

On Optimisation of Smart Card Face Verification Systems

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Abstract

The optimisation of a smart card face verification system (SCFVS) design is a complex task. As the parameters involved are not independent, the search space is of exponential complexity. We investigate simplified optimisation strategies and demonstrate that both system performance and speed of access can be improved by jointly optimised parameter setting and level of probe compression. Experimental results suggest that the choice of one strategy over another is a matter of the amount of time available for the system design, system performance and response time.

1. Introduction

The design of practical biometric face verification systems [8, 10] starts with the selection of a suitable suite of algorithms which then have to be ported to a target platform on which the biometric process should run. In some cases this may be a relatively simple task, involving the adaptation of the parameters of the implemented algorithms to the application envisaged. However, if the target platform imposes severe engineering constraints, the computational and performance aspects of the biometric process have to be investigated with a view of finding an acceptable trade-off between the system complexity and the verification accuracy. One of the most challenging requirements is to implement a face verification system on a smart card[6]. Smart cards are notoriously small platforms which impose extreme restrictions in terms of memory, communication bandwidth and speed of processing. The porting of algorithms on such devices requires all implementation issues to be revisited to find an acceptable solution.

An interesting SCFVS architecture was proposed in [1]. The key distinguishing feature of the architecture is that the verification process is carried out on the card. This contrasts with other solutions where the card is used simply as a means of storing the biometric template (reference face model). In this architecture the input image (probe) is first filtered and then geometrically, as well as photometrically normalised in a local host. The registered and normalised probe is then transmitted to the card where the verification step is executed and the decision communicated to the service provider. The

proposed system implements the revolutionary client specific linear discriminant analysis technique (CS-LDA) [3], which combines face representation and decision making into a single step that requires a template of the size of the input image. The solution avoids the need to implement the proprietary feature extraction computation in the host. This enhances the portability and security of the system.

The methodology of designing a SCFVS has been the focus of research for some time now [1, 7]. The underlying issue is that a full system optimisation is computationally not feasible. The complexity of the system, in terms of the number of processing stages and system design parameters is too large and as the parameters are not independent, the search space is of exponential complexity. This means that in practice a simplified optimisation strategy has to be adopted.

There is a subset of the parameters that have been demonstrated to be generally applicable for a wide range of application scenarios. These parameters include grey level resolution, spatial resolution, and fixed point number representation, geometric and photometric normalisation. Assuming that these parameters are fixed and provide a baseline for reference (REF parameter set), the key design issue is the degree of compression that can be applied to the probe image before it is transmitted to the smart card. This can be achieved by image compression or by reducing image resolution (or both). Compressed information can significantly influence the transmission time from the local host to the smart card and as a result the *user access time* (UAT).

Since image compression usually involves the loss of high frequency content, it interacts with image filtering, and in turn, with the feature extraction process, as the amount of variance retained by the image data will depend on image smoothing. Therefore, the optimisation of even this small set of parameters of the system is a serious undertaking.

In this paper we investigate two alternative system optimisation approaches and the effect of *image compression* on the resulting design:

- A *Simple Optimisation Strategy* (SOS), where we start with the REF parameter set and optimise over spatial resolution.
- A *Comprehensive Optimisation Strategy* (COS), where we start with the REF parameter set but apply Gaussian

filtering instead of binomial. We optimise over filtering parameters (mask size, bandwidth σ) and number of PCA components retained by the feature extraction system.

The computational complexity of the latter approach is two orders of magnitude greater than that of the simple optimisation strategy. However, the choice of one strategy over another is not simply determined by the amount of time available for the system design. We show that the simple optimisation strategy leads to a design with a much faster response time, and therefore throughput. In general, the performance of the system obtained by the comprehensive optimisation is better than that yielded by the simple strategy. However, for high compression rates the performance differential diminishes. Interestingly, even for the simple strategy the data compression delivers improvement in performance over the default system that was optimised without any engineering constraints. These results provide a basis for making an informed decision regarding the optimisation approach to be adopted.

The paper is organised as follows. In Section 2 we describe the generic and our smart-card based *face verification system* (SCFVS). In Section 3 we present the results of the design optimisation of a SCFVS for a particular face database and experimental protocol, carried out according to the two approaches outlined above. In Section 4 we discuss the effect of image compression on user access time as well as system performance. Conclusions are drawn in Section 5.

2. SCFVS: System Description

A typical face-verification system consists of three basic modules and each module is composed of a sequence of steps. The *first module* normalises all input face images. The *second module* extracts the suitable features for every subject in the training set. Finally, the *third module* performs the recognition/verification.

A *face recognition system* determines whether or not the face in a probe (either a new image of an individual in the gallery or not in the gallery) is of a person in the gallery (the set of known individuals). *The circumstance of verification* is a special case of recognition, where only the subject identity claimed for the test probe is considered. The claim is either accepted or rejected by the classifier. The critical parameters in the final module are, the subset of eigenvectors used to represent the face (in either the PCA or LDA method), and similarity measure used by the classifier.

Our SCFVS is based on the structure of the typical face-verification system described above. The face verification method adopted for the implementation on a smart card is the CS-LDA technique, which combines face representation and decision making into a single step, requiring a template of the size of the input image (see *Figure 1*). The overall SCFVS involves face registration (pre-processing) that performs geometric and photometric normalisation, feature extraction and

finally the verification test.

In our client specific face verification approach, the classification is performed in the linear discriminant subspace, which is only one dimensional subspace of the original face space. As far as the training set is concerned, in the CS-LDA approach, each client specific fisher face is obtained after the data has been projected into the PCA subspace. This subspace was obtained using the 600 (800) training images of the XM2VTS database in Configuration I (Configuration II). Its dimensionality is therefore at most 599 (799).

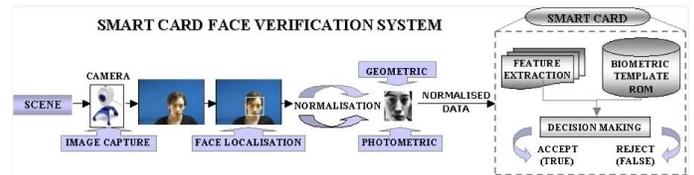


Figure 1. The Distributed SCFVS Architecture.

The original resolution of the image data is 720x576 in the case XM2VTS. Initially the experiments were performed at different spatial resolutions to identify the optimum one in terms of performance (a task that proved to be protocol dependent). However, a relatively low resolution for the face images, namely 55x51, with a grey level resolution of 8bpp are considered to be the reference resolutions for the experiments of this work.

The steps involved in the SCFVS are described below:

Face Registration: The aim of the face registration (pre-processing) stage is to normalise the pose and resolution of the face image after face detection. Initially, a low-pass binomial filter (with probability equal to 0.5 and mask size 1×11) is applied to the original image so as to remove the high-frequency noise. Then *geometric normalisation* is performed by a fast, flexible, semi-automatic geometric alignment method based on the positions of the two eyes. This utility is used to crop the face part of the original image and scale it to any desired resolution. It adjusts the face in a standard position by using rotation, scaling and translation of the centre of the eyes to fixed locations. *Photometric normalisation* is achieved by a homomorphic filter and histogram equalisation.

Feature Extraction: In this stage a compact set of inter-personal discriminating geometrical and/or photometrical features of the face are extracted. By using the CS-LDA technique the initial statistical model is built. Initially a *PCA model* is built to achieve a dimensionality reduction and then an *LDA model* is produced to get the overall client i specific linear discriminant transformation a_i , which defines the client specific fisher face for testing the claimed identity.

Verification: The verification process involves computing the score between the photometrically normalised image transmitted to the smart card and the user biometric template stored on the card. The verification score produced defines



Figure 2. XM2VTS sample of unregistered and registered images using our system.

how close the probe of the claimed identity is to the class of impostors. The final decision is taken depending on the relationship of the score to the decision threshold. The threshold in this stage is determined based on the EER criterion. By adopting the CS-LDA representation on the SCFVS, the measure for authentication used is the distance to the mean of impostors.

3. Optimisation Studies

In this work, the two alternative (face verification system) optimisation approaches investigated have been evaluated via a set of experiments using the XM2VTS database in two different testing configurations (C1 and C2). They differ by selecting particular shots of people into the training, evaluation and test sets. However, data is employed more efficiently in C2. Both test protocols represent a closed-set protocol where all the enrolled clients are known to the system.

The adopted methodology of optimisation of the relevant parameters is using the *half-total error rate* (HTER) on the test set of XM2VTS as a criterion of optimality. HTER is obtained using the *equal error rate* threshold determined from the ROC curve computed on an independent evaluation set.

3.1. Simple Optimisation Strategy

In the simple optimisation strategy **SOS** we optimise spatial resolution [2]. The other parameters of the system are set to the default values of the REF parameter set, where grey scale resolution is fixed to 8bpp. The pre-processing stage in REF involves binomial filtering with probability equal to 0.5 and mask size 1×11 , followed by geometric normalisation, histogram equalisation and homomorphic filtering.

In SOS, the initial raw face images of the XM2VTS database are normalised from their original resolution (720x576) to a spatial resolution that is varied from 110×102 down to 8×7 in 16 steps (see first column of Table 1). These steps were deliberately selected in an exponential form in order to emphasise more the lower image resolutions, that can

be interpreted in a lower memory volume and as a result a faster transfer of the normalised probe face to the smart card. Then we identify the optimum resolution for either protocol. Note that the REF system has image resolution of 55x51. By optimising one parameter only, the amount of time required for finding the optimum system design is very low (a matter of days). Moreover, the experimental results (see Table 1) show that the use of a lower image resolution can improve system performance and reduce the number of bytes required to represent the face image. As a result a faster transfer of the normalised probe face to the platform is achieved. Interestingly, the two XM2VTS protocols require a different image resolution for optimum performance.

Table 1. Results of the simple optimisation strategy.

| Image Resolution | Pixels | XM2VTS C1 | XM2VTS C2 |
|------------------|--------|-----------|-----------|
| 8x7 | 56 | 0.08025 | 0.08863 |
| 10x8 | 80 | 0.05482 | 0.06218 |
| 13x11 | 143 | 0.05296 | 0.04642 |
| 15x13 | 195 | 0.04662 | 0.03802 |
| 18x16 | 288 | 0.03977 | 0.03208 |
| 20x18 | 360 | 0.04340 | 0.03114 |
| 25x23 | 575 | 0.04190 | 0.02575 |
| 30x28 | 840 | 0.04025 | 0.02758 |
| 40x37 | 1480 | 0.04225 | 0.02214 |
| 55x51 | 2907 | 0.04588 | 0.02644 |
| 61x57 | 3477 | 0.04409 | 0.02465 |
| 70x65 | 4550 | 0.04494 | 0.02343 |
| 80x75 | 6000 | 0.04777 | 0.02535 |
| 90x85 | 7650 | 0.04711 | 0.02522 |
| 100x93 | 9300 | 0.04680 | 0.02524 |
| 110x102 | 11220 | 0.04647 | 0.02350 |

3.2. Comprehensive Optimisation Strategy

In the SOS optimisation strategy, the number of PCA components used was determined by the requirement to retain 95% of the total energy. Also the filtering stage was fixed. In the comprehensive optimisation strategy **COS**, the pre-processing stage and a part of feature extraction (when building the PCA model) are included in the optimisation process. Particularly, in this strategy the study is widened to consider the effect of optimising also over the number of PCA components and the parameters of the filter stage. The remaining parameters are set to default values with image resolution set to 55x51. The process is as follows:

- *First*, optimisation is performed over the image filter types (binomial, Gaussian) and the image filtering parameters. The search space is limited to four different binomial and Gaussian kernel sizes 13, 17, 21 and 25. Moreover, the range of the bandwidth in the Gaussian filtering is modified in twenty seven (27) different steps, initially from 0.5 to 7.0 in increments of 0.25. From

Table 2. Performance results in terms of HTER on the XM2VTS database when binomial filter was used and best results when Gaussian filtering was used.

| FILTER | LENGTH | SIGMA | HTERC1 | HTERC2 |
|--------|--------|-------|---------|---------|
| BINOM | 11 | 1.581 | 0.04588 | 0.02644 |
| BINOM | 13 | 1.732 | 0.04311 | 0.02404 |
| BINOM | 17 | 2.000 | 0.04281 | 0.02491 |
| BINOM | 21 | 2.236 | 0.04180 | 0.02497 |
| BINOM | 25 | 2.449 | 0.04182 | 0.02401 |
| GAUSS | 11 | 1.581 | 0.04041 | 0.02306 |
| GAUSS | 13 | 1.750 | - | 0.02125 |
| GAUSS | 13 | 5.000 | 0.03764 | - |
| GAUSS | 17 | 1.000 | - | 0.01942 |
| GAUSS | 17 | 5.000 | 0.03499 | - |
| GAUSS | 21 | 2.250 | - | 0.02072 |
| GAUSS | 21 | 6.250 | 0.03286 | - |
| GAUSS | 25 | 1.500 | - | 0.01809 |
| GAUSS | 25 | 3.250 | 0.03674 | - |

the results (see Table 2) it transpires that applying Gaussian filtering is preferable to binomial filtering and by optimising its parameters the performance can be maximised.

Then the optimum number m of PCA components needed by the system to maximise its performance is selected across a range of the bandwidth factor σ of the Gaussian filtering function $g(x,y) = \exp(-\frac{x^2+y^2}{2\sigma^2})$. In particular, in order to limit down the search space, the Gaussian filter is selected with kernels $(1 \times 21)/(1 \times 25)$ as the optimum ones in terms of performance for C1/C2 protocols respectively. Moreover, the range of the bandwidth was modified in nineteen different steps, initially from 0.5 to 5.0 in increments of 0.25 (this was extended up to 7.0 only for the C1 protocol to obtain the optimum results).

In the experiments performed, the dimensionality m of the PCA subspace is manually chosen from 1 and up to 550/600 number of PCA components m in increments of 10, for the C1/C2 protocol respectively. The system is evaluated in terms of HTER and for each bandwidth factor σ several cases of local minimum HTER were identified. Therefore, in order to obtain a potential global minimum and to keep the search space to reasonable limits, another 20 experiments have been performed for each σ and for each protocol, by selecting m in increments of 1. This has been done for m only on those ranges that covered the whole search space between the three local minimum HTER results i.e. if one local minimum HTER is obtained for $m=50$, then all cases of $n \in [40, 60]$ are being searched one by one. Such a suboptimal strategy has the advantage of performing $\cong 9$ times less experiments (from 32752 down to 3700).

In an alternative solution to that of PCA optimisation, the low-order eigenvectors are removed after optimising the filtering parameters in the normalisation stage. There are two advantages of adopting this method. It achieves competitive performance results compared to those achieved by PCA optimisation, and also it avoids the high computational complexity that PCA optimisation requires. However, it should be noted that, some gains can simply be achieved by the optimisation of the filtering parameters alone.

In the experimental results shown in Table 3 three cases are presented. The case where the REF parameter set is used (using the binomial filtering) and the one where the Gaussian filter is selected with kernels $(1 \times 21)/(1 \times 25)$ as the optimum ones in terms of performance for C1/C2 protocols respectively. For each of the above cases, we also present the results where a certain number of the low-order eigenvectors is removed to achieve maximum performance.

It appears that PCA dimension optimisation further ensures the preservation of the necessary face features and frequency components and renders the system robust in terms of informational content while maximising its performance. Maximum performance is achieved when m is manually optimised [9] (for each protocol of the XM2VTS database [4]). This is achieved with the following set of parameters: Gaussian filtering with 1×21 mask size and the filter width $\sigma = 6.75$ for C1 protocol and with 1×25 mask size and $\sigma = 2.25$ for C2 protocol respectively. PCA dimensionality is set to $m=106$ (330) for C1(C2).

The main disadvantage of the *COS strategy* is the significant computational complexity of the system design. The effort to optimise either the filtering parameters or the PCA dimension was enormous. The amount of time required for completing the system design was several weeks. However, in the alternative solution where a number of low-order eigenvectors (depending on protocol) [5] is removed, we achieved not only high performance but also to limit down significantly the system complexity.

4. Image Compression

In the SOS we showed that the use of a lower image resolution can improve system performance as well as increase the degree of compression applied to the probe image before it is transmitted to the smart card. One way of further decreasing the transmission time is by compressing the probe image using standard image compression algorithms. The appropriate compression method was considered to be JPEG. It is not the optimum compression method, but it outperforms the other methods in terms of the encoding and decoding time. Compression is applied using a JPEG library as a part of the Independent JPEG Group software, which has the additional feature that it ensures compatibility at low bit rates. Among many JPEG coders, sequential JPEG is selected because it is

Table 3. Performance vs filtering types and filtering parameters in XM2VTS C1/C2. (nPCAr= the number of low-order eigenvectors removed, A/M=Automatic/Manual selection of the number of PCA components, OPT = Gauss Optimum, S=Sigma, Le=length.)

| DB/PROT | FIL | Le | S | PCA | nPCAr | HTEr |
|---------|-----|----|------|------|----------|--------|
| XM C1 | BIN | 11 | 1.58 | 211A | No | 0.0459 |
| XM C1 | BIN | 11 | 1.58 | 258A | -(1,2,3) | 0.0452 |
| XM C1 | GAU | 21 | 6.25 | 96A | No | 0.0329 |
| XM C1 | GAU | 21 | 6.25 | 125A | -(1,2,3) | 0.0333 |
| XM C1 | OPT | 21 | 6.75 | 106M | No | 0.0312 |
| XM C2 | BIN | 11 | 1.58 | 247A | No | 0.0264 |
| XM C2 | BIN | 11 | 1.58 | 277A | -1 | 0.0236 |
| XM C2 | GAU | 25 | 1.50 | 279A | No | 0.0187 |
| XM C2 | GAU | 25 | 1.50 | 316A | -(1,2) | 0.0188 |
| XM C2 | OPT | 25 | 2.25 | 330M | No | 0.0176 |

the simplest to implement, fastest to execute and easiest to be ported on a small platform.

In this set of experiments we study the effect of image compression on performance and the transmission time. The experiments were conducted on the XM2VTS database. The effect of compression is measured for the reference system and the optimal designs obtained using the SOS and COS methods. Note that JPEG compression is applied to both training images and test set. Different quality settings for the compressor have been used. Image quality is traded off against file size by adjusting those settings. In all cases, the range of the quality factor has been modified from 5 to 100.

When JPEG is applied in all cases, experiments show that the smart card design is optimised when a potential JPEG quality factor is selected, which depends on the testing configuration. Below this quality threshold, the performance can degrade. Above that, there is a surprisingly wide quality range where *compression does not seem adversely to affect performance*, and for both testing configurations of the XM2VTS database *it may even improve system performance*. Generally speaking, when operating at the limit of the quality settings we can achieve good performance as well as gain in memory size and transfer speed.

In all cases (see Table 4), apart from one, the optimum compression ratio in terms of performance has been identified. No compression is required for the SOS protocol C1 design. In this case, the face representation is already compressed approximately 10 times (when the 18x16 resolution is used instead of the reference one) and JPEG compression would actually increase the number of bits to be transmitted. Furthermore, this particular design achieves relatively good performance.

In the case of the SOS C2 design, the use of JPEG slightly decreases the system performance (compared to REF and COS methods). Interestingly, when JPEG is applied to the

Table 4. Applying compression on the alternative parameter sets. FWork=FrameWork, SR=Spatial Resolution, IBS/FBS=Initial/Final Byte Size, C(R/Q)=Compression Ratio/Quality.

| FWork | SR | IBS | CR | CQ | FBS | HTEr |
|-----------|-------|------|--------|-----|------|--------|
| REFC1 | 55x51 | 2805 | - | - | 2805 | 0.0459 |
| REFC1+Jpg | 55x51 | 2805 | 5.1:1 | 7.5 | 550 | 0.0417 |
| SOSC1 | 18x16 | 288 | - | - | 288 | 0.0398 |
| COSC1 | 55x51 | 2805 | - | - | 2805 | 0.0318 |
| COSC1+Jpg | 55x51 | 2805 | 2.76:1 | 50 | 1016 | 0.0322 |
| REFC2 | 55x51 | 2805 | - | - | 2805 | 0.0264 |
| REFC2+Jpg | 55x51 | 2805 | 4.76:1 | 10 | 589 | 0.0220 |
| SOSC2 | 40x37 | 1493 | - | - | 1493 | 0.0204 |
| SOSC2+Jpg | 40x37 | 1493 | 2.78:1 | 20 | 537 | 0.0213 |
| COSC2 | 55x51 | 2805 | - | - | 2805 | 0.0177 |
| COSC2+Jpg | 55x51 | 2805 | 2.54:1 | 60 | 1104 | 0.0183 |

REF design we also obtain a viable solution achieving approximately 5:1 compression efficiency with improved system performance of more than 9% as well. Finally, in terms of performance and when time is of no importance to set up the system design, the COS C1/C2 designs are the optimum ones.

For every compression ratio the user access time **UAT** is also measured. It is defined as the Total CPU Time **TCPUT** in milliseconds that the process spends in user and kernel mode. TCPUT can be measured in face detection, normalisation, JPEG compression/decompression, transfer of the probe image to/from the card, decompression and matching. Since face detection and matching times are very small (a few msec), they are excluded from the measurements. Note that, when decompression is performed on the card, TCPUT will be higher. However, assuming that the card will use a sophisticated algorithm and with fixed point arithmetic, this time will be relatively low and comparable to the simulated time.

Since the data transfer rate achieved by the smart card employed for the experiments is the maximum allowed one (115.2Kbps or 14.4KBytes per sec) in the contact-less mode, the *Transfer Time (msec)* is equal to: $[Image.Size \times 4bytes] / [ComprRatio \times 14.4KBytesps]$ (4bytes since floats are used). Note also that each experiment is performed 10 times and the results are averaged.

The experimental results (as shown in Table 5) suggest that the choice of filter, the filtering parameters and the amount of compression (that can be applied to achieve maximum performance) affect the normalisation and transfer time respectively, and as a result UAT. Even though high compression can decrease the UAT (as obtained in the REF system), the optimisation of spatial resolution is the most effective solution to consider. The complexity of the COS strategy is also reflected in UAT.

An interesting point to note is that the compres-

Table 5. UAT Results when JPEG is applied. Note that qualities are the optimum ones in terms of performance for each case. FWork=FrameWork, C(R/Q/Time)=Compression Ratio/Quality/Time, (I/F)BS=Initial/Final Byte Size, Norm=Normalisation, DC=De-Compression, Trans=Transfer, T=TCPUT(ms), Re=Reference.

| FWork | ReC1 | SOSC1 | COSC1 | ReC2 | SOSC2 | COSC2 |
|--------|-------|--------|--------|--------|--------|--------|
| IBS | 2805 | 288 | 2805 | 2805 | 1493 | 2805 |
| CR | 7.5 | - | 50 | 10 | 20 | 60 |
| CQ | 5.1:1 | - | 2.76:1 | 4.76:1 | 3.79:1 | 2.54:1 |
| FBS | 550 | 288 | 1016 | 586 | 740 | 1104 |
| NormT | 87.5 | 80.18 | 87.64 | 86.75 | 85.67 | 89.22 |
| CT | 0.68 | - | 0.71 | 0.69 | 0.74 | 0.68 |
| TransT | 152.8 | 80.1 | 282.3 | 163.7 | 205.6 | 306.8 |
| DCT | 0.64 | - | 0.68 | 0.64 | 0.73 | 0.65 |
| TotalT | 241.6 | 160.3 | 371.4 | 251.8 | 292.7 | 397.3 |
| HTER | 0.417 | 0.0398 | 0.0322 | 0.022 | 0.0213 | 0.0183 |

sion/decompression times are very low due to the extremely optimised low level algorithm used (developed by the Independent JPEG Group).

5. Conclusions

The optimisation of a smart card face verification system is a very complex process with many key factors to consider. It involves the investigation of the effect the system parameters have on the system performance measured in terms of accuracy and speed. In practice only partial optimisation is feasible with many parameters taking default values. The key options are to optimise image resolution or/and image pre-processing. In addition the main design issue is the degree of compression that can be applied to the probe image before it is transmitted to the smart card. Both image compression and the reduction of image resolution have been considered and their effect on UAT has been studied when using the designs resulted from the two alternative system optimisation approaches investigated, SOS and COS.

The experimental results demonstrate that the amount of time required for the SOS system design is very low, while for the COS design time increases dramatically. No compression is required when the spatial resolution is very low (SOS C1). In all other cases compression is needed to limit the size of the probe image but it does not necessarily degrade performance. If optimum performance is the first priority and system complexity is not an issue for the system designer, COS is the favourite approach. However, higher specification smart cards would be needed to compensate for the additional user access time. Such an option would impose a severe additional economic burden.

The selection of the most convenient design in terms of

UAT depends on the size of the probe image to be sent to the card (affecting the transfer time) and the complexity introduced by the filtering parameters (affecting the normalisation time). SOS is the favourable design *in the case of C1 protocol* since no compression is required and UAT decreases considerable. It allows the use of low specification, low cost smart cards (i.e. 8KByte and 8 bit processor).

In the case of C2 protocol SOS can still be selected to be the favourable design. Even though the UAT is a bit slower compared to that of the default (REF) parameter set, it achieves better performance results. However, the final selection between the two strategies depends on the system designer and the application at hand. Finally, the default (REF) parameter set can still offer a viable solution in both protocols. It is the least complicated design, user access time is relatively low and it achieves acceptable performance as well.

Selecting different optimisation strategies on a face verification system is an interesting task. However, the conclusions of this work were drawn in the context of the CSLDA algorithm. For future work we plan to conduct the same evaluation on other typical face verification algorithms to check the general validity of the results.

References

- [1] T. Bourlai, K. Messer, and J. Kittler. Face verification system architecture using smart cards. *ICPR 2004*, 1:793–796, 23-26 August 2004.
- [2] T. Bourlai, K. Messer, and J. Kittler. Scenario based performance optimisation in face verification using smart cards. *AVBPA 2005*, 22-25 July 2005.
- [3] Y. Li, J. Kittler, and J. Matas. Face verification using client specific fisher faces. In *J. T. Kent and R. G. Aykroyd, editors, Proc. Int. conf. on The Statistics of Directions, Shapes and Images*, pages 63–66, September 2000.
- [4] K. Messer, J. Matas, J. Kittler, J. Luettin, and G. Maitre. Xm2vtsdb: The extended m2vts database. *AVBRA*, pages 72–77, March 1999.
- [5] H. Moon and P. Phillips. Computational and performance aspects of pca-based face-recognition algorithms. *Perception*, 30:303–321, 2001.
- [6] R. Sanchez-Reillo. Including biometric authentication in a smart card operating system. *AVBPA*, pages 342–347, June 2001.
- [7] B. Schouten and J.W.H..Tangelder. Non-intrusive face verification by a virtual mirror interface using fractal codes. In: *CD-ROM Proceedings Biometrics on the Internet - Third COST 275 WORKSHOP*, 2005.
- [8] M. Turk and A. Pentland. Eigenfaces for recognition. *Cognitive Neuroscience IEEE PAMI*, 3(1):71–86, 1991.
- [9] W. Yambor, B. Draper, and J. Beveridge. Analysing pca-based face recognition algorithms: Eigenvector selection and distance measures. *Empirical Evaluation Methods in Computer Vision, World Scientific Press*, 2002.
- [10] W. Zhao, P. P. R. Chellappa, and A. Rosenfeld. Face recognition: A literature survey. *ACM Computing Survey*, pages 399–458, December 2003.