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AIR WRITING RECOGNITION USING MACHINE LEARNING

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Abstract - Air-writing refers to writing of linguistic characters in a free space by hand or finger movements. Air-writing differs from conventional handwriting; the latter contains the pen-up-pen-down motion, while the former lacks such a delimited sequence of writing events. We address air-writing recognition problems in a pair of companion papers. The recognition of characters or characters is accomplished based on six-degree-of freedom hand motion data. We address air-writing on two levels: motion characters and motion words. Isolated air-writing characters can be recognized similar to motion gestures although with increased sophistication and variability. For motion characters recognition in which letters are connected and superimposed in the same virtual box in space, we build statistical models for characters by concatenating clustered ligature models and individual letter models. A hidden Markov model is used for air-writing modeling and recognition. We show that motion data along dimensions beyond a 2-D trajectory can be beneficially discriminative for air-writing recognition. We investigate the relative effectiveness of various feature dimensions of optical and inertial tracking signals and report the attainable recognition performance correspondingly. The planned system achieves a characters error rate of 0.8% for characters-based recognition and 1.9% for letter-based recognition.

***Key Words*:** Sensing, Spotting of handwriting, Hand writing and storing.

1. INTRODUCTION

Air-writing is an advanced user-interface that enables writing linguistic characters virtually in three-dimensional open space through hand motion gestures. Users can write text as if on an imaginary blackboard. Such interfaces are convenient alternatives to the traditional mechanism of typing on the keyboard or writing on the trackpad/touchscreen. However, air-writing using radars are a different problem to gesture recognition since character recognition in air writing system must utilize the temporal trajectory of the hand marker in 3D space. Air-writing systems, unlike conventional writing, have several challenges since users have to perform character gesture relying only on visual cues of imaginary axes in three dimensional spaces. Further such systems lack reference position on writing plane thus the notion of imaginary start and end coordinates, additionally; such systems need to automatically detect the start and end of a hand-written character in air. These considerations pose several challenges increasing the intra-class variability of writing patterns of a letter.

With the finger-precision tracking of the Leap device, the user can write in the air easily with his or her fingertip. To make the Leap a viable writing interface, nevertheless, an intelligent system that is capable of handling both detection and recognition of the air-writing mixed with other stray movements must be designed. Although some specific finger movements can used as in-line delimiter signals to provide endpoint information for a writing activity, writing with these explicit delimiters hinders the user experience of air-writing. In this work, we propose a system that automatically detects, segments, and recognizes the writing part from the continuous motion tracking signal.

2. PROPOSED SYSTEM

One level up, a motion letter is formed by connecting motion characters with ligature motions in-between. When there is no haptic or visual feedback, the ordinary left-to-right writing style is difficult to maintain without overlap or shape distortion. In our preliminary experiment, we discovered that users tend to shrink and overlap the last few letters. When the envisioned "writing space" is impacted by limited arm range. Therefore, we ask the user to write every character of a characters in a layer by-layer manner, overlapping all letters of the characters in the same envisioned, a writing style we term "overlapped airwriting," which supersedes the usual

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connected writing style and appears to be more suitable for air-writing.

3.1 Methodology

The method of air-writing recognition can be approached progressively. Isolated air-writing carries the assumption that the hand motion to render a letter has already been roughly localized in time and in space. Localization of motion rendering may be accomplished by use of a tracker, which can be easily turned ON or OFF, to signify the beginning and ending of a writing activity. The localization is only approximate and not fluctuation-free because most users cannot precisely synchronize the tracker control (ON–OFF) and the true writing trajectory. This is similar to the notorious problem of end-pointing in spoken utterance recognition even with a push-to-talk control. Between the approximate endpoints, the motion trajectory forms a letter that resembles a unistroke writing. Study of isolated air-writing is essential to provide the technological foundation for subsequent challenges. Beyond isolated letters, recognition of "word" poses two additional challenges: the contiguous writing of letters without segmentation, and the incorporation of sequential constraints between letters. The distinction between connected and overlapped air-writing mainly arises from system usability; the latter requires less limb movement. From the viewpoint of technology development, techniques for overlapped air-writing can be applied to connected-letter air-writing, and we shall address overlapped air-writing with emphasis.

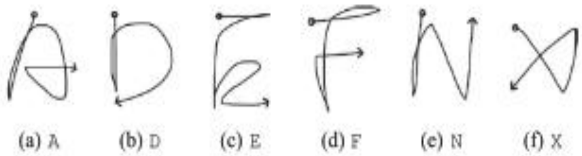

Fig. 1. Illustrations of the unistroke writing of isolated letters. (a) A. (b) D. (c) E. (d) F. (e) N. (f) X.

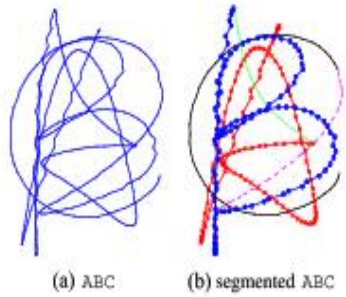

Fig. 2. Two-dimensional projected trajectory of a motion word. (a) ABC. (b) Segmented ABC.

3.2 Execution steps

1. Sensing

Sensing hand gesture recognition system is to create a natural interaction between human and computer where the recognized gestures can be used for controlling or conveying meaningful information. The resulted hand gestures to be understood and well interpreted by the computer considered as the problem of gesture interaction like Human computer interaction (HCI) also named Man-Machine Interaction (MMI).

2. Spotting of handwriting

The spotting stage is used to perform a binary classification of the data stream into segments that likely contain handwriting and segments that do not. The segments classified as potential handwriting motion are passed on to the recognition stage. The objective of the spotting stage is to discriminate these segments from the background activity. To allow real-time usage and operation on continuous data streams, we use a sliding window approach. Individual overlapping windows are classified and the classification results of all overlapping windows are then combined and passed on to the recognition stage immediately.

3. Handwriting storing and displaying

Text written in the air is defined by the spatial trajectory of the hand movement as this is the case for 2-dimensional pen-based handwriting. Then the written text can also be saved as image as well as pdf format.

4. RELATED WORK

To recognize cursive alphabet Author of [15] states Holistic technique. This technique utilized in signifying phrase via different transformation phases like contours, features, letters, phrase and points. Feature vector is exclusively created from image to utilizing arithmetical trusts among character and features, partially calculated characters are identified by evaluating through lexicon.Lexicon comprises of only 130 words, thus restricted number of words are identified.

For recognition of characters classifiers aren't used, a ranking is provided to every section which is detached with initial segmentation process utilizing character hypothesis and they identified on the basis of highest value of ranking [16]. This research work uses holistic technique to recognition of cursive alphabet. They remove some features from the frame of character. The vector of feature is produced from the boundary data of characters which comprises position of boundary connected to 4 situation lines, its curve node degree event to the boundary etc. 10 dimensional vectors of feature is produced. HMM for every character of alphabets is framed and by integration of these HMMs, HMM for every thesaurus alphabet is framed. Restricted ranged thesaurus is utilized. HMM is skilled via Baum Welch method and Viterbi algorithm is used for recognition.

To recognize both cursive and isolated handwritten alphabets the writer of [17] had executed recognition technique by applying HMM. Hybrid technique is utilized to make best use of the supremacy of HMM. To identify of alphabets features it utilized averages of black run in every scan line. Alphabet image is inspected in 4 various directions to mine features from it. Average of each direction rises for a sparse directional frame of the alphabet. The isolated compactness from left to right HMM method is utilized for identification. To recognize cursive alphabets writers utilized segmentation scheme for recognition. Features are supplied to the upper order of HMM and at last segmentation route are verified. To utilize graph search technique accurate segmentation points are created which is smallest route with smallest cost. The possibilities of chain of HMM are utilized for recognition.

To identify handwritten English cursive alphabets utilizing segmentation technique research work is presented in [18]. This research work states the evaluation among two techniques. The primary scheme utilizes mixture of NN (Neural Network) and HMM (Hidden Markov Model) for recognition and in second scheme discrete HMM is utilized for recognition. In primary scheme Pre segmentation of alphabet is executed utilizing segmentation graph. Neural network calculates the possibility for every alphabet hypothesis in graph and subsequently HMM determines possibility for every alphabet in lexicon by including the possibility along every probable route in graph. In second scheme 140 geometric characteristics are mined from every section which is divided by pre segmentation. This characteristic by vector quantization (VQ) modified to single symbol and ultimately by calculating the probability for every alphabet in lexicon characters is recognized.

In research paper [19] writer stated segmentation method to identify cursive alphabets. In this scheme cursive alphabets are primary segmented into particular characters, which are than identified and merged to create meaningful phrase by comparing with thesaurus. The thesaurus utilized in this research paper exists of 26 phrases. Hence range of this research paper is limited to only those 26 words.

Authors in [20] represent recognition scheme based on Neural Network based. They utilized various neural network methods like back propagation (BP) neural network, nearest neighbour network and radial basis function (RBF) network for similar training dataset. They matched the performance of every network and enhanced the amount of neurons in hidden layer which is not dependent on starting value and finished that mixture of standard feature extraction scheme with supplying forward method stated in [21] compromises with the identification of handwritten English alphabets utilizing multi resolution scheme through Discrete Wavelet Transform (DWT) together with Euclidean Distance Metric (EDM). Distances from unidentified input prototype vector to every mean vectors are proposed by EDM. Smallest distance verifies the cluster membership of input vector of pattern. EDM offers an identification precision up to 90.77%. For an instance the misclassification, the learning decision via ANN obtain enhanced recognition precision up to 95.38% via evaluating experimental results and after that produced result of recognition with Euclidean distances has additional obtain enhanced recognition precision up to 98.46%.

The research paper [22] illustrates neural network based methods for segmented alphabet recognition. Two neural models along with two feature extraction techniques were examined. Directional and Transition features are utilized and matched by utilizing Back Propagation (BP) and Radial Basis Function (RBF) networks classifiers. The amount of feature vector is 100 in case of transition feature and 81 for directional feature. Research was executed by utilizing the CAS dataset, the BP (Back propagation) and RBF (Radial basis function) algorithm which utilizing two feature extraction techniques for both lower and upper case alphabets, likewise for BAC database. Directional features utilizing neural network execute enhanced than transition features.

Comparison among traditional and directional feature extraction technique is discussed in research paper [23]. 12 directional features are employed for identification of characters and digits. With the purpose of extract directional characteristic of incline feature of every pixel are removed from the incline costs which are plotted onto 12 way costs to the slant distance of 30 ° among either two adjoining way costs. Vector of feature of every category is gained by getting average of feature matrix of every category. The alikeness among examine vector of feature and vector of feature of every categories is computed, examine image related to the category which has the maximum alikeness.

Handwritten character identification method of lowercase English alphabets is stated in research work of [24] via employing binarized pixels of the image as features and multilayer back propagation neural network as classifier. The alphabet image is binarized, filtered and reshaped to 15X12, therefore vector of feature of volume 180 is generated of every character which is provided to neural network for its learning. MSE (mean square error) be employed as weight function. The exploit of binarization characteristics with back propagation neural network classifier provides classification precision up to 85.62%. It has ease of characteristics like straight pixel values are occupied.

Identification of different handwritten cursive alphabets is proposed in research work carried out in [25]. In this method various characteristics are extracted between them, two features customized edge map and multiple zoning are projected by writers. 9 characteristics are extracted and disadvantage of every characteristic is defeats by alternative. Every characteristic are independently provided as input to 9 multilayer perceptron network and outcomes this classifier are merged with every alternative by various law similar to max, mean, product and sum rule etc amongst them trained MLP merger provides highest outcome. Between projected characteristics customized edge map characteristic provides maximum outcome.

The major steps of an OCR engine are extraction of feature and classification. Numbers of extraction methods of features are combined with various classification techniques along with their result which have been used by the researchers are discussed in Table I:

Table I comparative analysis of various HCR system

Ref.	Publication Year	Classifier Used	Features	Accuracy
[16]	1995	HMM	Location, curve of edge& pixels	98%
[17]	1998	HMM	Medium of black run in all directions	65%
[18]	2001	HMM &NN	140 geometrical features of every pre segmented frames	96.1%
[19]	2011	NN&SVM	Fourier Descriptors	62.9%
[20]	2012	NN	Character reshaped into 30X20 pixels gets like feature	94.1%
[21]	2012	ANN	Discrete Wavelet Transform (DWT)	98.4%
[22]	2003	P and RBF networks	Directional and Transition features	85.4%
[23]	2013	directional Pattern matching	12 directional features	88.2%
[24]	2013	NN	Character image reshaped to 15X12 volume, feature vector of volume 180 is produced	85.6%
[25]	2010	MLP	Customized Edge Maps and Multi zoning	91.3%
[15]	1989	Word formation Using letter hypothesis	Contour tracing, event construction, Letter hypothesis and word hypothesis	77%

5. CONCLUSION

The spotting and continuous recognition of text written in the air based on gesture sensors is possible. The proposed system can serve as an input device for wearable computers, allowing the input of text in an intuitive way and without the need to operate any handheld devices. The results can be transferred to other domains of gesture recognition tasks where specific gestures are built from a smaller set of primitives. None of the used techniques is tailored to the problem of handwriting recognition. The proposed architecture and methods allow the implementation of a system operating in real-time on continuous data.

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