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Predictive Quality Management in Nepalese In-air Handwritten Kannada Numeral Recognition Using LMC

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Abstract
Traditional interfacing or interaction with computers using keyboards, mouse, etc., may become obsolete after few years due to the rapid development of human computer interactions (HCI) technology. From the last two decades, in-air hand written text recognition is one of the newest and latest way to recognize the character or text written on free air. Because of this, many researches have engaged in the design of recogntion modules for characters or texts written on air for non-Indic characters and Indic characters. In this paper, explanation of the work carried out to create in-air handwritten dataset of Kannada numerals using LMC and then the design of recognition system for the classification of Kannada numerals is given. The collected data is subjected to pre-processing and feature extraction. The first-derivative features are extracted from the preprocessed data and k-NN is used as the classifier. The simulation experiments has given the average recognition accuracy of 96.33%.

Keywords: HCI, LMC, In-air handwriting, Indian script, Kannada language, Kannada numerals.

Introduction

The ways in which humans interact can engage with computer technology is known as Human Computer Interaction (HCI). It is the field of study focused on how user can interact with technology, particularly computers and digital systems. It is a multidisciplinary field that combines insights from computer science, psychology, system design, and other areas to improve the usability and effectiveness of technology. The primary goal is to create user-friendly, efficient, and enjoyable interactions between humans and technology. Traditional methods of HCI include the use of keyboard, mouse, touch screen, and similar other devices. These interaction tools may not adequately meet the natural interaction requirements due to various limitations and they demand the need of additional hardware. Further, these devices require contact-based interaction and hence physical touch with the device during operation raises the concern regarding users' health and safety. In contrast, contactless interaction methods such as speech [1], gesture [2, 3], and in-air [4, 5] have emerged as the most prevalent forms of HCI technology and hence there is a focus on the design and development of required non-contact type HCI schemes.Speech recognition identifies signals from lip movements or vocal sounds and converts it into the written text [6]. Hand gestures [7, 8] convey variety of information and the user need to memorize certain shortcuts to give commands to the interacting devices. These hand gesture based devices have practical applications in areas such as medical treatment, controlling household devices, and virtual reality gaming. In-air handwriting refers to the act of writing in the air using a free hand, finger, or any other recognizable device. Here, the movement of the finger is tracked within a three-dimensional coordinate system utilizing Leap Motion Controller (LMC) to create the handwritten data patterns. The generated data through LMC represent three-dimensional coordinate system. This allows users to write freely in the air. The system of in-air handwriting recognition identifies handwritten data created in free air. This data may include single points, characters [9, 10], signatures [11], words [12, 13], sentences [14, 15], or even paragraphs. In-air handwriting recognition is particularly advantageous compared to the conventional HCI methods due to its flexibility, minimal health risks, and suitability for virtual reality applications.
In this paper, the work carried out to recognize in-air handwritten Kannada numerals (IAHKN) is discussed. To explain the research work carried out, the paper is organized as follows. Section 2 briefs the literature review on the work carried out for the recognition of Indic and non-Indic scripts. Section 3 discusses the introduction to Kannada numerals. Section 4 presents the proposed in-air writing systems. Section 5 narrates results and discussions, and Section 6 gives the concluding remarks and future work.

2. Literature Review

In this section, overview on the research works carried out for in-air handwritten numeral recognition for Indic and Non-Indic scripts is summarized.
Wei Zeng, et al., [16] have created the dataset for Arabic numerals (0-9) using LMC device. They extracted hand

gesture characteristics, dynamics of hand motion, and specific positions and the orientation of fingertips. The RBF neural network is employed for the recognition process. The recognition accuracy of 95.1% is reported. Roy P., et al., proposed a method for air-writing recognition of English, Bengali, and Devanagari numerals using a standard video camera and a marker of a fixed color for data extraction [17]. The color-based segmentation scheme and CNN were employed to identify the marker and track the trajectory of the marker tip. Under conditions of stable illumination, the system successfully recognized isolated uni-stroke numerals across multiple languages. This approach achieved recognition rates of 97.7%, 95.4%, and 93.7% for English, Bengali, and Devanagari numerals, respectively. A method for converting slopes into directions to represent alphanumeric letters is proposed by Tolentino, et al., by utilizing LMC [18]. Subsequently, these features of the slope orientation sequence are aligned with the reference slope orientation sequence within the system program to identify alphanumeric characters. During the algorithm's matching process, the concepts of sets and subsets are employed. The average recognition accuracy of 97.6% is reported for identifying the numbers. Adil Rahman, et al., proposed a robust and hardware-independent framework for recognizing multi-digit single stroke numerals in the free air writing context [19]. A dataset comprising approximately 8000 samples of English numerals in free air handwriting (ISI-Air dataset) was created by 16 individuals. The data collection utilized a standard video camera with a colored marker for capturing free air handwriting. Segmentation was performed by distinguishing the color of the writing material from the background. A sliding window approach was employed for eliminating noise before segmenting the digits. The system achieved the recognition accuracy of 98.45% for single digits and 82.89% for multiple digits (up to 3 digits). Handwritten digits of 0 to 9 were collected in the air using LMC by Grigoris Bastas, et al., [20]. The data is collected from 10 users leading to 1200 samples. Various models like TCN, LSTM, BLSTM, and CNN-LSTM were employed for digit recognition by utilizing dynamic, static, and the combination of both dynamic and static methodologies. Among these models, LSTM model reported the highest average recognition accuracy of 99.5%. To filter out unnecessary lifting strokes in in-air handwritten data, a reverse time-ordered algorithm is proposed by Tsung-Hsien Tsai, et al., [21]. In order to address the issues of multiplicity and confusion, various sampling rates have been suggested. The Kinect sensor and LMC were utilized to gather upper and lower case English letters, as well as numerals. The recognition scheme employs the DTW approach. The reported average recognition accuracy is 99%. Yunzhe Li, et al., [22] have created 0 to 9 decimal digit dataset through an Android application in the mobile that has the built-in acceleration sensors. The datasets are compiled during the writing process by positioning the mobile phone in both vertical and horizontal orientations. A Deep Neural Network (DNN) that integrates Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BLSTM) networks is employed. An impressive recognition accuracy of 99% has been reported. Rahman A, et al., introduced a cost-effective standard camera based system for recognizing multi-digit English numerals written in the air [23]. A sliding window algorithm is employed to extract a small segment of the input data for further processing. RNN-LSTM networks are implemented for the purposes of noise reduction and digit recognition. The system achieved recognition accuracies of 98.75% for single-digits and 85.27% for multi-digits. Ananya Choudhury, et al., proposed a method for recognizing in-air Assamese handwriting, including vowels, consonants, and numerals using a dataset collected from LMC [24]. This method employs an ensemble model based on CNN and LSTM-NN. To identify air-written characters, they integrated character trajectory appearance modeling with temporal trajectory feature modeling. They formulated a Markov Random Field model to detect air-written datasets and implemented a Mahalanobis distance classifier to segment writing events into relevant handwriting segments and redundant sections. The average recognition accuracy achieved was 98.12%. Chayti Saha, et al., introduced a model for recognizing Bangla digits written in the air by utilizing CNN to forecast Bangla numerals [25]. The dataset employed is BanglaLekha-Isolated that consists of 50 fundamental characters, 10 Bangla numeric values and 24 Bangla compound characters. The accuracy achieved in recognizing Bangla numerals is 98.37%.

The literature review shows that considerable research has been conducted on the recognition of in-air handwritten non-Indic characters and Indic characters in the same context. However, there is an absence of research concerning the recognition of Kannada numerals written on air. To fill this gap, effort is made to create in-air handwritten Kannada numeral dataset and to design the recognition scheme.

3. Kannada Numerals

Kannada is one of the well-structured scripts among Indian languages and is predominantly spoken in the state of Karnataka, India [26]. It serves as the administrative and official language of Karnataka [27]. The Kannada script follows decimal number system. The Kannada numerical character samples and its pronunciation is given in Table 1. There are totally 10 numerals in Kannada corresponding to Indo-Arabic numerals from 0 to 9 and are shown in Table 1. Among these ten numerals, certain numerals exhibit closely related variations, resulting in increased recognition difficulty and reduced recognition accuracy rate.

Table 1. Kannada numerals.

Kannada Numerals	Indo-Arabic	Pronunciation
೦ (ಸೊನ್ನೆ)	0	Sonne
೧ (ಒಂದು)	1	Ondu
೨ (ಎರಡು)	2	Yeradu
೩ (ಮೂರು)	3	Muru
೪ (ನಾಲ್ಕು)	4	Nalku
೫ (ಐದು)	5	Aidhu
೬ (ಆರು)	6	Aaru
೭ (ಏಳು)	7	YeLu
೮ (ಎಂಟು)	8	YenTu
೯ (ಒಂಬತ್ತು)	9	Ombatthu

4. Proposed In-air Writing System

The proposed IAHKN recognition system consists of data collection, data annotation, preprocessing, feature extraction, design of training and testing modules.

4.1 Data Collection and Annotation

The IAHKN data are collected by using LMC by interfacing it to a Dell Latitude 3450 Laptop, equipped with an Intel(R) Core(TM) i3 CPU operating at 1.70GHz, 4GB of RAM, and a 64-bit operating system. The ten Kannada numeral data is collected from 25 volunteers. Each individual is given a preliminary training of using the device and then instructed to write each of ten Kannada numerals five times. This process of data collected has resulted in 25 × 5 = 125 samples per digit and the total size of the dataset is 1250 samples. The collected data are analysed and annotated with appropriate labels to each numeral.

4.2 Preprocessing and Feature Extraction

The collected data of each numeral consist of time-series data corresponding to$x-, y-, z-$coordinate values. These coordinate values are corresponding to horizontal, vertical and depth direction movement of fingertip. The graphical representation of Kannada numeral '4' for different combination of coordinate values is shown in Figure 1. In the present work, the data corresponding to only $x-$ and $y-$coordinate values are considered. Sample of Kannada numerals, 0 to 9, showing xy-coordinate values that are collected using LMC are shown in Figure 2. The raw data is pre-processed to eliminate noise, thereby enhancing the data's utility for the recognition process. The pre-processing steps include filtering, resampling and normalization. The Gaussian filtering operation with window-size of five is carried out to smooth the collected data. The smoothed data is normalized to fit into size ranging from 0 to 1. The first derivative feature [28] is extracted from the normalized data using Eq. 1 and 2.

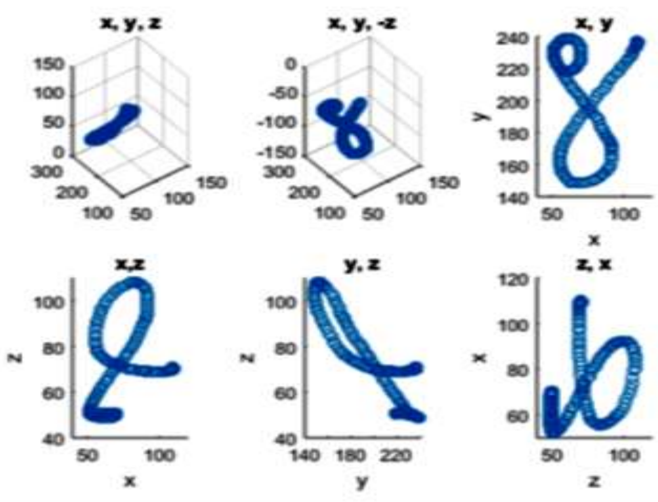

Figure 1. Graphical representation of Kannada numeral '4'.

Figure 2. Kannada numerrals, 0-9 collected using LMC.

$$X'_{(p)} = \sum_{1}^{N} \frac{q \times [x(p+q) - x(p-q)]}{2\sum_{1}^{N} p^2} \quad (1)$$

$$Y'_{(p)} = \sum_{1}^{N} \frac{q \times [y(p+q) - y(p-q)]}{2\sum_{1}^{N} p^2} \quad (2)$$

Where, pand qare current and subsequent coordinate values, x and y represent x − andy −coordinate values, and Nis the length of the stroke of the character data.

5. Results and discussions

As mentioned in section 4.1, the IAHKN dataset consists of 1250 samples. Out of 1250 samples in the dataset, 1000 samples are considered in the present work. From 1000 samples, 700 samples (70%) and 300 samples (30%) are used for training and testing the recognition system. The k-NN classifier is used as the numeral classifier. Table 2 gives the digit-wise and average recognition accuracy of the proposed recognition system. As given in Table 2, the obtained average recognition accuracy is 96.7%. The confusion matrix generated due to the simulation experiment is given in Table 2. Since, this is the first effort made to recognize IAHKN dataset, the performance of this work is not compared with others.

Table 2. Recognition accuracy for IAHKN dataset.

Kannada Numerals	Recognition Accuracy
೧	96.67
೨	93.33
೩	93.33
೪	100.00
೫	100.00
೬	96.67
೭	100.00
೮	93.33
೯	93.33
೦	96.67
Average Recognition Accuracy	96.33

Class	Kannada Numerals	Recognition Accuracy (%)
1	೧	96.67
2	೨	93.33
3	೩	93.33
4	೪	100.00
5	೫	100.00
6	೬	96.67
7	೭	100.00
8	೮	93.33
9	೯	93.33
10	೦	96.67
Average Recognition Accuracy		96.33

Table 3 gives the confusion matrix for the proposed scheme. 100 % accuracy is observed in Kannada numeric characters 4, 5, and 7.

Table 3. Confusion Matrix

Confusion Matrix											
	Target Class										
		1	2	3	4	5	6	7	8	9	10
Output class	1	29	0	0	0	0	0	0	0	0	1
	2	0	28	0	0	0	0	0	0	0	2
	3	0	0	28	0	0	0	1	0	0	1
	4	0	0	0	30	0	0	0	0	0	0
	5	0	0	0	0	30	0	0	0	0	0
	6	0	0	0	0	0	29	0	1	0	0
	7	0	0	0	0	0	0	30	0	0	0
	8	0	0	0	0	0	2	0	28	0	0
	9	0	0	2	0	0	0	0	0	28	0
	10	0	0	0	0	0	0	0	1	0	29

6. Conclusion and future work

For the first time, the IAHKN dataset is created and the recognition of IAHKN is designed. The recognition system is designed using first derivative feature with KNN classifier. With 1000 data samples, the average recognition accuracy of 96.33% is achieved. In future, the recognition of IAHKN is considered with different types of features and classifiers to improve the performance of the system.

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