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A writer identification system for on-line whiteboard data

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Abstract

In this paper we address the task of writer identification of on-line handwriting captured from a whiteboard. Different sets of features are extracted from the recorded data and used to train a text and language independent on-line writer identification system. The system is based on Gaussian mixture models (GMMs) which provide a powerful yet simple means of representing the distribution of the features extracted from the handwritten text. The training data of all writers are used to train a universal background model (UBM) from which a client specific model is obtained by adaptation. Different sets of features are described and evaluated in this work. The system is tested using text from 200 different writers. A writer identification rate of 98.56% on the paragraph and of 88.96% on the text line level is achieved.

Keywords: Writer identification; On-line handwriting; Gaussian mixture models

1. Introduction

The work described in this paper has been conducted in the context of research on smart meeting rooms. The aim of this research is to automate standard tasks usually performed by humans in a meeting [1–5]. To record a meeting, smart meeting rooms are equipped with synchronized recording interfaces to capture audio, video, and handwritten notes.

Smart meeting rooms pose interesting pattern recognition and classification problems. Speech [6], handwriting [7], and video recognition systems [8] have been developed. Other tasks include segmenting a meeting into meeting events [3,4], indexing the recorded data [9] or extracting non-lexical information, such as prosody, voice quality variation, and laughter. To authenticate the meeting participants and to assign utterances and handwritten notes to their authors, identification and verification systems are developed. They are based on speech [10] and video interfaces [11,12] or on a combination of both [13].

An important task in a smart meeting room is to capture the handwriting rendered on a whiteboard during a meeting. In this paper we address the problem of identifying the author of a text written on a whiteboard. Solving this problem enables us to label the handwriting with the writer's identity. Furthermore, it allows us to validate the identification results of a video- or audio-based person identification system within the smart meeting room scenario.

The text written on the whiteboard is recorded by the eBeam interface.[1] A normal pen in a special casing sends infrared signals to a triangular receiver mounted in one of the corners of the whiteboard [14]. The acquisition interface outputs a sequence of (x, y)-coordinates representing the location of the pen-tip together with a time stamp for each location. The sampling resolution varies around 30–70 samples per second with a sampling resolution of 4 points per millimeter. Spurious points and gaps within strokes can occur if the writer's hand is between the pen and the receiver, or if the pen is tilted too much. An illustration of the data acquisition device is shown in Fig. 1.

The input to our system are lines of handwritten text. Typical data acquired from a whiteboard in a meeting may also include sketches, tables or enumerated lists. However, there exists techniques to extract text regions from the data collected [15,16].

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[1] eBeam system by Luidia, Inc.—www.e-Beam.com.

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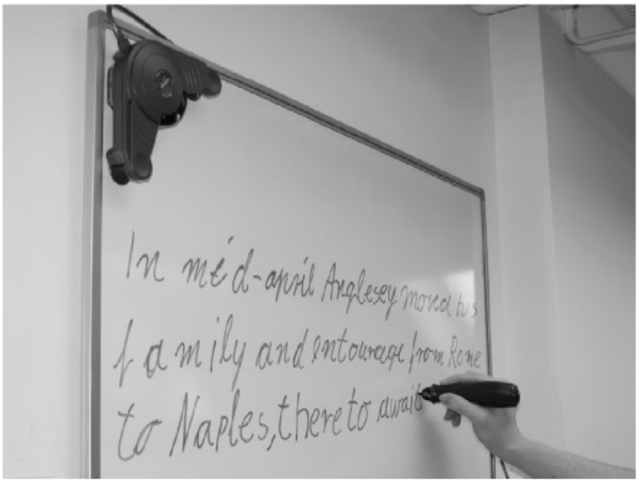

Fig. 1. Recording session with the data acquisition device positioned in the upper left corner of the whiteboard.

We use Gaussian mixture models (GMMs) to model a person's handwriting. GMMs provide a powerful yet simple means of representing the distribution of the features extracted from the text written by one person. GMMs have a mathematically simple and well understood structure, and there exist standard algorithms for training and testing. Formally, GMMs consist of a weighted sum of uni-modal Gaussian densities. While GMMs have first been used in speech recognition [17,18], to the best of our knowledge, they have not been applied to on-line writer identification of whiteboard data before.

For each writer in the considered population, an individual GMM is trained using data from that writer only. Thus for n different writers we obtain n different GMMs. Intuitively, each GMM can be understood as an expert specialized in recognizing the handwriting of one particular person. Given an arbitrary text as input, each GMM outputs a recognition score. Assuming that the recognition score of a model is higher on input from the writer the model is trained on than on input from other writers, we can utilize the scores produced by the different GMMs to identify the writer of a text.

The outline of this paper is as follows. In the next section related work is presented. Section 3 gives an overview of our system and describes the normalization operations applied to the acquired data. In Section 4 the feature sets extracted from the normalized data are described. The GMMs used to model a person's handwriting are presented in Section 5. In Section 6 the experimental setup is described, while the results of our experiments are presented and discussed in Section 7. Section 8 concludes the paper and proposes future work.

2. Related work

The topic of writer identification from on-line whiteboard data has not been addressed in the literature to the best of our knowledge. However, much research has been performed in related fields, such as identification and verification of signatures and general handwriting.

Work in these fields can be differentiated according to the available data. If only a scanned image of the handwriting is available then writer classification is performed with *off-line* data. Otherwise, if temporal and spatial information about the writing is available, writer classification is performed with *on-line* data. On-line handwritten data contains more information about the writing style of a person, such as speed, angle or pressure. This information is not available in off-line handwritten data. Thus the on-line classification task is considered to be less difficult than off-line classification [19].

Surveys covering work in automatic writer identification and signature verification until 1993 are given in Refs. [19,20]. Subsequent works up to 2000 are summarized in Ref. [21]. Recently, several additional approaches have been proposed. In Section 2.1 work on off-line writer identification and verification is presented. Section 2.2 summarizes papers on signature verification. Work in the new field of on-line writer identification and verification is presented in Section 2.3.

2.1. Off-line writer identification and verification

Said et al. [22] treat the writer identification task as a texture analysis problem. They use global statistical features extracted from the entire image of a text using multi-channel Gabor filtering and gray-scale co-occurrence matrix techniques. In Ref. [23] this approach is extended to Chinese handwriting. He et al. [24] present a wavelet-based generalized Gaussian density (GGD) method which decomposes the image into subbands of different frequencies and orientations and uses its parameters as features.

Srihari et al. [25–27] address the problem of writer verification, i.e., the problem of determining whether two documents are written by the same person or not. In order to identify the writer of a given document, they model the problem as a classification problem with two classes, *authorship* and *non-authorship*. Given two handwriting samples, one of known and the other of unknown identity, the distance between two documents is computed. Then the distance value is used to classify the data as positive or negative.

Zois et al. [28] base their approach on single words by morphologically processing horizontal projection profiles. The projections are partitioned into a number of segments from which feature vectors are extracted. A Bayesian classifier and a neural network (NN) are then applied to the feature vectors.

In Ref. [29] a system for writer identification is described. The system first segments a given text into individual text lines and then extracts a set of features from each text line. The features are subsequently used in a k-nearest-neighbor classifier that compares the feature vector extracted from a given input text to a number of prototype vectors coming from writers with known identity.

Bulacu et al. [30] use edge-based directional probability distributions as features for the writer identification task. The authors introduce edge-hinge distribution as a new feature. The key idea behind this feature is to consider two edge fragments in the neighborhood of a pixel and compute the joint probability distribution of the orientations of the two fragments.