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Brief paper

Decision fusion of horizontal and vertical trajectories for recognition of online Farsi subwords

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ABSTRACT

Online handwriting is formed by a combination of horizontal and vertical trajectories. If these trajectories are treated separately, new recognition methods are emerged. In contrast, one classifier is often used to recognize handwriting. In this work, some features for $x(t)$ and $y(t)$ signals were proposed and used to make two separate classifiers. After initial recognition by these classifiers, their results were fused for final recognition. Using HMM classifiers and simple product rule for decision fusion, the recognition results of 42 classes of Farsi subwords showed promising achievements.

1. Introduction

In recent years, the recognition of online handwriting gained a renewed interest due to expansion of the applications of digitizing tablets, digital pens, pen-based mobile phones and PDAs (Jaeger et al., 2003; Liu et al., 2004; Plamondon and Srihari, 2000).

In offline Farsi/Arabic handwriting, efficient ideas were revealed (Alirezaee et al., 2006; Dehghan et al., 2001; Khosravi and Kabir, 2009; Lorigo and Govindaraju, 2006). AlKhateeb et al. (2011) has presented a method to recognize offline handwritten Arabic cursive text in three stages: preprocessing, feature extraction and classification. This method has been employed hidden Markov models also re-ranking using structure-like features to improve the recognition rate.

A number of online Farsi/Arabic handwriting recognition systems have been proposed in Abed et al. (2010) and Sajedi et al. (2007). Sternby et al. (2009) have explored the application of a template matching scheme to the recognition of Arabic scripts with a novel algorithm for dynamically treating the diacritical marks. An elastic fuzzy pattern recognition method has been suggested in Halavati and Shouraki (2007) and tested on a set of 1250 words resulting in 78% and 96% correct recognition without and with a dictionary checking, respectively. In Baghshah et al. (2005), the representation of handwriting parameters has been accomplished by fuzzy linguistic modeling. It has been shown that fuzzy linguistic terms provide robustness against handwriting variations. The accuracy rate of 90.3% has been achieved for this method on a database of Farsi isolated handwritten characters. Using structural features, Farsi characters have been divided into nine groups in Ghods and Kabir (2010) and a recognition rate of 92% has been achieved. An online Arabic handwriting recognition system based on visual coding and genetic algorithm has been developed in Kherallah et al. (2009). A method to classify words and lines in an online handwritten document into one of the six major scripts: Arabic, Cyrillic, Devnagari, Han, Hebrew, or Roman has been proposed in Namboodiri and Jain (2004). 11 different spatial and temporal features were extracted from the strokes of the words for classification. The recognition of online handwritten Arabic words of the ADAB-database has been studied in Ahmed and Azeem (2011). The main feature of the system was that delayed strokes were removed from the online word. Biadsy et al. (2011) has introduced an online Arabic handwriting recognition system. The recognition has been performed on the continuous word-part level and training on the letter level. It has handled delayed strokes by first detecting them and then integrating them into the word-part body. The implementation was based on hidden Markov models.

Decision fusion is a powerful approach to enhance the recognition performance, especially in complex classification problems. It avoids weaknesses and emphasizes on the strengths of individual classifiers. A comprehensive overview of classifier fusion methods

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has been presented in Kuncheva (2004). In Mercier et al. (2009), combining the outputs of several postal address readers was employed to improve the mailing address recognition.

In Farsi, some of the letters in a word are joined to each other. These letters create a subword; for example, “فا, ر, سی” are the subwords of the word “فارسی”. Generally, subwords in a word are not joined to each other. Online handwriting is formed by the combination of horizontal and vertical trajectories. For example, the separated ‘*x*–*t*’ and ‘*y*–*t*’ plots of the main body of the subword “سیو” are shown in Fig. 1. The purpose of this work is to classify Farsi subwords using $x(t)$ and $y(t)$ signals separately. We exploited the whole-subword HMM for each signal and fused the results of two classifiers. Ibrahim et al. (2010) have proposed to use horizontal and vertical trajectories separately for online signature verification by first decomposing the pressure and velocity profiles and then extracting the underlying trajectories. The shape of a signature is mainly caused by the wrist and fingers movements; therefore, the movement of the wrist was represented by the horizontal trajectory while the finger movement was represented by the vertical trajectory.

In this paper, Section 2 explains the basic definition of HMMs. Suitable features for ‘*x*–*y*’, $x(t)$ and $y(t)$ signals, used by HMM, are presented in this section. Sections 3 and 4 describe the experimental setup and the classification results using horizontal and vertical signals, respectively. In Section 5, the results are analyzed, and a discussion on errors is given. Finally, in Section 6 conclusions are drawn.

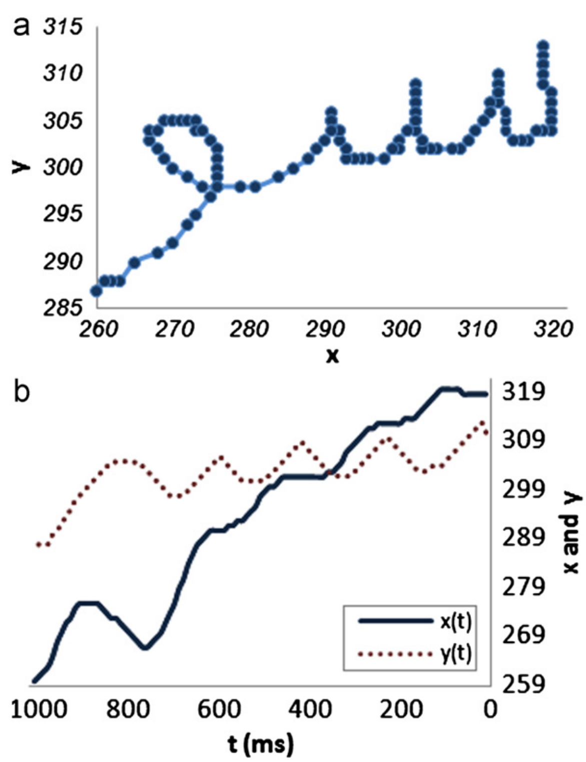

Fig. 1. (a) Main body of subword “سیو”, (b) $x(t)$ and $y(t)$ signals vs. time.

2. Hidden Markov model

A hidden Markov model (HMM) is a statistical model in which the modeled system is supposed to be a Markov process with unknown parameters, and the problem is to determine the hidden parameters from the observable parameters (Rabiner, 1989). HMM is a remarkably powerful tool for modeling and classification of one-dimensional signals. HMM classifier has been used for offline, e.g. Plötz and Fink (2009), and online, e.g. Sajedi et al. (2007), handwriting recognition. A new method for writer adaptation in a handwritten word-spotting task has been presented in Rodriguez-Serrano et al. (2010). This method exploits the fact that the semi-continuous HMM separates the word model parameters into a codebook of shapes and a set of word-specific parameters. The authors of Rodriguez-Serrano et al. (2010) have employed this property to derive the writer-specific word models by statistically adapting an initial universal codebook to each document.

In this paper, the whole-subword HMM was selected for classification. If suitable features are extracted, a better model is learned for each subword. In this work, most of the proposed features for $x(t)$ and $y(t)$ signals were different from ‘*x*–*y*’ signal features.

2.1. ‘x–y’ features

Jaeger et al. (2001) and Liwicki and Bunke (2006) have introduced different features for online handwriting. In Liwicki and Bunke (2009), a feature selection strategy has been investigated to find out discriminant features on a set of 25 online and pseudo-offline features for online handwriting. In the present work, a set of features were selected for subword classification using ‘*x*–*y*’ representation which are f_1 to f_{10}.

$f_1.x_i$: The normalized sample point of x.
$f_2.y_i$: The normalized sample point of y.
$f_3.\theta$: The angle between the line connecting two adjacent sample points and horizontal line.
$f_4.\Delta\theta$: The difference of two adjacent θ.
$f_5.\sin\theta$: Writing direction.
$f_6.\cos\theta$: Writing direction.
$f_7.\sin\Delta\theta$: Curvature.
$f_8.\cos\Delta\theta$: Curvature.
$f_9.V_X(i)=x_i-x_{i-1}$: The difference of xs of two adjacent sample points.
$f_{10}.V_y(i)=y_i-y_{i-1}$: The difference of ys of two adjacent sample points.

2.2. x(t) (and y(t)) features

Two sets of features, extracted from $x(t)$ and $y(t)$, are separately fed to two HMM classifiers. The results of these classifiers

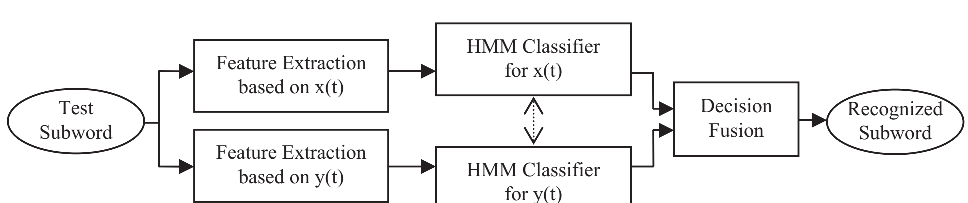

Fig. 2. Proposed scheme for subword recognition.