Off-Line Writer Verification: A Comparison of a Hidden Markov Model (HMM) and a Gaussian Mixture Model (GMM) Based System

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Abstract

In this paper, we introduce and compare two off-line, text independent writer verification systems. At the core of the first system are Hidden Markov Model (HMM) based recognizers. The second system uses Gaussian Mixture Models (GMMs) to model a person's handwriting. Both systems are evaluated on two test sets consisting of unskillfully forged and skillfully forged text lines, respectively. In this comparison, different confidence measures are considered, based on the raw log-likelihood score, the cohort model approach, and the world model approach.

Keywords: Writer Verification, Off-Line Handwriting, Hidden Markov Model, Gaussian Mixture Model.

1. Introduction

Writer verification is the task of determining whether or not a handwritten text has been written by a certain person [20]. Given a handwritten text and a claimed identity, a verification system must decide whether or not the text has in fact been written by this writer. In the former case a person is called a *client*, in the latter case he or she is called an *impostor* [5]. If the system is text independent, any text can be used for verification, otherwise the system is text dependent and a specific text has to be written.

A verification system can make two types of errors. First, the system can falsely reject a text written by a client or, second, it can falsely accept a text coming from an impostor [5]. The data presented by impostors can be divided into unskilled forgeries, where the impostor makes no effort to simulate a genuine handwriting, and skilled forgeries, where the impostor tries to imitate the handwriting of a client as closely as possible [21].

Often the decision to accept or reject a text is based on a confidence measure: If the confidence measure of a text is above a certain threshold, we assume that the text is in fact written by the claimed writer; otherwise the input is classified as not being of the claimed identity.

In this paper, we evaluate two text independent writer verification systems in conjunction with different confidence measures. Both systems use text lines as their basic input unit. The first system is based on the idea of utilizing a Hidden Markov Model (HMM) based handwriting recognition system, which has been developed for text recognition, for the purpose of writer verification [27]. For each writer a recognizer is trained with data coming from that writer only. The recognizers are built from character models using HMMs which are concatenated to form word models. After training, each recognizer is an expert on the handwriting of one writer. If confronted with a text line of unknown origin, we expect that the recognizer which was trained with data from this author achieves the highest text recognition rate.

The second system uses Gaussian Mixture Models (GMMs) to model a person's handwriting. The handwriting of every writer is modeled by one GMM. A GMM can be viewed as a single-state HMM with a Gaussian mixture density. Compared to the HMM based system, the GMM based system has a number of advantages. First, GMMs are conceptually less complex than HMMs, consisting of only one state and one output distribution function. Second, every writer is represented by exactly one model. Because only the parameters of the output distribution function have to be estimated, this leads to significantly shorter training times. Furthermore, neither characters nor words have to be modeled using GMMs and therefore no transcription of the text lines are needed during training. This also means that the GMM based system is language independent.

Significant progress has been achieved in writer identification in recent years. Surveys on early work in automatic writer identification and signature verification are given in [10, 20]. New approaches to writer identification have been proposed recently. Said et al. [26] treat the writer identification task as a texture analysis problem using multi-channel Gabor filtering and grey-scale cooccurrence matrix techniques. Srihari et al. [6, 31] address the problem of writer verification by casting it as a classification problem with two classes, *authorship* and *non-authorship*. Zois et al. [32] base their approach on single words by morphologically processing horizontal projection profiles. Hertel et al. [9] describe a system for writer identification that extracts a set of features from a text line and uses a k-NN classifier to determine the author. Edge based directional probability distributions and connected-component contours as features for the writer identification task are proposed in [28, 29]. Bensefia et al. introduce graphemes as features for describing the individual properties of handwriting [2, 3]. Leedham et al. [11] present a set of eleven features which can be extracted easily and used for the identification and verification of documents containing handwritten digits.

The rest of this paper is structured as follows. In Section 2 we present the HMM based and in Section 3 the GMM based verification system. The confidence measures to decide whether or not to accept a text line are described in Section 4. In Section 5 the data and the experimental setup are introduced. The results of the experiments are presented in Section 6 and discussed in Section 7. Section 8 concludes the paper and proposes future work.

2. HMM based verification system

The Hidden Markov Model (HMM) based verification system is based on the idea of utilizing a HMM based handwriting recognition system for the task of writer verification. The verification system is built from HMM based recognizers that are designed and optimized for the task of handwritten text line recognition. A short description of the system is given in this section; for a more detailed description see [27].

After some common normalization operations are applied to a text line, a sliding window moves from left to right over the text line and extracts nine features, three global and six local ones. The global features are the fraction of black pixels in the window, the center of gravity and the second order moment. The local features represent the position and the orientation of the upper and the lower-most pixel, the number of black-to-white transitions in the window, and the fraction of black pixels between the upper- and the lower-most black pixel. Using these features, an input text line is converted into a sequence of nine-dimensional feature vectors. A more detailed description of the normalization operations and the feature extraction process is given in [12].

For each upper and lower case character an individual HMM is built. Additionally, frequent punctuation marks, such as full stop, colon and space are modeled. Other, infrequent punctuation marks are mapped to a special garbage model. Each character HMM consists of 14 states connected in a linear topology. These character models are concatenated to word models which in turn are concatenated to model a complete text line. The HMMs are implemented using the HTK toolkit [30].

The system is trained by applying the Baum-Welch algorithm [22] with the following training strategy. In the first step, a single Gaussian output distribution for each state is used. Each model is trained with four iterations. Then in the second step, the number of Gaussian mixture components is increased. This is implemented by splitting the Gaussian distribution with the highest weight [30]. In the third step, we again train each model in four iterations using the new mixture components. Steps 2 and 3 are repeated until the desired number of Gaussian mixture components is reached.

For recognition, the Viterbi algorithm is used. Presented with a text line, a recognizer produces a sequence of words together with their log-likelihood scores. Summing up the scores of all words gives us the log-likelihood score of a text line.

3. GMM based verification system

This writer verification system uses Gaussian Mixture Models (GMMs) to model a person's handwriting. GMMs have first been used in speech recognition [23, 24]. However, to the best of our knowledge, they have not yet been applied to off-line, text independent writer verification.

A GMM models the distribution of the feature vectors extracted from a person's handwriting by a Gaussian mixture density [24]. For a D-dimensional feature vector, $\mathbf{x}$, the Gaussian mixture density is a weighted linear combination of M uni-modal Gaussian densities, p_i, parameterized by a $D \times 1$ mean vector, μ_i, a $D \times D$ covariance matrix, C_i, and a mixture weight, w_i:

$$p(\mathbf{x}|\lambda) = \sum_{i=1}^{M} w_i p_i(\mathbf{x}). \qquad (1)$$

The weights w_i sum up to one. The parameters of a writer's density model are denoted as $\lambda = \{w_i, \mu_i, C_i\}$ with $i = 1, \ldots, M$. While the general model supports full covariance matrices, diagonal covariance matrices are used in this paper as they are computationally more efficient while achieving an equal or even better performance than full covariance matrices [24].

For each writer, one GMM is trained using features extracted from text lines coming from the specific writer only. Before feature extraction, a series of normalization operations are applied to each text line. The contrast of a text line is enhanced first. Then the writing is vertically scaled (see [12] for a detailed description of the vertical scaling operation) and thinned using the MB2 thinning algorithm [4].

The features are extracted using a sliding window. The window moves from left to right one pixel per step. For every column of pixels in the sliding window, the same nine geometrical features as the ones used by the HMM system are extracted (see Section 2). The window width is 14 pixels and was optimized in an independent validation experiment. The feature vectors of every column in the sliding window are averaged to produce the final feature vector. At last, the feature vectors which do not contain any upper and lower-most black pixels are deleted. As a result of the feature extraction process we get a sequence of nine-dimensional feature vectors.

The GMM is trained using the Expectation-Maximization (EM) algorithm [8]. The EM algorithm iteratively refines the GMM parameters so as to monotonically increase the likelihood of the estimated model for the observed feature vectors. We apply variance flooring to impose a lower bound on the variance parameters [16]. The GMMs are implemented using the Torch library [7].

During decoding of the feature sequence extracted from a text line, the feature vectors of $X = \{\mathbf{x}_1, \ldots, \mathbf{x}_T\}$ are assumed to be independent. The log-likelihood score of a model λ for a sequence of feature vectors X is

$$\log p(X|\lambda) = \sum_{t=1}^{T} \log p(\mathbf{x}_t|\lambda), \tag{2}$$

where $p(\mathbf{x}_t|\lambda)$ is computed according to Eq. 1 [24]. Similarly, the standard deviation of a text line is calculated as the standard deviation of the feature vectors.

4. Confidence Measures

Various confidence measures for off-line handwriting recognition have been presented in the literature [14, 18, 19]. In this paper, three common types of confidence measures for writer verification are evaluated. The first confidence measure uses the recognition score produced by the model of the claimed identity only. The two other types of confidence scores normalize the recognition score based on a *cohort model* or a *world model* approach, respectively. The cohort model approach normalizes the score of the model of the claimed writer with respect to the score of the most competitive writers [25]. The world model approach normalizes the score of the claimed writer by a model which is trained on a large number of samples from many writers [15].

The first simple confidence measure for a text line t is the log-likelihood score of the claimed identity, $ll_{\text{ClaimedID}}$, returned by the model:

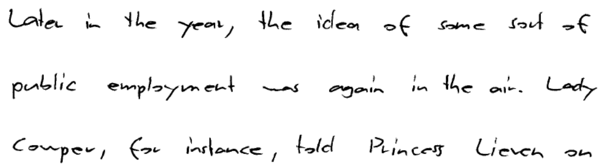
$$cm_{\text{LLScore}}(t) = ll_{\text{ClaimedID}} \tag{3}$$

The next two confidence measures are inspired by the cohort model approach. They both are based on the ranking of the log-likelihood scores returned by the models of each writer. A text line together with a claimed identity is presented to all writer models and the returned log-likelihood scores are sorted. Based on this ranking the confidence measure is calculated from the difference of the log-likelihood score of the claimed identity, $ll_{\text{ClaimedID}}$, and the first best ranked competing writer, $ll_{\text{BestRanked}}$. This score is normalized by the length of the text line $|t|$:

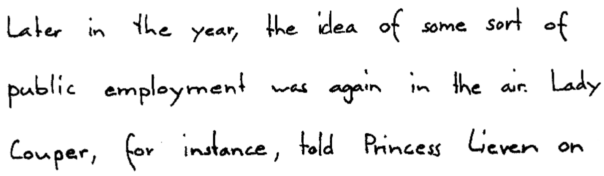
$$cm_{\text{CohortModel}}(t) = \frac{ll_{\text{ClaimedID}} - ll_{\text{BestRanked}}}{|t|} \tag{4}$$

If the recognizer returns a standard deviation together with the log-likelihood score for a text line, we can use it to normalize the difference between the log-likelihood score of the claimed identity and the first best ranked competing writer. The following confidence measure uses the standard deviation σ_1 of the first ranked text line for normalization:

$$cm_{\text{CohortModel}_\sigma}(t) = \frac{ll_{\text{ClaimedID}} - ll_{\text{BestRanked}}}{\sigma_1} \tag{5}$$



Example of original text lines.



Example of skillfully forged text lines.

Figure 1. Examples of original and skillfully forged text lines.

The fourth confidence measure uses a world model to normalize the log-likelihood score of the claimed writer. The world model is trained on a large number of text lines coming from different writers. A text line is presented to the model of the claimed identity and the world model only. This confidence measure is based on the difference of the log-likelihood score of the claimed identity $ll_{\text{ClaimedID}}$ and the world model $ll_{\text{WorldModel}}$:

$$cm_{\text{WorldModel}}(t) = ll_{\text{ClaimedID}} - ll_{\text{WorldModel}} \tag{6}$$

In order to calculate the cohort model based confidence measures, we need the scores of every client model known to the system. In contrast, the world model based confidence measure is independent of the number of writers considered, only the score of the claimed model and of the world model are needed. Thus, it is much faster to calculate for a large number of clients.

Both GMM and HMM return a log-likelihood score when confronted with a text line from an unknown author. Thus, cm_{LLScore}, $cm_{\text{CohortModel}}$, and $cm_{\text{WorldModel}}$ are applicable in both systems. In order to calculate $cm_{\text{CohortModel}_\sigma}$, the standard deviation, which is only available in the GMM based system, is needed as well.

5. Data and Experimental Setup

The text lines used in our experiments are part of the IAM handwriting database [13][1]. The database currently contains over 1,500 pages of handwritten text from over 650 writers. For each writer we use five pages of text from which between 27 and 54 text lines are extracted.

The training set for the HMM based and the GMM based system is identical and contains 4,103 text lines from 100 different writers. Four-fold cross validation is used, i.e, the data set is split up into four sets and itera-

[1]The IAM handwriting database is publicly available at: www.iam.unibe.ch/~fki/iamDB

Table 1. Equal Error Rates (EERs) for unskillfully and skillfully forged test set.

Equal Error Rate (ERR) (in %)	Unskilled Forgeries	Skilled Forgeries
GMM, cm_{LLScore}	12.5	39.5
HMM, cm_{LLScore}	34.0	34.0
GMM, $cm_{\text{WorldModel}}$	3.0	13.0
HMM, $cm_{\text{WorldModel}}$	2.0	5.9
GMM, $cm_{\text{CohortModel}}$	1.5	10.6
GMM, $cm_{\text{CohortModel}_\sigma}$	1.5	8.2
HMM, $cm_{\text{CohortModel}}$	0.9	2.6

tively three of the sets are used for training and one for testing.

The unskillfully forged test set consists of two disjoint subsets coming from clients and impostors. The unskilled forgeries that form the impostor set are obtained from the database by extracting 571 text lines produced by 20 writers. The writers of these text lines are disjoint from the 100 clients and no model exists that is trained on the handwriting of any of these 20 writers. Based on these text lines the impostor data set is constructed by assigning, to each of these text lines, seven identities of writers known to the system. In total, the impostor data set consists of 7×571=3,997 and the complete test set of 8,100 text lines. The rationale is that the number of text lines to be accepted is approximately the same as the number of text lines that have to be rejected.

The skillfully forged test set is again composed of two subsets, a client and an impostor subset. The client data set consists of one page of text from 20 different writers which are part of the 100 clients. A total of 169 text lines are extracted from these 20 pages. The same 20 pages are then skillfully forged. The acquisition protocol was as follows. A person was presented with a page of handwritten text and given 10 minutes to train the writing. Then he or she was asked to forge the text. An example of three original and three skillfully forged text lines are given in Fig.1. From the forgeries thus created, another 169 text lines are extracted. Hence, in total 338 text lines are used in this test set.

For each writer, a HMM based system was trained using the strategy described in Section 2 with a maximal number of five Gaussian mixture components. This number of Gaussians produced the highest writer identification rate in a writer identification experiment on the client test set of the unskillfully forged test set used in this paper. The world model was trained with the same number of Gaussians using all training data from all 100 writers.

Similarly, for every writer a GMM based system is trained using 200 Gaussians and a variance flooring factor of 0.005. These parameters yielded the best writer identification rate in a writer identification experiment on the client test set of the unskillfully forged test set used in this paper. Additionally, with the same parameter set a world model is trained on all data from all writers.

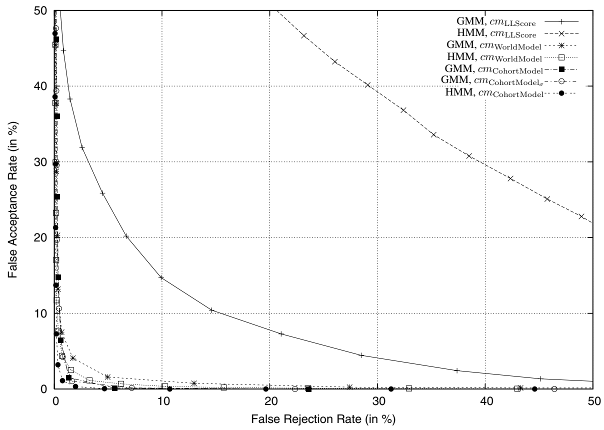


Figure 2. ROC curves of the HMM and the GMM based system on the unskillfully forged test set.

6. Results

The results of the experiments are reported as Receiver Operator Characteristic (ROC) curves in Figs. 2 and 3. An ROC curve describes the performance of a verification system on a test set by plotting the False Acceptance Rate (FAR) against the False Rejection Rate (FRR) [5]. In Table 1 the estimated Equal Error Rates (EERs) for the ROC curves are given [5]. Because the HMM recognizer does not return a standard deviation for a given text line, the ROC curves for the HMM based system and $cm_{\text{CohortModel}_\sigma}$ can not be plotted.

In Fig. 2 the ROC curves on the unskillfully forged test set for the HMM based and the GMM based system are shown. The ROC curves produced using the raw log-likelihood score (cm_{LLScore}) have the lowest performance for both systems. The HMM based system achieves an EER of approximately 34.0% and the GMM based system yields an EER of 12.5% for cm_{LLScore}. The world model based approach ($cm_{\text{WorldModel}}$) achieves an EER of 3.0% for the GMM and an EER of 2.0% for the HMM based system. For both the HMM and the GMM based system, the ROC curves based on $cm_{\text{CohortModel}}$ produces EERs of 1.5%. The best ROC curve with an EER around 0.9% is produced by the HMM based system and the $cm_{\text{CohortModel}}$ confidence measure.

The ROC curves on the skillfully forged test set for the HMM based and the GMM based systems are shown in Fig. 3. The ROC curves with the lowest performance are produced using the raw log-likelihood score (cm_{LLScore}) for both systems with EERs above 30%. The GMM based system with $cm_{\text{WorldModel}}$ produces an EER of around 13.0%. For the cohort model confidence measures, if we use $cm_{\text{CohortModel}_\sigma}$ instead of $cm_{\text{CohortModel}}$ the EER drops from 10.6% to 8.2% for the GMM system. The two best performing ROC curves are generated by the HMM based system. An EER of 5.9% results using the world model approach ($cm_{\text{WorldModel}}$) and an EER of 2.6% is achieved by the cohort model approach ($cm_{\text{CohortModel}}$).

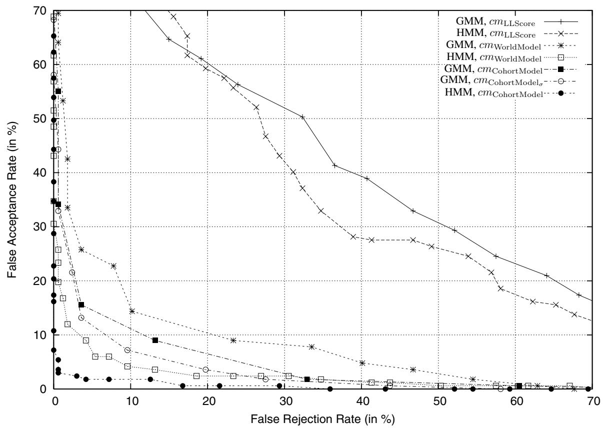


Figure 3. ROC curves of the HMM and the GMM based system on the skillfully forged test set.

7. Discussion

In the unskilled forgeries experiment, the best performing ROC curves are produced by the cohort model based confidence measure for both the HMM and the GMM based system. The best ROC curve of the conceptually and computationally less complex GMM based system is only slightly inferior to the best ROC curve of the HMM based system.

In contrast, in the skilled forgeries experiment, the best ROC curves are produced by the HMM based system for both the cohort model and the world model based confidence measure. There is a substantial difference in performance compared to the GMM based system. This result can be explained by the fact that the HMMs encode time information about the handwriting which is not available in the GMM model. This additional information allows to better distinguish skillfully forged text lines from original text lines.

Independent of the statistical model employed by the verification system, in both experimental setups the best ROC curve is produced by the cohort model based confidence measure. However the calculation of this confidence measure is costly compared to the world model based approach. For every text line, the log-likelihood scores of all 100 models have to be computed and then sorted. In comparison, the world model based confidence score uses the score of the claimed system and the world model only and is independent of the number of client models.

8. Conclusions and Future Work

In this paper we have compared two off-line, text-independent writer verification systems. While the first system uses HMM based recognizers to model a person's handwriting, the second system employs GMMs to accomplish this task. Three different types of confidence measures are studied based on the raw log-likelihood score, a cohort model, and a world model approach. The performance of both systems is evaluated on two test sets. The unskillfully forged test set contains in total 8,100 text lines from 100 clients and 20 impostors. The skillfully forged test set contains 338 text lines from 20 clients and 20 impostors.

While the GMM- and the HMM based system perform similarly on the unskillfully forged test set, the HMM based system outperforms the GMM based system on the skillfully forged test set. An EER of around 0.9% is achieved on the unskillfully forged test set and an EER of approximately 2.6% is obtained on the skillfully forged test set. On both sets, the best ROC curves are produced by the cohort model based confidence measure. However, the computation of this confidence measure is dependent on the number of clients and thus expensive to calculate for a large number of clients.

For future work, an interesting question is to investigate whether modifications of the world model based confidence measures as presented in [1] would yield performances similar to the ones obtained by the cohort model based confidence measure. Another interesting task is to try to improve the performance on both unskilled and skilled forgeries by combining the HMM and the GMM based system using a Multiple Classifier System (MCS) approach [17].

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