ENROLMENT MODEL STABILITY IN STATIC SIGNATURE VERIFICATION

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ENROLMENT MODEL STABILITY IN STATIC SIGNATURE VERIFICATION

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The stability of enrolment models used in a static signature verification system is assessed, in order to provide an enhanced characterisation of signatures through the validation of the enrolment process. A number of static features are used to illustrate the effect of the variation in enrolment model size on the stability of the representation of signatures.

1 Introduction

The development of a practical signature verification system is limited by a number of factors. Arguably the most significant limitation is that imposed by the lack of sufficient data with which to characterise the signature styles[1], due to the inherent nature of the signature data (including complexity of characterisation, number of reference samples and variability between samples from an individual signer as well as the level of effort and skill involved in any forgery attempt[2]). This limitation means that all methods of describing a signature class are approximations, and this will have a detrimental effect on the system performance. Work has been carried out to investigate the use of statistical methods for applications with limited training data[3], seeking to improve the estimation of the characterisation offered by the reference data through the selection of a sub-set of an overall database of reference signatures[4], but any statistical-based method of signature verification faces severe limitations if sufficient reference information is not available. Heuristic enrolment validation offers a solution to the lack of training data in that it provides an improved description of a signature class, resulting in the enhancement of class description in situations of limited reference data. An additional aspect of the analysis of the signatures presented for inclusion in a reference model is the consideration of the effect on model stability when additional signatures are included in the reference model. This is of particular importance when the number of signatures available to characterise a given signature class is limited, as is generally the case in practical applications.

2 Enrolment Model Validation

The amount of information that is available to form an accurate model of the signature classes is a significant issue to resolve in the implementation of a signature verification system. Here, too small a number of available signatures makes it difficult to characterise the way in which people sign. A significant amount of reference data for a single signature class will improve the description for that class,

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but unfortunately this is generally not available. As a practical solution to the problem of a lack of a suitable volume of data with which to characterise a signature class, enrolment model validation makes use of limited existing data, through the assessment of the individual samples comprising the reference database, with the aim of removing any unsuitable samples through the identification and rejection of "rogue" samples, or in order to generate an awareness of an unsatisfactory enrolment model, through the analysis of the signatures forming the reference model. If the reference model is found to provide an unsatisfactory signature class characterisation, it is considered “invalid” and additional or replacement samples are sought. The exploitation of this technique depends on the mode of operation. On-line capture of signatures allows the immediate comparison of samples and the replacement of unacceptable samples, until a representative set is obtained. Off-line, the treatment of signatures must be different, given that there will typically be a fixed number of signatures from which an optimum set must be obtained.

3 Implementation of off-line enrolment validation

The information gained through enrolment validation can be used in a number of ways, depending on the requirements of the system, particularly with respect to whether the signatures are processed on-line or off-line. Any signatures identified as being unrepresentative may be:

- Removed from the set of candidate reference signatures
- Retained at the cost of a reduction in the level of security given to the individual signer
- Replaced with a new signature, donated upon request

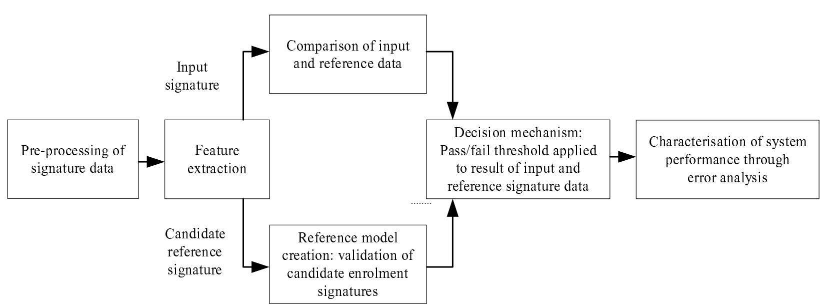

Figure 1: Enrolment validation through comparison of candidate signatures with mean feature vector

Given a fixed reference database, enrolment validation lends itself to the ranking of a set of candidate reference signatures, according to some quality criterion, with the better ranked samples being selected for inclusion in the reference model. The validated reference model is then used to characterise the signature class in subsequent verification attempts, as described in Figure 1. The validity of the candidate reference model is tested according to some quality criterion, for example the measurement of the closeness of feature vectors representing the candidate reference signatures in N-dimensional feature space, through the calculation of the Euclidean distance between the feature vectors. The implementation of enrolment validation is summarised in Figure 2.

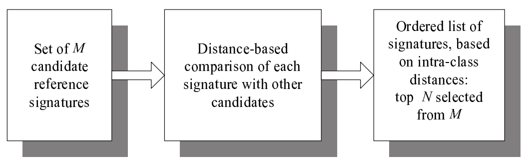

Figure 2: Implementation of enrolment validation in an off-line environment

4 Signature representation

Two feature types were used to characterise the static signature images used in the experimental study to be reported here:

- Fourier Power Spectrum[6] coefficients extracted from the upper contour profile of signature images
- Complex Moment Descriptors[7] (a total of 20 coefficients representing 6^{th} order moments were used)

Complex Moment Descriptors are a translation-, scaling- and rotation-invariant feature set, based on a holistic treatment of the pixels forming the signature image. The feature sets were chosen to represent different forms of holistic image representation. The contour profiles make use of the way in which the signature image is constructed, through the representation of information extracted from the letters forming the signature in the contour profile. Power spectrum coefficients extracted from the profiles encapsulate frequency information relating to the shape of the profiles, in terms of the peaks and troughs formed by the individual characters forming the signature. The Complex Moment Descriptors are also a holistic treatment of the signature image, with each pixel comprising the image contributing to the calculation of the set of invariants. An example of an upper contour profile extracted from a signature is shown in Figure 3.

(i) Skeletonised signature with upper and lower contour profiles

(ii) Extracted upper contour profile

Figure 3: Extraction of upper contour profile

5 Enrolment model stability

In order to provide a stable characterisation of a signature class, the reference model must exhibit low intra-class variation, compared to the inter-class variation[5].

An investigation was undertaken to determine the stability of the reference model in terms of the effect on verification performance when additional signatures were required to be added to obtain a validated reference model. The validation of the signatures forming the set of candidate reference signatures was made in two stages; five samples were initially included in a set of *candidate* reference signatures and this set of signatures was evaluated, using a distance-based comparison between the candidate reference signatures. The identification of an invalid reference model resulted in addition of further signatures. The stability of the reference model was assessed for the initial reference model, and as any subsequent additional signatures were added. A total of up to five additional signatures was allowed (this limit of five additional signatures was set to reflect the number of samples likely to be available in a typical application).

6 Results

The results are presented in the form of graphs showing the number of invalid reference models as the number of additional samples donated varies, as shown in Figure 5, which shows respectively for the two different feature sets considered, how, as the number of training samples is varied, the number of invalid reference models varies. The classification of a reference model as being valid is based on the analysis of the distance of each candidate reference sample from the mean feature vector calculated from each of the individual feature vectors.

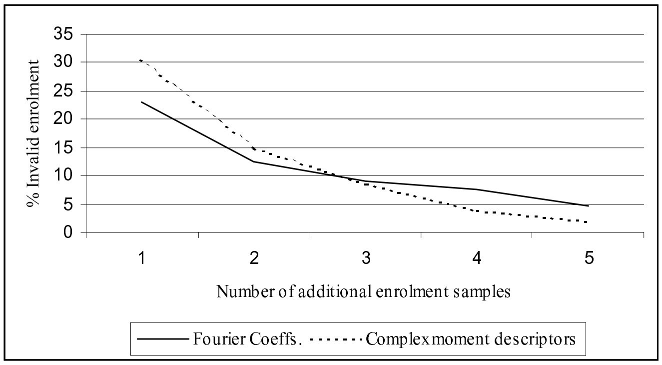

Figure 5: Effect of number of training samples on validity of reference model

The effect of the removal of invalid reference models using the Complex Moment Descriptors is summarised in Table 4.6, which shows the change in Type I error rate when invalid reference models are rejected. The effect of the removal of the invalid reference models is to produce a set of stable reference models, each exhibiting a low intra-class variability relative to their inter-class variability.

Table 4.6: Percentage Type I error rate for CMD features with and without removal of invalid reference models

TREATMENT OF GROUPS	DISTANCE THRESHOLD					
	1.1	1.0	0.9	0.8	0.7	0.6
Invalid models removed	1.9%	3.7%	3.9%	3.8%	4.4%	6.6%
With all groups	2.3%	4.8%	5.0%	5.4%	7.0%	10.4%
Difference	0.4%	1.1%	1.1%	1.6%	2.6%	3.8%

7 Conclusions

The effect of allowing additional signatures to be donated demonstrates a clear improvement in the characterisation of individual signature classes within a larger population of signature classes. As the number of additional enrolment samples allowed is increased up to ten, the number of invalid reference models is significantly reduced for all feature types.

An experiment was performed to assess the stability of the enrolment models as the number of reference signatures is varied. Additional signatures, up to a total of ten, were allowed to replace samples identified as invalid and the overall number of invalid enrolment models identified as each replacement signature was added was measured. The results in Figure 5 shows a clear improvement in the number of valid reference models as the number of additional samples allowed is increased. This demonstrates that the number of potential enrolees who fail to generate an adequate enrolment model decreases progressively as the number of donated samples is increased. Thus, the incorporation of a validation procedure is effective in improving attainable performance with a practical system. It should be noted that the presence of a core group of signers who are unable to provide a valid reference model is to be expected, reflecting the existence of a small number of signature styles which are inherently unstable.

The use of enrolment validation methods as introduced here is based on the comparison of sets of descriptive features. Other signature verification methods, particularly those based on the comparison of functions, require a modification of the way in which similarities between candidate signatures are measured in order for enrolment validation to be possible, but the filtering of signatures to obtain an optimised reference model is still possible, and the validation of reference models and the addition of replacement signatures as part of the validation process can be applied to these alternative methods of signature representation.

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