriting recognition system is still there for recognizing mid air handwritten numerals or

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characters. Numerous applications such as "Bank cheque processing", "Document digitization" and "Postal address recognition for mail sorting" etc. need an automated system for Mid-Air-Writing. Finally, various classifiers or their combination can be used to classify mid air handwritten document images. Feedforward Neural Networks, together with multilayer perceptron (MLP), Radial Basis Function (RBF), Support Vector Machine (SVM), Neuro-Fuzzy classifier, Associative Memory, Recurrent Networks (RN), K-nearest neighbor (KNN) classifiers, probabilistic neural network (PNN) classifier, quadratic discriminant function (QDF) classifier and linear discriminant function (LDF) classifier are some well-known classifiers used in the field of mid-air writing recognition.

The Human-Computer Interaction (HCI) or Man-Machine Interaction/Interface is a field which focuses on how human communicates with the computer (machine). HCI mainly rely on the physical devices. In general humans communicate with computers through interfacing devices such as mouse and Keyboard. For very long term HCI techniques were based on Graphical output devices, on input keyboards and mouse. The Human Beings are highly expressive of their ideas and feelings. Their ideas and feelings are articulated through facial expression, voice modulation, mid air hand gestures, eye movements etc. Thus an interface which connects any one of these expressions to computer so as to achieve the desired function would be more users friendly2. Hence the framework of interactive and smart computing, HCI with pattern recognition is gaining an absolute significance in the research field.

1. 2 Introduction to gestures

A gesture is defined as a means of communication between two persons through exchange of wordless actions or signals. Humans have the tendency to make actions along with oral communication3. These actions are used as gesture to provide an interaction between man and machine. Gestures are usually associated with facial expression, mid air hand gestures, lip movement, eye ball movement, etc Gesture recognition is a stream of computer science which helps in understanding the human gestures by means of mathematical models and algorithms4. The gesture recognition can be applied in various fields like:

- Helping the deaf people
- In Legal investigations
- In medical applications such as rehabilitations of the muscles in case of paralytic patient.
- Recognition of sign language.
- Gaming and Entertainment.

The human beings have the practice of making mid air hand actions along with the verbal communications. Hence hand actions also termed as mid air hand gestures effectively reinstate the rigid interfacing input and output devices between the man and computer and facilitating the man to interact with the computer physically without any mechanical devices5. Human mid air hand gestures can be applied in fields such as multi touch screen interfaces, MS surface computer, camera based gesture recognition, health clinics, sports, entertainment, etc The different types of gestures are :

- Object manipulation gestures: The position or size of the object is varied. Examples: Displacement of an object.
- Command gestures: Action oriented gestures like drawing a line, making sound, etc.
- Static gestures: Gestures with single postures. Example: thumps up signal indicates good luck
- Dynamic gestures: Gestures associated with motions Example: waving of mid air hands

1.3 Mid-air Hand gesture recognition system

Human mid air hand gestures are interpreted through a system called as Gesture Recognition system. Gesture recognition system can analyze single hand or two hand gestures along with static or dynamic hand gestures. Human hand gesture recognition has evoked extensive consideration due to an intensive work on improved algorithms on computational concepts6, resolution and operation of the camera etc. These improved algorithms have taken a lead in designing Gesture User Interface that requires gesture knowledge.

The important step in gesture recognition is modelling the hand. Modelling the structure of the hand on the basis of motion is fundamental step in recognition system. The gesture modelling can be done in both spatial and temporal. In spatial domain, static characteristics like shape of the gesture, colour, etc are considered. The hand modelling can be executed in 2-

Dimentional or 3-dimentional spatial domain. Modelling in 2-Dimentional spectral space consider parameters like colour, shape, motion, deformable templates etc. Shape can be represented as geometric and non geometric models. Geometric models of the hand include parameters such as location of the palm and fingers. The non geometric model includes silhouette and texture, edges, boundaries, etc. The motion models are based on the colour cues to recognize and locate the mid air hand and fingers7.

The 3-dimentional models are based on volume, joint coordinates (skeleton) and shape. Models based on volume are complicated with large number of parameters. Skeletal model requires less parameters compared to volumetric model. Geometric is simple and hence most commonly used. Modelling in temporal domain uses dynamic characteristics like gesture movements. The technologies for the recognition of gestures are divided into following types based on the input devices:

- Data glove approach
- Coloured marker approach
- Vision based approach

Data glove approach

Data gloves are electronic device provided with electromagnetic sensors. It is widely used in virtual reality applications as an input device. Sensors are used to capture mid air hand location and motion8. They give precise X-Y values of finger tip position and direction, and mid air hand arrangements. The sensors sense the movements of the mid air hand and these movements are converted into digital signals and transmitted to the computer. The data gloves measure finger bending, position and orientation, in terms of angular measurement between the bones of the fingers. Depending on the sensor output data gloves are classified into two categories:

1. Linear Data Glove
2. Nonlinear Data Glove

Data gloves are to be calibrated before applying to the application. Linear data gloves can be calibrated using a simple linear mapping where as nonlinear data gloves calibrations are complex due to the lack of output references from the sensors9. The finger bend sensors consist of transmitter and receiver embedded in a flexible pipe as shown in the FIGURE 1.

The flexible pipe acts as channel for the transmission of the infrared signal. When the user bends the finger, the finger bend sensor also bends in the same shape as the finger. This causes the decrease in the transmission of infrared signal to the receiver10. This reduces the impedance of the receiver. Since the output of the sensor and the bend angle are nonlinear, calibration of the data glove is needed before applying to the applications. The process of gesture recognition using data gloves is shown in the FIGURE 2.

The finger bend sensor produces an output proportional to the bending of the finger. This output is converted into electric output using transducers. A uniform sampling is applied to the different gestures defined. The sampled data is then segmented using algorithms based on grouping of pixels11. Finally the classified patterns are recognized by applying classifiers such as KNN, SVD, etc.

Limitations of data glove approach are,

- The data glove is tailored to a general model irrespective of hand size of the users.
- User will not be comfortable in wearing the data glove

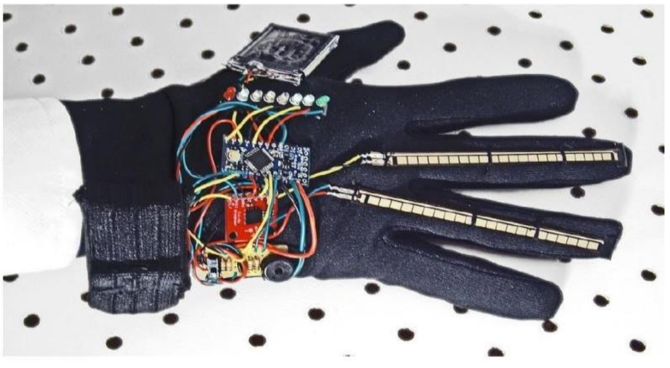

FIGURE 1 Image of a Finger bend sensor

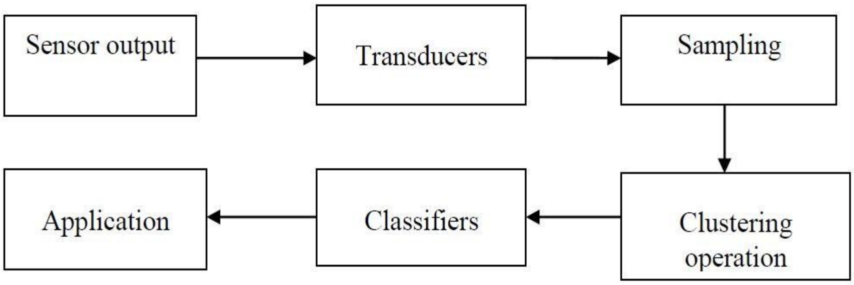

FIGURE 2 Gesture recognition process using data gloves

- The gloves provide limited flexion degree of freedom on each joint.
- The movement of certain fingers are not independent.
- One finger movement may affect several sensors in the glove, thereby reducing the accuracy of the gesture recognition. The approach is applied in
  1. Teleoperations and robotic control
  2. Surgery training and in rehabilitations of muscles in medical application
  3. Entertainment and sports.
  4. Industrial development of CAD and CAM applications.

Coloured marker approach

Coloured gloves on mid air hand assist the process of identifying the fingers and palm. They provide the geometric features for acquiring the shape of the mid air hand. The main benefit of this approach is that it is simple to use and economically cheaper. The drawback of this technique is that it is does not provide an easy interaction with the system.

Vision based approach

Vision based mid air hand recognition system is more attractive because it provides a natural, responsive and contactless interaction. These techniques are non persistent and based on the way user takes the information from the environment. Cameras are used to capture the mid air hand image. The limitation of the approach is that cameras are sensitive to illumination, complex background and other skin colour objects. The systems requirements are velocity, recognition time, robustness, and computational efficiency. The vision based mid air hand gesture recognition system as shown in FIGURE 3. In this approach the user need not have to wear any colour caps or gloves. The vision based technique is further categorized as:

- Three dimensional based model
- Model based on the appearance.

The Three dimensional model based approach uses the 3D information obtained from the body parts. The different parameters like joint angles, palm position, palm orientations, etc are obtained from the 3D information. This approach uses volumetric or skeletal models or the combination of both the models. The volumetric model is applied in animation, computer vision, etc. The computation in volumetric model is very rigorous.

The appearance model uses the image or the video frames as input. The parameters are acquired from the image or the video using template database. Templates are the deformable 2D templates, which are set of points on the outline of the object of the human body in particular human mid air hand. Templates are the frames of images. The simple linear interpolation function executes an average shape from point set, point variability parameters and external deformations. The parameters may be the images or the attributes derived from the images. These models are applied to mid air hand tracking and also for mid air hand gesture classification.

The classification of vision based gesture recognition based on the feature extraction is:

(a). **High level feature based approach:** In this approach the palm and finger locations are detected from the high level features like finger tip, joint angles, etc. This approach uses the finger colour caps. The drawback of this approach is that point features are inclined to occlusions.

(b). **3D feature based approach**: The movement data of the palm and fingers are obtained from 3D trajectories from the point. This overcomes the limitation of the high level feature based approach. The limitations are that the exact 3D reconstruction is not possible and the high computational cost restricts its application in real time systems.

(c). **Low level feature based approach:** Low level features that are highly resistive to noise are extracted. The full reconstruction of mid air hand is not possible. The principle axis of the elliptical boundary of the mid air hand, contour, edges, skin colour, etc is used as low level features. This approach cannot be applied to the tangled background. The vision based mid air hand gesture recognition system involves image acquisition, preprocessing, feature extraction and classification of the objects.

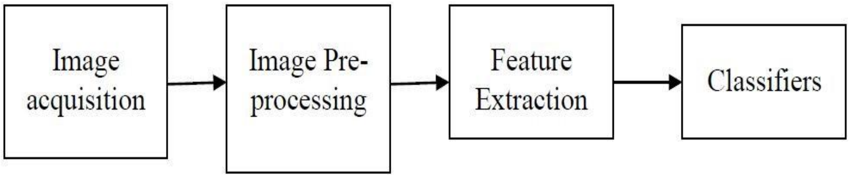

FIGURE 3 Vision based mid air hand gesture recognition system

Image Acquisition:
image is formed by the amalgamation of illumination source which incident the light energy on to the object/scene to be imaged and the reflected or absorbed light energy from the object/scene. The illumination energy may be from Radar, Infrared or X-ray sources. Depending upon the type of energy source the incident energy may be reflected or transmitted through the object/scene.
The different types of Image acquisition are,

• Image acquisition using single sensor.
Example: Photodiode
• Image acquisition using sensor strip.
Example: CAT scanning machine
• Image acquisition using sensor arrays.
Example: CCD sensor array.

Image Preprocessing:
The main objective of pre-processing is gaining improvement in the image quality, mitigating the datasets size. The preprocessing includes the following steps:

1. Re-sampling of the image to increase or reduce the number of pixels in the datasets.
2. To improve the brightness of an image by manipulating the gray values of the pixels in the datasets.
3. Noise removable using low-pass, high-pass, band-pass filters, mean filters, median filters or by using morphological operations.

The pre-processing action includes segmentation and morphological filtering operations.

Segmentation:
Image segmentation is separation of a single image to into dissimilar sections, showing particular characteristics. Pixels in the segmented image are not individual but interlinked with the other pixels in the same region. Measurements on the segmented regions are performed to derive a relationship between the regions. Hence segmentation provides an effective lead to precise assessment of image data. Segmentation techniques are mainly based on boundary detection, sector-based processing, threshold, morphological techniques and pixel intensity. Segmentation procedures may be in spatial or frequency domain. The spatial domain techniques are as follows:

(a). **Basic Approach:** The concept is to find the difference image by comparing the two image frames pixel by pixel. In stationary segmentation the reference image with all stationary components of a scene is compared with succeeding image of the same scene but with a moving object. The result is a difference image with the stationary components cancelled leaving only the nonzero components corresponding to the moving object. In case of dynamic segmentation all the pixels in difference image with a value equal to 1 are considered as the result of the moving object. The major drawback in dynamic segmentation is that only two images can be indexed spatially, the illumination is relatively constant within the limit of the threshold value and noise can also be interpreted as a pixel with value 1 in the difference image.

(b). **Differences corresponding to location of the pixel:** The entries corresponding to the noise in the difference image can be isolated and removed in the form of a region. This also results in the deletion of small and slow moving objects. This problem can be can be tackled by recording changes at a pixel location over a number of frames, thereby incorporating the memory element into the system. Thus it avoids the changes that occur occasionally over a frame sequence. Therefore, Accumulative Difference Image (ADI) is created through contrasting the reference image to each consecutive image.

(c). **Creation of a reference image:** Creating a reference image with one or two moving objects is as follows: The first image in a sequence is taken as reference image. On the complete displacement of a moving object from its location in the reference frame, the related background in the current frame can be replaced in the location initially occupied by the object in the reference frame. Once all moving objects are shifted completely out of their original positions, a reference image containing only stationary components is produced.

In Frequency domain Fourier Transform formulation is applied to determine the motion estimates of an object.

Morphological operation:

Morphological operations are the tools used for the extraction of image components which represents and describes the region shape (Boundary, Skeleton and Convex Hull). These operators are employed for pre processing or post processing of images such as filtering, thinning (transforming a digital image into a skeleton) and pruning (process of removing parasitic components after the thinning and skeletonising process). The morphological operation is required to remove errors which still exist after segmentation process. These errors results in poor object recognition system and reduce the system performance.

The two primary morphological practices constitute dilation and erosion.

Feature extraction:

Feature is defined as a function or a part of information of an image which are measurable and significant. Features are definite structures such as boundary, edges, points or objects. Features are classified as:

- Domain Specific Features: Facial expression, finger prints, etc
- General Features: Examples colour, shape, texture, etc Global features are in turn classified as follows:
- Pixel level features: features classified at each pixel attributes. Example location, colour
- Local features: features of a sub- region in an image are measured.
- Global features: features of the entire image are calculated.

Features are further categorized as:

- Low level features: These features are derived from original images directly. Example: colour, shape, texture, etc.
- High level features: These features are obtained from low level features. Motion based, object based, keywords, text descriptors, etc.

Colour feature is amongst the most common factors utilized for retrieval of images.The advantages of colour attribute are computationally simpler; simple in implementation; colour attributes are invariant to rotation and changes in small steps when images are rotated or scaled. They are numb to variations in images, histogram resolution and occlusions. Lastly they require less storage space. The feature extraction process is as shown in the FIGURE 4. The object is separated from the background

ISSN: 2395-3519

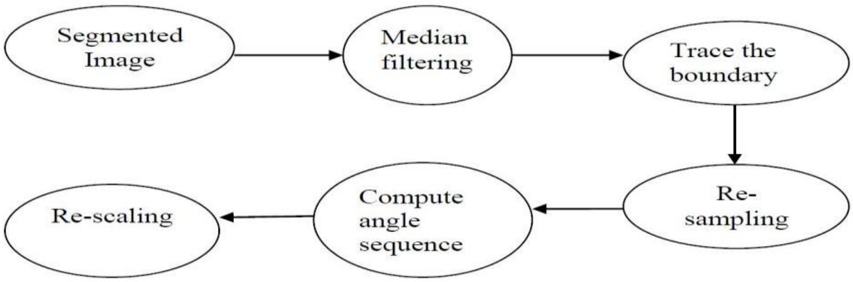

FIGURE 4 Feature extraction process

resulting in the binary image. The boundaries of the segmented image are smoothened by using the median filters. With multiple uncoupled objects, the object with longest boundary is retained. The curve undergoes re-sampling to facilitate its extension to a particular length. Re-sampling process ensures a change in the scale. The 2D sections are utilized for computation of the sequence of angels. Conclusively, a stage of rescaling takes into consideration angle values towards Reference/Query symbols.

Classifiers:

Classifiers assign levels to a remotely sensed data with respect to the groups of corresponding characteristics, with an objective of differentiating objects from each other in an image. Each level is called as Class. Classifications are often placed over features, i.e. density, texture, and colour etc. which are spectrally defined under feature space. The procedure of classification encompasses dividing the feature space based on the decision rule. This process is implemented by using computers with the aid of mathematical models.

FIGURE 5 depicts the classification procedure. The classification classes are defined based over objectives and characteristics for images data. Features are to be selected based on multi-spectral or multi-temporal properties, texture, etc. Data for training needs to be sample in effect to elaborate the rule decisions appropriately. Procedures for classifications are chosen based on these trained data sets. Different procedures for classifications are contrasted with data sets and proper rules are chosen for their selected classification. Then the pixels are classified in a single class based on the decision rule. The classified results are verified for their precision and consistency.

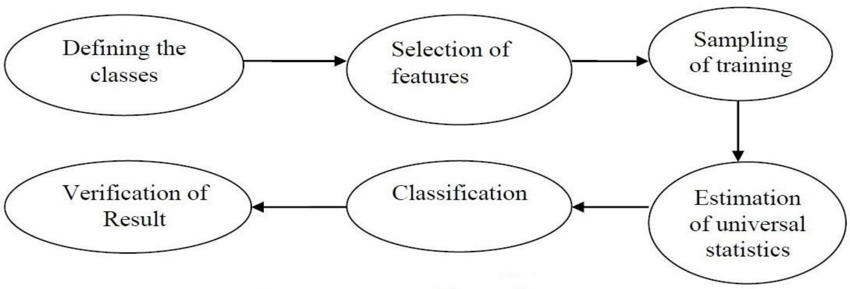

FIGURE 5 Classification process

Motion detection

Motion detection is the detection of change in position of an object with respect to the environment or vice-versa. Motion is a highly potential cue to extract object of significant from an image with unrelated surroundings. Motion happens mainly due to the displacement of camera or sensing elements and the scene to be imaged. The purpose of motion detection is to extract the changed area in the sequences of image from the background. Hence effective motion segmentation is essential in process like target classification, tracking and behaviour understanding. The dynamic changes in the background images because of weather influence, illumination and shadows, the motion detection becomes complicated.

Motion segmentation is a challenging task is locating a moving object in a video. The techniques for motion segmentation prove to be simple when the camera is at a standstill, but intangible when the camera is in action.

Hence the use of motion segmentation is considered in both spatial and frequency domain.

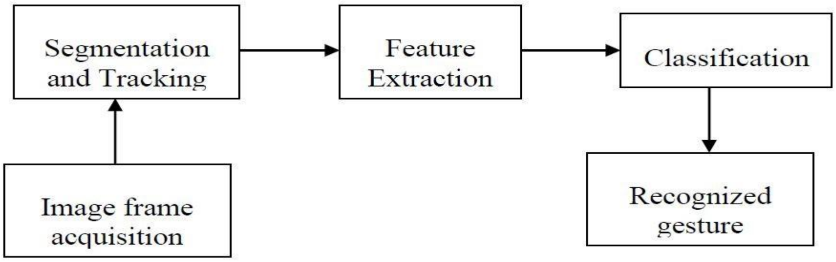

FIGURE 6 Motion detection process

The motion gesture detection is similar to that of static/dynamic gesture recognition. As shown in FIGURE 6, image frames are acquired from the camera. Segmentation is performed in order to separate the mid air hand from the background. The transformation and thresholding are important steps in segmentation. Segmentation is mainly based on skin colour, image intensity, background subtraction, etc.
Tracking system focuses on user- data interaction. Tracking system is categorized into two groups:

1. Tracking with interface: In this system we are recording the movement of object. The location of the object or the pattern drawn by the objects is recorded. The marker locations are identified and labelled according to its position.
2. Tracking without interface: Here the limbs are replicated as an articulated mechanics. This model can be applied to describe the mid air hand movement or the entire body movement. It can detect the finger location even without detecting the mid air hand location.

Supervised or unsupervised classifiers are used to recognize the mid air hand or pattern drawn by the finger.

Tracking and Recognition:
The human mid air hand is traced by calculating the 3D positioning of mid air hand joints using single depth image. Temporal information is not required.
Hand recognition can be accomplished by using the following approach: • Single per pixel classification

• Training the data sets.

1.4 Mid-air Hand recognition challenges

The major challenges of the data gloves and vision based mid air hand gesture recognition are,

1. The lighting condition affects the segmentation of the skin colour
2. The rotation problem occur when the mid air hand is rotated in the scene
3. Difficult to recover the mid air hand from the complex back ground with the objects with same colour as that of hand.
4. The variation in size and position of the mid air hand results in detection error.

1.5 Motivation for the research in 3D Trajectory-Based Mid-Air-Writing Recognition Systems

The following facts about HCI (Human-Computer Interaction) provide us motivation for research:

- The gesture may be the most natural way for humans to communicate with their environment and fellow humans, and it is the second form of speech.
- Gesture recognition system allows us free-air movement to do a various activity such as, to control smart TV and gaming. Motion and vision are two primary sensors used in natural HCI technology.
- Vision-based gesture recognition system offers a non-cumbersome and intuitive way of interaction compared to a wearable motion sensor based gesture recognition systems.

- An intangible writing interface can relieve the user from carrying external devices and relieve from device damage or loss. Through, such type of interface user can freely write in the air with hand or figure. A feasible and convenient intangible writing interface should allow a user to write multiple characters continuously in writing trajectory12.

II. LITERATURE REVIEW

A lot of research has been going on since 1928 in the area of mid air hand writing communication such as,

The research work, since 1956, led to the development of several automatic pattern recognition systems like Optical Character Recognition (OCR), Handwriting Recognition (HWR), Text to Speech conversion, Document Classification, Computer Vision, Shape Recognition, Biometric Authentication etc. The performance of these systems is controlled by many constraints. Any deviation from these constraints cause a large deterioration in the specified performance13. The ability to recognize patterns with the same fluency as human beings, remains to be a distant dream. The OCR systems are currently an integral part of document scanners, mobile phones, security cameras, and are used in many applications such as postal processing, vehicle number plate recognition, script recognition, banking, security (i.e. passport authentication) and language identification. The research in this area has been continuing for over half a century. The outcome has been found astonishing with more than 99% recognition accuracy for printed characters and exceeded 90% mark for the mid air handwritten cursive characters14.

A technique for automatic estimation of the rejection threshold on the confidence index of the OCR is developed15. Several thresholding approaches are developed in past based on histogram shapes. The semantic description of the histogram is efficiently utilized for developing a neuro-semantic thresholding technique for high precision OCR applications16. These thresholding techniques have been fully utilized for reduction in the computational cost for image processing in pattern matching problems17,18,19.

The Otsu method has been one of the widely used techniques in the field of computer vision and image processing. The method is based on converting a grey-level image into a binary image and calculating optimum threshold separating those two classes by maintaining minimal intraclass variance. The authors analyzed the performance of more than 20 global thresholding algorithms and observed Otsu class separability method as the best performing thresholding method20,21. The Otsu method has been found as the best performer among many other global thresholding techniques22,23. The poor performance of the Otsu method as compared with other global thresholding methods is also reported in the literature24.

Niblack's Techniques, Sauvola's Technique, T.R Singh's Technique, LAAB (Local Adaptive Automatic Binarization), Bernsen's Technique, Yanowitz&Bruckstein's Method are some of the local thresholding techniques available in the literature25,26,27,28,29.

The average stroke width is compared with the size and shapes of the connected component of the image to identify the noise in a word image30. Some scanned document image can contain clutter noise because of the presence of scanned punch holes. A noise removal algorithm is also developed considering clutter's position, size, shape, and text connectivity31.

a modified decision based median filter to remove impulse noise from word images is investigated32. Earlier many researchers worked on noise removal from word images and used standard median filter33,34,35,36, weighted median filter37,38 and adaptive median filter39,40,41. A new method for removing margin noise from scanned document images is also investigated where the authors used a layout analysis method for detecting words, lines and paragraphs from the document images42.

The size normalization can increase the recognition capability of the mid air handwritten character recognition system. Many authors investigated several normalization techniques and analyzed their impact on recognition rate43. Previous studies have shown the importance of size normalization in improving performance. The role of scaling in obtaining excellent recognition results; investigating normalization in numeral recognition; determining image invariants from normalization; normalizationcooperated gradient feature (NCGF) extraction; irrelevant variability normalization (IVN) for Chinese character recognition, are some of the work done in the field of normalization.

De-skewing is the process of correcting the skew of mid air handwritten words by removing the gap between the baseline of word image and its (word image) horizontal direction. On the other hand, slant correction is the process of removing the deviation of average near the vertical stroke of the word image from its vertical direction. Both slant and skew correction are important pre-processing steps in the mid air handwritten character recognition system.

The equivalence of slant and skew correction methods is analyzed for word recognition applications44. The authors used two methods for correcting slant and skew angles. The skewing process is performed before slant correction in one method, while the other method performed slanting before skewing. A new skew correction technique based on bounding box skew detection algorithm is investigated and reported efficient results for detecting and correcting the skew45. It has also been observed that some degree of skew is unavoidable whenever a paper is scanned manually or mechanically.

A multi skewed text technique is presented for mid air handwritten Devanagari and Bangla scripts46. The work observed recognition accuracy of 98.3on 225 document images and reported not suitable for those documents where the skew was beyond ±45deg. A procedure to detect the skew angle of individual text line and to detect text lines (arbitrary orientation) in a single document page are also developed. The authors used labelled Connected Components and performed clustering to make word groups. The text lines of arbitrary orientation are segmented from these word groups. However, it is not applicable to the extraction of text line having two or lesser number of components. This method reported a success rate of 97.7%.

The other skew detection work used the Run Length Smoothing Algorithm (RLSA) in textual documents. The RLSA is a block segmentation technique. The author also proposed one-pass skew correction and multi-pass skew correction method of skew correction. This method achieved a success rate of 94% when tested using 50 pages.

Another skew detecting and skew correcting technique is developed using connected component analysis and clustering technique and tested for "UW-I" database47. The text areas are selected/ identified based on a text localization technique. A skew angle estimation algorithm is applied locally in each identified text area and connected component analysis along with clustering technique are applied for forming words and lines. The proposed method observed 98% success rate with a skew estimation error of 0.5%. For old printed documents, the convex hull extraction and morphology method have also been used for skew estimation. In later years, a skew estimation technique using piecewise painting algorithm (PPA) has also been investigated for scanned multilingual documents48. However, this technique is not applicable if the document contains multi-skewed text lines.

One of the drawbacks of slant correction algorithms is the introduction of noise in the contour of the word images. Thinning and skeletonization are used to remove this noise which may be present in the form of bumps and holes in the word images. In the thinning process, the object is reduced and converted in one-pixel wide object making character recognition process simpler. Some researcher used the skeleton of the word images for normalizing the stroke width. On the other hand, some authors used medial axis transformation. Furthermore, the Laplacian and Sobel operations have been tried to enhance the contrast properties of degraded historical documents along with the study of the cursiveness of components using skeletonization. However, the pre-processing step of skeletonization is still a topic of debate as it involves some advantages as well as some disadvantages.

Segmentation is defined as the method of extracting the individual characters/word from the digital images. It is a very challenging process in mid air Handwriting Recognition. Segmentation is categorized into three types such as line segmentation, word segmentation and character segmentation. The segmentation is considered a challenging task in any character recognition system. Some of the challenges are,

- large variations in writing styles, size and shape of characters
- the irregular spacing between words
- characters may vary in shape depending on the position inside word
- broken characters
- presence of noise
- cursive writing style

International Journal of Advanced Trends in Computer Applications (IJATCA)
Volume 11, Number 1, Feb - 2026, pp. 1-28
ISSN: 2395-3519

- degraded paper or poor pen quality
- some characters such as ’u’ & ’v’ having similar contours
- some letters may give the illusion of two similar characters at the time of segmentation (character ‘w’ can be considered as two consecutive ‘v’ and ‘v’)

The research work on script independent line segmentation method reported good results in comparison to projection and connected component based traditional segmentation algorithms49. The authors used density estimation and level set method for determining the boundary of neighboring text lines. Similarly, a new method for evaluating segmentation of characters, text lines and words is developed and termed as Adaptive Run Length Smoothing Algorithm (ARLSA). The proposed algorithm successfully detected noisy areas and punctuation; a possible obstacle in separating text columns and text lines; and skeleton paths used in the segmentation of the connected characters. The average detection rate has been found to be 84.5% for the character, 85% for line and 81.5% for word segmentation.

The line segmentation and word segmentation techniques for mid air handwritten documents using the “Viterbi” algorithm are developed and tested for the ICDAR07 dataset50. The “Viterbi” algorithm is used to locate the optimal succession of text and gap areas in each vertical zone. For word segmentation, the authors used the gap metric results to separate consecutive connected component. The proposed method reported good results when evaluated for the ICDAR07 dataset.

A segmentation approach to detect text lines for multi-oriented mid air handwritten Arabic documents is investigated for Arabic documents51. The orientation of lines is determined by the Wigner-Ville Distribution. The segmentation process used baseline and connected component proximity for text line extraction in each zone. The approach received a segmentation accuracy of 98.6% for text lines. The line and word segmentation using a bounded box approach reported 100% accuracy for scanned Devnagari documents.

A Spiral Run Length Smearing Algorithm (SRLSA) used for extracting words from the text lines is investigated for mid air handwritten Bangla document images52. The SRLSA is a modified Run Length Smoothing Algorithm (RLSA). The proposed algorithm is evaluated on “CMATERdb1.1.1” database and achieved 86.01% accuracy for word extraction. The authors also proposed a practical solution for segmentation of mid air handwritten Bangla script into constituent characters.

Furthermore, two nonlinear clustering methods – “SegNcut” (segmentation with Normalized cut) and “SegCOLL” (segmentation with Conscience On-Line Learning) are proposed for performing segmentation. The idea was to first segment all text into strokes and calculate similarity matrix using stroke gravities. The nonlinear clustering on the similarity matrix is used to obtain cluster labels for the strokes. These cluster labels are further used for forming characters after combining the strokes. The proposed method has been evaluated and reported the best segmentation results.

AdaBoost with MLP classifier based scene text detection algorithm is employed in mid air handwriting recognition where one classifier is designed to generate candidate’s regions and the other classifier is designed for the filtering of non-text candidates53.
The authors observed an accuracy of 75.3% on ICDAR 2005 dataset and 78.72% on ICDAR 2011 dataset.

A method is proposed for extracting textual information from born-digital images. A new edge detection technique is also investigated for low contrast web images. The broken edges of the components are connected using morphological dilation. The K-means clustering is used for classification in text and non-text regions. This approach achieved 76.88% accuracy using the ICDAR 2011 dataset.

A solution for the word segmentation problem using binary quadratic assignment problem is presented54. Here, the authors used pair-wise correlations between the gaps and likelihoods of individual gaps for the word segmentation. All parameters are estimated using structured SVM. The authors evaluated the proposed method on ICDAR 2009/2013 mid air handwriting segmentation databases and achieved an average success rate of 92.82%.

In the field of historical document recognition, the work of Kavitha et al. proposed a new text segmentation approach by enhancing the contrast of the degraded input images 55. The contrast is enhanced by Laplacian and Sobel operations. Additionally, skeletonization is also used to find cursive characteristics of the component from the images. The proposed approach is evaluated on degraded historical document images and reported good results for text line segmentation.

Recently, a character segmentation using a modified projection method is employed in machine typed documents56. In the modified projection method, the count of the black pixel in a sliding window is calculated and decisions are made based on histogram processing. The proposed approach performed very well in terms of both accuracy and time.

The pattern recognition techniques are classified in feature-based and templatebased approaches57. Earlier, many optical character recognition systems were based on the template-based approach in which classification directly depends on the degree of correlation between the unknown patterns and the ideal patterns. But nowadays, it is a usual practice to combine the templatebased approach with a feature-based approach to get better results.

Shape-based feature extraction techniques are widely used in many pattern recognition systems and reported good results34,35. In one of gradient-based feature extraction research work,58 proposed enhanced “Harmony” search method to identify most informative regions for correctly recognizing mid air handwritten characters. The proposed approach is evaluated for three datasets and found to be more suitable for mid air handwritten character recognition.

A new feature extraction method based on moments is investigated59. The method consists of a combination of six different types of moments for recognition of mid air handwritten digits. The proposed approach is evaluated on CMATER and MNIST databases for five popular scripts such as Roman, Indo-Arabic, Telugu, Bangla and Devanagari. The authors reported good recognition accuracy for all script using MLP classifier.

Some of the researchers worked on contour-based features. Basu et al. proposed an approach for recognition of cursive mid air handwritten Bangla characters60. The authors used longest-run features, octant-centroid features and modified-shadow features for making powerful feature set of Bangla characters. The character is divided into a lower zone, middle zone and upper zone segments. A set of classifiers is used to recognize the character segments separately and recognition results are combined to get the final output. The proposed approach is evaluated using MLP classifiers and reported good recognition results.

A genetic algorithm based region sampling of local features is used for recognition of mid air handwritten Bangla digits. The method successfully collected the best discriminating features and used with SVM classifier. The proposed method reported a recognition accuracy of 97%.

An MLP classifier is implemented to recognize and predict mid air handwritten digits. The author used a gradient descent back-propagation algorithm for training data, a feed-forward algorithm for testing the MNIST database. The work reported a good recognition accuracy of 99.32%.

Recently, a Genetic Algorithm (GA) based feature selection method is investigated after combining multiple features of mid air handwritten characters61. The approach observed percentage gain in recognition accuracy along with a reduction in computational time when the method is evaluated using adaptive Multi-Layer Perceptron classifier for off-line mid air handwritten English alphabet recognition of the CEDAR database. Additionally, a recurrent neural network (RNN) framework for online mid air handwritten Chinese characters is employed by combining both discriminative and generative model62. The RNN based approach does not require any domain-specific knowledge and directly deals with the row sequential data. It is observed that the RNN based approach combining with the gated recurrent unit (GRU) and bidirectional long short term memory (LSTM) is better than convolution neural network based approach63.

In the recognition step, the discriminative features extracted in previous steps are given to the classifiers for recognition. The mid air handwritten character recognition system’s performance directly depends upon the type of classifiers used. More powerful is the discrimination capability of a classifier, better is its recognition accuracy. The classification performance greatly depends on the characteristics of the data to be classified. There is no single classifier that works well for all types of data. Some of the common classifiers are Bayes Classifier, Parzen window classifier, linear discrimination function, quadratic discrimination function, radial basis function (RBF), KNN (k-nearest neighbours), polynomial classifier (PC), learning vector quantization (LVQ), self-organization map (SOM), multilayer perceptron (MLP), probabilistic neural network (PNN), neural network classifier, fuzzy classifier, fuzzy c-means classifier, Neuro-Fuzzy classifier, support vector machine (SVM), hidden Markov model (HMM) etc.

For the classification of mid air handwritten numerals, characters and words, a number of soft computing-based classification techniques involving Artificial Neural Network classifiers (ANN), Fuzzy Logic (FL), Genetic Algorithm (GA) and various hybrid methods like neuro-fuzzy, neuro-fuzzy-genetic are developed and investigated in past. A multistage cascade recognition approach using wavelet-based multiresolution representation is investigated for isolated mid air handwritten numeral recognition (Bhattacharya & Chaudhuri, 2009). The proposed method cascaded three MLP classifiers in the recognition step. In case of rejection, outputs of three classifiers of the previous stages are combined to be used as input of new MLP to recognize the input numeral. The proposed approach is evaluated for mid air handwritten numerals of English, Devanagari and Bangla along with the development of the mid air handwritten numeral database in Devanagari and Bangla script.

A hybrid model consisting of HMM and ANN is employed for recognizing unconstrained offline mid air handwritten texts64. A new technique is also developed for normalizing text images and for removing slant and skew from mid air handwritten text. The proposed hybrid model reported a remarkable reduction in Word Error Rate (WER) in comparison to a simple HMM model and reported a WER of 29.8% for the test set.

A modification in the membership function of the fuzzy set for Hindi and English numeral recognition is suggested65. The approach used two structural parameters to modify the membership functions. These parameters are estimated using the minimizing/optimization function. The feature extraction step consists of calculating normalized distance using the Box method. The proposed method achieved significant recognition accuracy of 95% and 98.4% for Hindi and English numerals respectively. Hanmandlu et al. also introduced a new learning technique named as bacterial foraging in their another work of Hindi numeral recognition66. The authors used the box approach for feature extraction. A set of optimization function and test function are applied to 3500 samples for evaluation purpose. A recognition accuracy of 96% for Hindi numerals is reported using the proposed method.

A recognition method is introduced for faster training of high-resolution character images67. The method is based on multiscale neural training with modifications in the input training vectors. The authors also showed the use of selective minimum distance thresholding technique for increasing the accuracy level of character recognition. They designed a simulator program (a GUI) to locate characters on any mid air handwritten paper. In the recognition of mid air handwritten English characters (upper case) and numerals, the proposed method reported more than 85% recognition accuracy. Bio-inspired computing also known as evolutionary algorithms is one other method of soft computing that simulate the natural biological behavior of entities. The Evolutionary computing techniques can be hybridized with other techniques like fuzzy, neural network and can be implemented independently.

Genetic programming based learning method for producing classification rules is employed for mid air handwritten character recognition system68. The method proved to be efficient for pre-classification of the mid air handwritten digits of NIST database. The method consists of a structure of fine classification rules, the grammar used in the generation of rules, a fitness function and genetic operators for evaluating and manipulating rules respectively.

Lately, hybrid evolutionary algorithms are investigated in detail for mid air handwritten English alphabet recognition69. The research provided a performance comparison of the feed-forward neural network with the proposed hybrid evolutionary algorithm, backpropagation and simple evolutionary algorithms. The proposed hybrid evolutionary algorithms outperform in terms of recognition accuracy and rate of convergence in case of handwritten English alphabet recognition.

A new class of membership function known as Fuzzy-membership functions (FMFs), is presented by Pirlo et al. for zoningbased classification70. A zone feature membership function is used in the proposed method to identify the influence of a feature in different zones of a zoning method. The authors applied optimal FMF, optimal zoning and combination of both for mid air handwritten numeral and character recognition problems. The method is evaluated on CEDAR and

Electrotechnical Laboratory (ETL) databases and achieved significant improvement in recognition accuracy. The results also indicate the better performance of optimal FMF over other membership functions used in past.

Additionally,Neuro-fuzzyapproachhasbeencommonlyusedformidairhandwrittencharacterrecognition.Thelargeambiguities, uncertainty and impreciseness present in handwriting style of individuals are some of the challenges of mid air handwritten character recognition processes. So, there is a demand for an efficient network which must be invariant to the distortions in the input and also involve less training efforts.

The neuro-fuzzy based recognition system has been a good choice for Brahmi characters. The Fuzzy Min-Max (FMM) neural network based recognition system proved to be efficient for printed English upper case letters. The GA based rule selection method for FMM, when evaluated on five benchmark databases, observed high recognition accuracy with lesser computation time71. The method used Guided Elitism Genetic Algorithm (GEGA). The algorithm works by creating elitism in the population by extracting information from the previous generation individuals. The fuzzy hyper line segment neural network classifier has been proved superior to FMM and Fuzzy neural net (FNN) when used for rotation invariant mid air handwritten character recognition72. The classifier used the fuzzy set as pattern classes. Each fuzzy set consists of a union of fuzzy set hyper line segments.

Later, an Enhanced FMM (EFMM) network is developed to overcome the limitations of the original FMM network and to improve the classification performance (Mohammed & Lim, 2015). The author introduced three rules for the enhancement in the original FMM. The rules include hyperbox expansion rule, hyperbox extension rule and hyperbox contraction rules. The effectiveness of proposed EFMM has been proved by comparing the outcomes with SVMs, FMM variants, fuzzy based, Bayesian-based, neural network based and decision tree based classifiers for eight benchmark databases. A new classifier combining neural network and genetic algorithm is evaluated and proved efficient for totally unconstrained mid air handwritten numerals recognition. The evolutionary optimization approach is investigated and found effective for augmented Radial Basis FNN (RBFNN)73. The Adaptive Neuro-Fuzzy Classifier (ANFC) performed well for isolated Gujarati handwritten character recognition.

III. METHODOLOGIES USED IN MID-AIR HANDWRITING SYSTEMS

This section presents the state of the art in mid air handwriting recognition technology with an emphasis on Online mid air Handwriting Recognition of Assamese characters. Online and Offline Handwriting Recognition is discussed. We discuss issues related to datasets, online text input devices and online data acquisition methodology. This section further highlights a few datasets of online mid air handwritten characters for Western Scripts as well as Indian Scripts.

3.1 Mid-air Handwriting recognition

Handwriting properties and issues related to problems involved in the machine recognition of handwriting are explained by20.22 describe the nature of handwritten language and how it is transduced into electronic data and highlight application areas of both online and offline recognition systems. Applications of Online Handwriting Recognition (OHR) are found in handheld computers such as PDAs and Tablet PCs. The success of online systems opens the idea of developing offline systems that first estimate the trajectory of the writing from offline data and then use online recognition algorithm.

3.1.1 Online and Offline Mid-air Handwriting Recognition

The offline/online data contains the temporal information about the writing process, in addition to the spatial shape information of the characters. A recognition process can make use of both the above information for robust performance. On the other hand, in offline system, recognition is performed after the digitized image of the handwritten document is captured by a scanner. Offline Handwriting Recognition system is a subfield of Optical Character Recognition (OCR), where OCR is the mechanical or electronic conversion of scanned or photographed images of printed or handwritten text into computer readable text. Online recognition is more accurate than that of offline due to the additional temporal information.

3.1.2 Mid-air Handwriting Recognition in Writer Dependent and Independent

Mid-air handwriting recognition systems can be classified into writer dependent and writer independent recognition systems. Writer dependent systems are developed for recognizing a specific or known pattern of handwriting. Writer dependent recognition systems are trained and tested for a specific group of writers and the system aims at recognizing the handwritings of only those writers for which it is trained and tested. Writer dependent recognition systems deal with lower variability in handwriting, which leads to higher recognition rate in such systems. On the other hand, writer independent recognition systems are developed for recognizing handwritings with unknown patterns. In this case, the recognition system has to deal with high variability in patterns of handwriting, since the system is not limited to a specific group of writers. In the category of writer independent recognition systems, recognition is performed on the handwritings of those writers for which the system is not trained. Writer independent recognition systems are difficult to develop in comparison to writer dependent recognition systems.

3.1.3 Mid-air Handwriting Recognition in Constrained and Unconstrained Systems

There is flexibility of writing in unconstrained mid-air handwriting. Writing of each character can be highly variable in unconstrained writing for each individual writer as there are no such specific instructions in writing as described above for constrained handwriting. Writings tend to be cursive in unconstrained system. Due to writing variations, mid air handwriting recognition is difficult in case of unconstrained recognition systems.

3.1.4 Variability in Mid-air Writing Styles

Writing style is mainly person dependent. Apart from that, factors that influence writing styles are writing surface of the tablet, writing posture, writing environment etc. Each individual character is written by different writers in different ways. Even the same writer tends to write a character differently at different times. Characters can vary in terms of the position at which these are written in the writing surface. Moreover, the characters can have variability in terms of size and direction of strokes.

3.2 Data Acquisition and Datasets

This sub-section presents a brief discussion on data acquisition for the purpose of online handwriting recognition experiments and highlights a few standard datasets available in Western and Indian Scripts.

3.2.1 Data Acquisition

The typical format of online mid air handwriting data is a sequence of (X, Y) coordinate points (horizontal and vertical coordinates). Online handwriting data is captured by writing with a special pen called stylus on an electronic surface such as a digitizer combined with a liquid crystal display. The data in online handwriting is spatio-temporal in nature. The two dimensional coordinates of successive points are stored as a function of time. Apart from the capture of these successive coordinate points, the data acquisition program typically captures two actions of the electronic pen as the writer writes on the digitizer surface. These two pen actions are Pen-down and Pen-up. Pen-down action is captured when the pen touches the digitizer surface at the start of writing and the pen-up action is captured when the pen is lifted at end of writing. A stroke is a sequence of (X, Y) coordinate points captured between a pen-down and a pen-up action. In case of single stroke characters we have occurrences of pen-down and pen-up actions only for once. In case of characters composed of multiple strokes in the occurrences of pen-down and penup actions for multiple times which is equal to the number of strokes of the characters. While writing, writer applies pressure with the pen tip on the surface of the digitizer. The acquisition program may also capture the pressure of the pen tip at each coordinate point which the writer applies while writing on the pressure sensitive surface of the digitizer.

3.2.2 Data Acquisition Methodology

In the context of OHR, data acquisition methodology describes the systematic steps of collection of online handwriting samples. The first step in data acquisition methodology is the selection of online handwritten characters to be collected. A list of attributes or requisite information (for example, pen-down and pen-up events, number of strokes etc.) to be captured is prepared. Then a software application or a data collection tool which runs on handheld devices like Tablet PC is developed. Writers input the selected text through a GUI available in the data collection tool. The data collection tool captures the requisite information as the writer writes.

3.3 Datasets

This sub-section briefly describes a few datasets of online handwriting available in Western and Indian Scripts.

Few datasets of online handwritings in the context of Indian scripts are namely, HP Lab Tamil Dataset36, HP Lab Telugu Dataset42, Bangla Numeral Dataset46, Devanagari Character Dataset47 and Online Handwritten Assamese Characters dataset51. HP Lab Isolated Online Handwritten Tamil Character Dataset contains approximately 500 isolated samples each of 156 Tamil characters written by native Tamil writers. HP Lab Isolated Online Handwritten Telugu Character Dataset contains approximately 270 samples each of 166 Telugu characters written by native Telugu writers.

3.4 Preprocessing

Preprocessing of online handwriting data is performed prior to the application of character recognition algorithm. Preprocessing usually deals with filtering, smoothing and different types of normalization operations applied to online handwritten data. The online handwritten data usually include noise. Noises may be in the form of jitters or roughness and missing points in the strokes. The characters may also vary in terms of size, orientation, number of coordinate points and the range of horizontal and vertical coordinate values. Variability in number of points results in variable lengths of the characters. Similarly, the characters may be written at different regions of the writing pad in the tablet. Besides noise removal, preprocessing involves the normalization of size, orientation, length and region of writing. Preprocessing is an important step in character recognition system. The noise and other variations in online handwritten data complicate handwriting recognition.

3.4.1 Preprocessing Steps

This section briefly describes various preprocessing steps. The preprocessing steps which usually are applied in character recognition system are noise reduction which deals with removal of jitters and other irregularities like hook. Smoothing operation removes jitters or roughness from the strokes. Jitters results from hardware problem or erratic hand motion. Jitters make the trace of the stroke angular. Moving average filters are used to smooth the strokes by reducing roughness or jitters. Smoothing at a point P is performed by computing the average of the point positions in a specific neighbourhood of the P, where P is the center of the neighbourhood. When the pen moves at high speed some intermediate points of the stroke may be missing. Interpolation is used to approximate the missing points.27 describes a method to interpolate missing points using Bezier curve. Author reported a minor impact of interpolation of missing point on the recognition rates. Hooks are imperfections at the beginning and at the end of a stroke. Hooks result from erratic hand motion and inaccuracies in the contact of pen and the writing surface at the time of penup and pen-down movements. These are small in size and have great angular variations.21 describes a hook removal process where strokes are processed at their extremities to remove hooks from that portion of the stroke based on the thresholds on the length and the angular variation between the points. Size normalization is the process of removal of variation in size. Normalizing writing size is used to simplify the character recognition process. Characters of different sizes are normalized to a fixed size. The numbers of points in characters are variable. The variable numbers of points of the strokes are normalized to a fixed number of points.

3.5 Features of Online Mid-air Handwritten Characters

Features should represent the characters properly. The efficiency of a character recognition system depends on relevant features. A large variety of features of online handwritten characters are available. The features of online handwriting can be categorized as geometrical

International Journal of Advanced Trends in Computer Applications (IJATCA)
Volume 11, Number 1, Feb - 2026, pp. 1-28
ISSN: 2395-3519

features, structural or topological features, and statistical features.

3.5.1 Geometrical Features

Geometrical features represent the geometrical properties of the character. The coordinate points of strokes, direction of strokes, start point and end point information of strokes; curvature etc. can be categorized as geometrical features.

Resampled Horizontal and Vertical Coordinates

Two dimensional (x,y) coordinate points are the basic geometrical features of online handwritten characters. The online handwritten characters are normalized (or resampling) in preprocessing step to have equal number of points. The resampled horizontal (x) and vertical (y) coordinates are considered as features (pen coordinate features) for online handwritings.

Pen-down and Pen-up Positions

Pen-down and pen-up features are binary features. Pen-down feature indicates the start of writing and pen-up feature indicates the end of writing. A pen-down event consecutively followed by a pen-up event represents a single stroke of a character.

Mid-air Writing Direction

The change of writing direction is regarded as the change of orientation of stroke from one pen position to the next pen position.

The writing direction is similar for one particular character or digit, though its stroke order may be different. The angles associated with this computation are shown in the FIGURE 7.

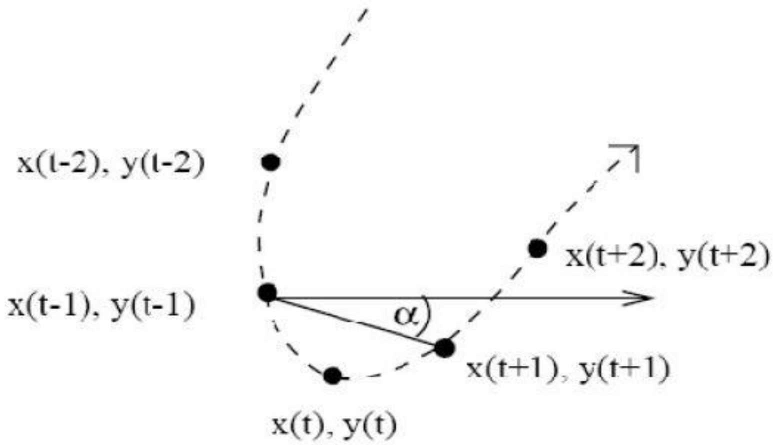

FIGURE 7 Mid-air Writing Direction

$\cos\alpha(t) = \frac{\Delta x(t)}{\Delta s(t)}$ and $\sin\alpha(t) = \frac{\Delta y(t)}{\Delta s(t)}$, where $\Delta s(t)$, $\Delta x(t)$ and $\Delta y(t)$ are defined as follows:

$$\Delta s(t) = \sqrt{\Delta x^2(t) + \Delta y^2(t)}$$
$$\Delta x(t) = x(t+1) - x(t-1)$$
$$\Delta y(t) = y(t+1) - y(t-1)$$

Curvature Feature

Curvature is the reciprocal of the radius of a circle touching and partially fitting the curve. Curvature feature of an online handwritten character indicates the degree by which the trajectory of writing deviates from being straight. The curvature at a point (x(t),y(t)) can be implemented using the Cosine and Sine of the angle with the following series of points (x(t - 2), y(t - 2)), (x(t), y(t)), (x(t + 2), y(t + 2)). The angles associated with this computation are shown in the FIGURE 8.

The angle $\beta(t)$ is given by $\beta(t) = \alpha(t + 1) - \alpha(t - 1)$. The curvature in terms of Cosine and Sine is defined as,

Eight-directional Feature

Eight-directional feature of online handwriting is based on Free-man Code. Starting from first pen-down event, direction in which the pen tip moves is recorded along the directions, namely 0,1,2,3,4,5,6 and 7 as shown in the FIGURE 9 and outputs a feature value representing the direction of this movement. The eight-directional feature is mostly used in Chinese, Japanese, and Korean characters from 1-8.

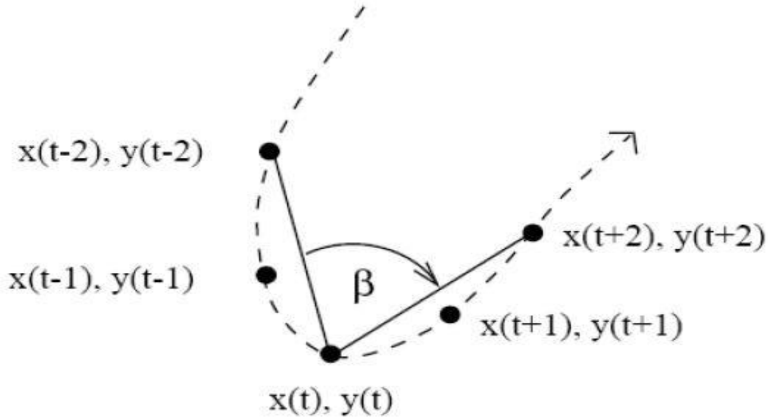

FIGURE 8 Curvature

$$\cos\beta(t) = \cos\alpha(t-1)\times\cos\alpha(t+1) + \sin\alpha(t-1)\times\sin\alpha(t+1)$$

$$\sin\beta(t) = \cos\alpha(t-1)\times\sin\alpha(t+1) - \sin\alpha(t-1)\times\cos\alpha(t+1)$$

where $\cos\alpha(t) = \dfrac{\Delta x(t)}{\Delta s(t)}$, $\sin\alpha(t) = \dfrac{\Delta y(t)}{\Delta s(t)}$ and $\Delta s(t)$, $\Delta x(t)$ and $\Delta y(t)$ are defined as

$\Delta s(t) = \sqrt{\Delta x^2(t) + \Delta y^2(t)}$, $\Delta x(t) = x(t+1) - x(t-1)$ and $\Delta y(t) = y(t+1) - y(t-1)$.

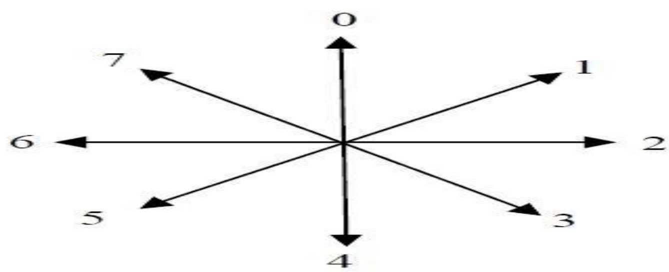

FIGURE 9 Freeman code

3.6 Structural or Topological Features

Structural features are based on topological properties of the character, such as aspect ratio, cross points or junction points, loops, cusps, hook, isolated dots etc.

3.6.1 Junction Point

Junctions are the intersection of strokes. FIGURE 10 shows a junction point. Junction points are obtained when two or more strokes intersect. Junction points are present in multi-stroke characters only. This feature happens to be missing in cursive writing, since most of the characters are written using single stroke in cursive writing.

3.6.2 Loop

Loops are the small circular parts attached to the main body of the character. Loops result from self intersecting strokes. When a stroke intersects itself at

International Journal of Advanced Trends in Computer Applications (IJATCA)
Volume 11, Number 1, Feb - 2026, pp. 1-28
ISSN: 2395-3519

some point then a loop is created at that point. FIGURE 11 shows a loop. Loop extraction techniques for online Thai character recognition are found in37,56.

FIGURE 10 Junction Point

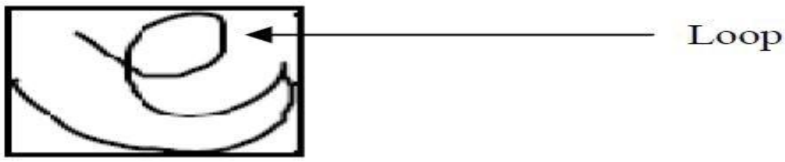

FIGURE 11 Loop

3.6.3 Cusp

Cusps are points of sharp directional change. 48 define cusp points as high-curvature points in the input. A cusp is a point at which two branches of a curve meet such that both the tangents one for each branch coincide. FIGURE 12 shows a cusp. Cusp feature is used in online handwriting recognition.

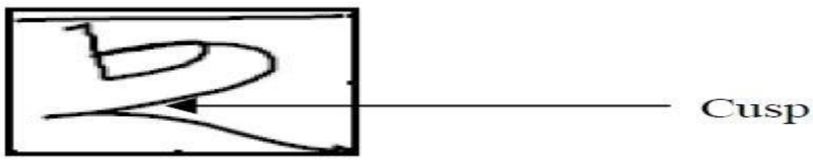

FIGURE 12 Cusp

3.6.4 Dot

A dot appears to be a very small stroke and it is an isolated stroke. FIGURE 13 shows a dot. The detection of dot feature from online handwritten characters depends on stroke length, stroke direction, stroke position and nature of points in the stroke. The use of dot feature is mostly found in Arabic characters. The extraction of dot feature is also performed in7,45.

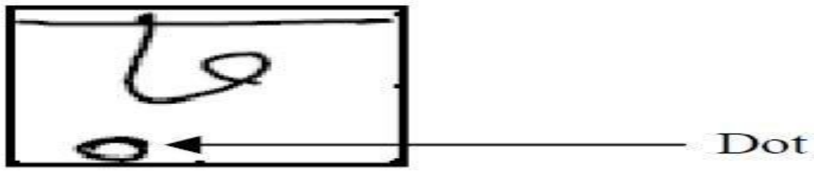

FIGURE 13 Dot feature

3.6.5 Head Line

Head line is the horizontal stroke at the upper zone of the character. FIGURE 14 shows a head line. The horizontal stroke is drawn on top of all associated character which is also referred Shirorekha. The head line vertically separates a character from its neighbours. Roman character set does have the head line feature and it exists mostly in case of Indian scripts.13,45 used headline as a feature in online character recognition.

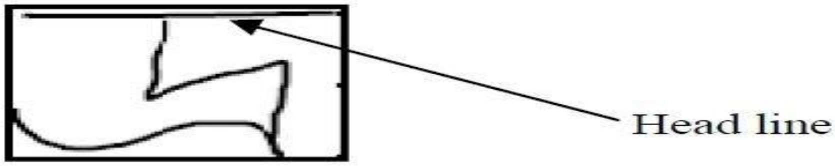

FIGURE 14 Head Line

3.6.6 Vertical Line

The use of vertical line feature for online handwritten character recognition found in50,51. FIGURE 15 shows a vertical line. The feature values extracted from vertical lines are namely the numbers and positions of the vertical lines in the characters.

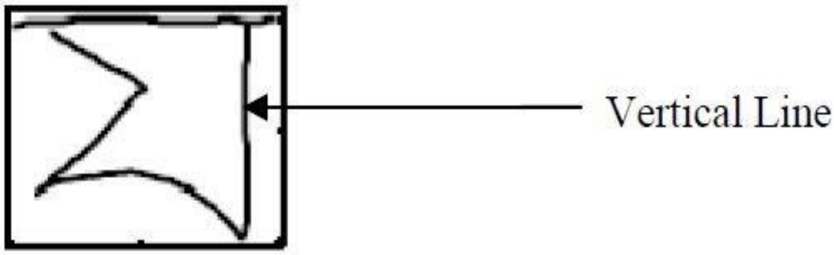

FIGURE 15 Vertical Line

3.7 Statistical Features

Statistical features are numerical measures derived from the constituent points of the strokes. Some examples of statistical feature include normalized horizontal coordinates, normalized vertical coordinates, zoning, distance, number of strokes, character length, aspect ratio etc.

Normalized horizontal and vertical coordinates

Normalized pen coordinates are used as features described in$^{x^{-}\mu}y_{i-\mu y}$38,53,54,55. Normalized horizontal and vertical coordinates are given by x_i= $_{i\sigma y x}$and y_i= —— $_{\sigma y}$, where (x_i,y_i) is the point in the online handwritten stroke having horizontal coordinates $x_i$and vertical coordinates y_i, normalization is performed with mean $\mu_x$and $\mu_y$of horizontal $x$and $y$coordinates and σ_y.

Zone

The bounding rectangle of a character is divided into M × N zones of equal intervals. Each zone contains distinct information. Stroke information, for instance number of points in each zone is used as features. The use of zoning information as feature is explained in35.44 has also proposed a zoning algorithm.

Mean of horizontal and mean of vertical coordinates

Mean of horizontal coordinates (x) and that of vertical coordinates (y) of the pen coordinate point (x,y) are used as features for online handwriting recognition in13.

Standard Deviation

In the context of online handwriting recognition standard deviation of horizontal coordinates (x) and that of vertical coordinates (y) of the pen coordinate point (x,y) is used as a feature. Standard deviation feature is used in55,57.

Number of strokes

The number of constituent stroke in an online handwritten character is derived from the pen-down events. The number of constituent strokes in an online handwritten character is equal to the number of occurrences of pen-down operations.

Stroke length

The lengths of the individual strokes of an online handwritten character are computed and used as a feature. The length of a stroke is defined as the number of points in the stroke. The usage of stroke length as feature is defined in34. The eight-directional feature of a stroke conveys more information if it is supplemented by the length of the stroke as explained in36,58

Aspect Ratio

The aspect ratio of an online handwritten character is defined as the ratio of the height to the width of the character. The use of aspect ratio as feature is used in34,59. When long shaped characters are converted to square shape, the conventional normalization method may distort the shape of the character excessively. A new method for normalization of character called aspect ratio adaptive normalization (ARAN) by incorporating aspect ratio into normalization procedure to control the aspect ratio of the normalized image.

Distance

Distance measures are used as features for the recognition of online written characters.49 used a distance feature by incorporating the horizontal and vertical distances between terminal and the final points in a stroke.56 introduced a distance feature called center distance feature [CDF] for online handwriting Uyghur character.37 introduced modified center distance feature [MCDF] by incorporating stroke number feature, additional part's location feature, shape feature, bottom-up and left-right density feature into CDF.

3.8 Qualitative Representation of Planar Outlines

This sub-section explains the representation of planar shapes in qualitative domain. The shape of an object can be described in both quantitative and qualitative ways. The quantitative representation of a planar shape involves a set of mathematical functions of plane coordinates and features described as in previous section. If the shape is more complex, it is difficult to find a mathematical function for the curve describing the outline or boundary of the shape. Qualitative representation makes use of symbolic schemes for describing shapes as shown in TABLE 1. Qualitative representation of describing shapes is considered preferable to quantitative techniques. This is because qualitative techniques can deal with abstract or complex shapes more efficiently than purely quantitative models. Descriptions about qualitative representation of shape can be found in49,50,51.

Codon Theory of Richard and Hoffman

Contour cordons or simply codons are simple shape primitives. Codons can be used as shape descriptors for describing planar curves. A codon can be defined as a small a curve segment that is characterized by curvature minima. A codon can contain zero point of zero curvature, one point of zero curvature or two points of zero curvature. The four basic types of codon as described by Hoffman & Richards are symbolized as 0, 1-, 1+ and 2 depending on the number of zero curvature points present in segment of curve. Type 0 codon contains no zero curvature point, type 1- codon contains one point of zero curvature which occurs before the point of maximum curvature, type 1+ codon contains one point of zero curvature which occurs after the point of maximum curvature and type 2 codon contains two points of zero curvature. FIGURE 16 shows all four types of codons where dots in the curve indicate zeros of curvature and slashes denote curvature minima.

TABLE 1 Direction Relations

Sl. No.	Base Relation	Angle Range	Converse of Base Relation	Sl. No.	Direction Relation	Angle Range	Converse of Base Relation
1	$Same$	$[0, 0]$	$Same$	7	lr	$[270, 270]$	rl
2	$Same+$	$]0, 45]$	$Same-$	8	$lr+$	$]270, 315]$	$rl-$
3	$Same-$	$]315, 360[$	$Same+$	9	$lr-$	$]225, 270[$	$rl+$
4	$Opposite$	$[180, 180]$	$Opposite$	10	rl	$[90, 90]$	lr
5	$Opposite+$	$]180, 225]$	$Opposite-$	11	$rl+$	$]90, 135]$	$lr-$
6	$Opposite-$	$]135, 180[$	$Opposite+$	12	$rl-$	$]45, 90[$	$lr+$

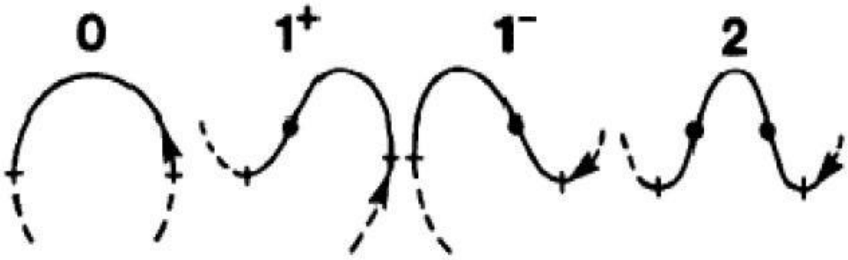

FIGURE 16 Contour Codons

A curve is divided into segments using the curvature minima. Both open and closed planar curves can be represented by strings of contour codons. Moreover, only certain codon joins in pairwise connections are allowable. The allowable pairwise connections of codons are shown in TABLE 2, rows and columns are labeled by codon types where a tick mark indicates allowable codon joins and a cross mark indicates a non allowable codon join. An example of a shape represented in terms of string of contour codons is shown in FIGURE 17.

TABLE 2 Allowable Codon Joins

	0	1^-	1^+	2
0	√	√	√	√
1^-	√	×	×	√
1^+	√	√	×	√
2	√	√	×	√

Leyton's Process Grammar for Shape

Curves can be divided into smaller curves based on the symmetry axis of curves and can be described in terms of curvature extrema. Four types of curvature extrema are namely, M+, m-, m+ and M-. All these four types of curvature extrema are shown in FIGURE 18. Among these four curvature extrema, M+ and m- are the sharpest curvature extrema having exactly the same shape. However, M+ differs from m- in the sense that, in M+, the solid portion (shaded) is on the inside, and, in m-, the solid

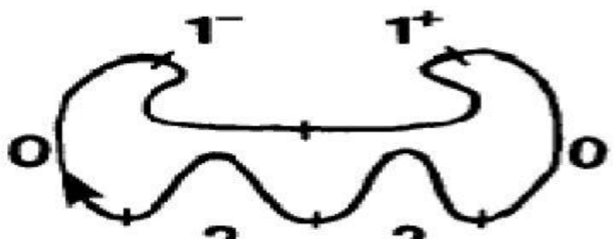

FIGURE 17 Codon String: 01-1+022

portion (shaded) is on the outside. This characteristic make them figure/ground reversals of each other. The other two extrema m+ and M- are also figure/ground reversals of each other. In this case, the extrema m+ and M- are the flattest points on the respective curves. In FIGURE 19 a planar curve is represented in terms of six curvature extrema, where arrows denote axes of symmetry.

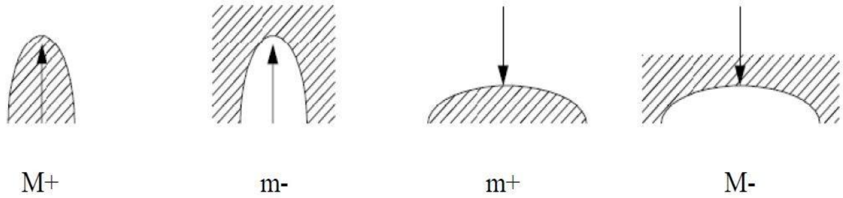

FIGURE 18 The Four Types of Extrema (Adopted from Leyton

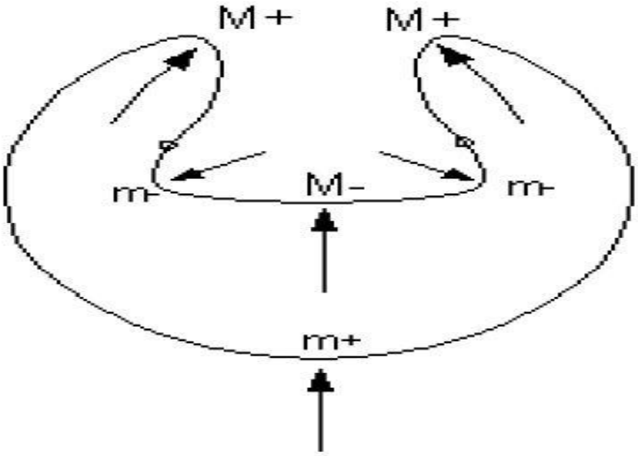

FIGURE 19 A planar curve with six extrema

IV. RESULTS DISCUSSION WITH STATE-OF-THE-ART TECHNIQUES

The bar chart has been used to represent the recognition accuracy of all the four feature extraction methods in FIGURE 20. It is clear that the various feature technique are shown more accurate for mid air handwritten numeral recognition. The bar chart clearly compared the capacity of the individual features with the capacity of hybrid features in the domain of numeral recognition. The existing state-of-the-art techniques as shown in TABLE 3.

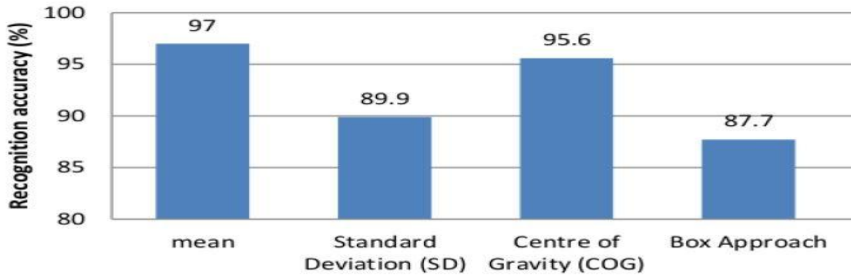

FIGURE 20 Recognition Accuracy of Different 3D trajectory mid air hand written Methods

TABLE 3 Comparisons of Numeral Recognition Accuracies on 3D trajectory mid air hand wriiten Methods

Researcher	Dataset	Feature Extraction Method	Classifier	Recognition Rate (%)
(Ramana Murthy & Hanmandlu, 2011)	Sample from MATLAB	Directional features	Fuzzy Logic	83.85
(Nasien, Haron, & Yuhaniz, 2010)	NIST	Freeman chain code	Support Vector Machine	88.46
(Ali, Ali, & Sultana, 2010)	-	Wavelet compression	Euclidean Distance	89.68
(Katiyar & Mehfuz, 2015)	CEDAR	Combined features	MLP NN	93.22

The work done in recent years in the field of scene character recognition in natural scene images using “The Chars74k_EnglishImg” database and character recognition using “The Chars74k_EnglishHnd” database of mid air hand-drawn characters has been mentioned in TABLE 4. The algorithm used and the recognition accuracy achieved has also been reported. The scene character recognition system has text detection from natural scenes and text recognition as its subparts.

V. CONCLUSION

This paper summarizes research work done in the field of mid air handwritten character recognition using soft computing techniques. The practical challenges like a lot of variability and ambiguities present in the individual’s hand writing styles demand an efficient recognition system. The recognition system must have high accuracy, less training efforts and less computational cost. The combination of neural networks, fuzzy logic and genetic algorithm (neuro-fuzzy-genetic tools) gives a new understanding of the analysis, design and development of efficient handwritten character recognition. In this context, hybrid soft computing methods find an appropriate place in handwritten character recognition tasks.

TABLE 4 Comparison of various Algorithms applied on “The Chars74K” Database

Algorithm	Dataset	Accuracy (%)
Histograms of oriented gradients feature (HOG) + support vector machine (SVM) (Shi, Gao, Liu, Qi, Wang, & Xiao, 2015)	Chars74k_EnglishImg	62
Stroke Bank (Gao, Wang, Xiao, Shi, & Zhang, 2014)	Chars74k_EnglishImg	65.7
Discriminative multi-scale stroke detector-based representation (DMSDR) (Shi, Gao, Liu, Qi, Wang, & Xiao, 2015)	Chars74k_EnglishImg	66.1
Spatiality embedded dictionary (SED) (Gao, Wang, Xiao, Shi, Zhou, & Zhang, 2014)	Chars74k_EnglishImg	67.1
Discriminative spatiality embedded dictonary learning-based (DSEDR) representation (Shi, Gao, Liu, Qi, Wang, & Xiao, 2015)	Chars74k_EnglishImg	71.8
CNN_Softmax (Shi, Wang, Jia, He, Wang, & Xiao, 2017)	Chars74k_EnglishImg	73.5
Deep contextual stroke pooling (DCSP) (Zhang Z. , Wang, Liu, & Xiao, 2018)	Chars74k_EnglishImg	76.1
ANN (Xingyu & Laure, 2017)	Chars74k_EnglishHnd	90
Nearest neighbour classification using geometric blur (GB) feature (Zhang Z. , Wang, Liu, & Xiao, 2018)	Chars74k_EnglishHnd	65

An extensive literature review, most of which was presented in this paper, revealed a dearth of information regarding mid air handwritten character recognition. Different authors used benchmark databases such as NIST, CENPARMI, CASIA, MNIST etc. for the mid air handwritten character recognition. In the era of Facebook, Twitter and other social networks, where a larger amount of data is available in few seconds; recognition of mid air handwritten characters is an important aspect and demands high accuracy. For a large database, a machine learning algorithm proved better than any other algorithm. But, the machine

ISSN: 2395-3519

learning algorithm or statistical-based classification techniques do not perform well for a small database. On the other hand, soft computing techniques outperforms with small databases.

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