Grip-Pattern Recognition in Smart Gun Based on Likelihood-Ratio Classifier and Support Vector Machine

Xiaoxin Shang, and Raymond N.J. Veldhuis

Signals and Systems Group, Electrical Engineering, University of Twente
P.O. Box 217, 7500 AE Enschede, the Netherlands
x.shang@utwente.nl

Abstract. In the biometric verification system of a smart gun, the rightful user of a gun is recognized based on grip-pattern recognition. It was found that the verification performance of this system degrades strongly when the data for training and testing have been recorded in different sessions with a time lapse. This is due to the variations between the probe image and the gallery image of a subject. In this work the grip-pattern verification has been implemented based on both classifiers of the likelihood-ratio classifier and the support vector machine. It has been shown that the support vector machine gives much better results than the likelihood-ratio classifier if there are considerable variations between data for training and testing. However, once the variations are reduced by certain techniques and thus the data are better modelled during the training process, the support vector machine tends to lose its superiority.

1 Introduction

We develop a prototype recognition system as part of a smart gun, where the hand-grip pattern recognition ensures that the gun can only be fired by the rightful user. This system is intended to be used by the police, since carrying a gun in public brings considerable risks. In the US, for example, vital statistics show that about 8% of the law-enforcement officers killed in a shooting incident were shot by their own weapons [1].

Figure 1 shows both the prototype of the smart gun and an example of the grip-pattern image. One can see from the right-side figure the pressure pattern of the thumb in the upper-left corner of the image, and those of fingers in the remaining part. Note that only three fingers are present, because the index finger is near the trigger of the gun. We collected the grip-pattern data from a group of police officers in three sessions with a time lapses in between [2]. The data were processed for verification based on a Likelihood-Ratio Classifier (LRC) described in [3]. Initial experimental results indicate that if data for training and testing come from the same collection session, the verification results are fairly good, with an equal-error rate (EER) below 1%; otherwise the results are unsatisfactory, i.e., about 15% EER on average. Since in practice there will always be a time interval between data enrollment and verification, the across-session results are more relevant and, therefore need to be improved.

Having analyzed the data collected all sessions, we found that the data of one subject collected across sessions vary greatly, even though the grip-pattern images of this subject from one same session look fairly similar [2]. There are mainly two types of

A. Elmoataz et al. (Eds.): ICISP 2008, LNCS 5099, pp. 289–295, 2008.

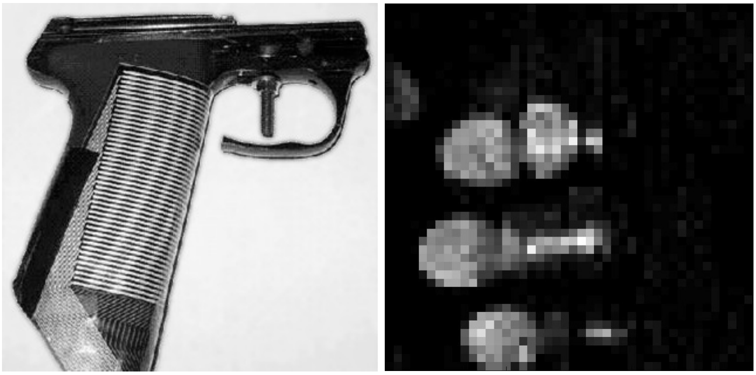

Fig. 1. Left: prototype of the smart gun. Right: an example of grip-pattern image.

across-session variations. First, a variation of pressure distributions occurs between grip patterns from a subject collected in different sessions. A second type of variation results from the hand shift of a subject across sessions [2]. Figure 2 shows two images collected from one subject in two different sessions, respectively. One can see that these two images have quite different pressure distributions. Besides, the hand-grip pattern in the image on the right side is located higher, than that in the image on the left side. Further research showed that these variations are the main reason for the unsatisfactory across-session verification results [2].

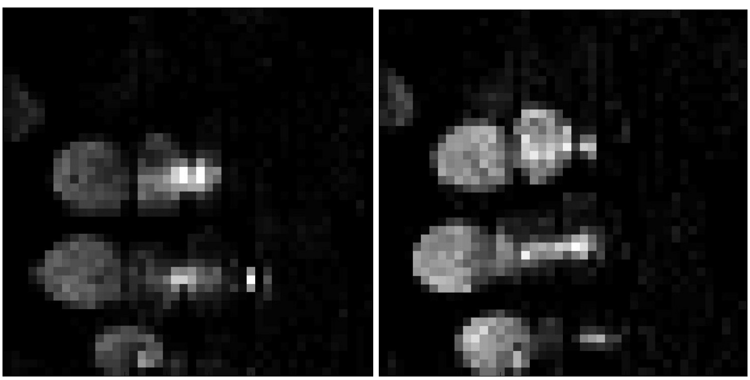

Fig. 2. Grip-pattern images of a subject in different collection sessions

Based on the characteristics of the grip-pattern images mentioned above, the verification results can be improved by reducing the across-session variations of data. In earlier work we applied three methods, each of which effectively improved the verification results, respectively. Firstly, we used template-matching registration (TMR) to reduce the across-session variation due to the hand shift [4][5]. By doing this the EER was reduced to about 13% from about 15%. The second technique that we applied was the double-trained model (DTM), where the data from two out of three collection sessions were combined for training, and those of the remaining session were used for testing. With DTM, the across-session variations of data were much better modelled in the training procedure, compared to the case where only one collection session of data were used for training. The verification results proved to be greatly improved by DTM, with the EER reduced from 15% to about 8% on average. Thirdly, we applied an image preprocessing approach, Local Absolute Binary Patterns (LABP), prior to classification [6]. This technique can reduce the across-session variation of hand-pressure distribution. Specifically, with respect to a certain pixel in an image, the LABP processing quantifies how its neighboring pixels fluctuate. It was found that the application of LABP improved the verification results significantly, with the EER reduced from 15% to about 9% on average. Finally, the verification results were improved greatly when all these three methods were applied together, with an average EER of about 3% approximately.

Note that all the verification results given above are based on LRC, which requires estimation of the probability density function (PDF) of the data [3]. Therefore, if there exist large variations between data for training and testing, the verification results will be greatly degraded. To further improve the verification results and also to set a reference for evaluation of the results obtained so far, we decided to implement another classifier which is more capable to cope with the across-session variations of data. With these motives, we chose the Support Vector Machine (SVM). As a contrast to LRC, SVM does not estimate the data's distribution. Instead, it tries to maximize the margin between different classes. Therefore, it is expected to be more robust to across-session data variations than the PDF-based classifiers in a many cases.

This paper presents and compares the verification results by using SVM and LRC. The remainder of this paper is organized as follows: Section 2 briefly describes the verification algorithms based on LRC and SVM, respectively. Subsequently, Section 3 presents and discusses the experimental results. Finally, conclusions are given in Section 4.

2 Verification Algorithms

2.1 Likelihood-Ratio Classifier

In classification by the LRC, it is assumed that the data is Gaussian [7],[8]. The pixel values of a grip-pattern image are arranged into a (in this case $44 \times 44 = 1936$-dimensional) column vector $\mathbf{x}$. The feature vector $\mathbf{x}$ is normalized, i.e. $\|\mathbf{x}\|_2 = 1$, prior to classification. A measured image originates either from a genuine user, or from an impostor. The grip-pattern data of a certain subject is characterized by a mean vector $\boldsymbol{\mu}_{\mathrm{W}}$ and a covariance matrix $\boldsymbol{\Sigma}_{\mathrm{W}}$, where the subscript W denotes 'Within-class'; while the impostor data is characterized by $\boldsymbol{\mu}_{\mathrm{T}}$ and $\boldsymbol{\Sigma}_{\mathrm{T}}$, where the subscript T denotes 'Total'. The matching score of a measurement $\mathbf{x}$ with respect to this subject is derived from the log-likelihood ratio. It is computed by

$$\begin{aligned}\mathrm{S}(\mathbf{x}) = &-(\mathbf{x}-\boldsymbol{\mu}_{\mathrm{W}})^{\mathrm{T}}\boldsymbol{\Sigma}_{\mathrm{w}}^{-1}(\mathbf{x}-\boldsymbol{\mu}_{\mathrm{W}}) \\ &+ (\mathbf{x}-\boldsymbol{\mu}_{\mathrm{T}})^{\mathrm{T}}\boldsymbol{\Sigma}_{\mathrm{T}}^{-1}(\mathbf{x}-\boldsymbol{\mu}_{\mathrm{T}}).\end{aligned} \tag{1}$$

If $\mathrm{S}(\mathbf{x})$ is above a preset threshold, the measurement is accepted as being from the genuine user. Otherwise it is rejected [3]. The threshold determines the false reject rate (FRR) and the false acceptance rate (FAR) of verification.

In practice the mean vectors and covariance matrices are unknown, and need to be estimated from a set of training data. In our case, the number of training samples from each subject should be much greater than 1936. Otherwise, the algorithm would become overtrained [3]. However, we cannot make this large number of measurements, for it would be very impractical for the training of the classifier. In addition, the estimated values of the covariance matrices would be rather inaccurate if the feature dimensionality is too large.

This problem can be solved by the following steps prior to classification. Firstly, we project all the data into a whitened PCA (Principal Component Analysis) space, such that $\mathbf{\Sigma}_{\mathrm{T}}$ becomes an identity matrix with a lower dimensionality of N_{PCA}. At this point, we make a simplifying assumption that each subject shares the same within-class covariance matrix with each other, so that it can be estimated more accurately from the data of all the subjects. It was proved in [3], that in this new feature space, the number of modes of variations contributing to the verification, is not more than $N_{\mathrm{user}} - 1$, where N_{user} is the number of subjects for training. Besides, these modes of variations have the smallest variances of each individual subject's data. A further dimensionality reduction can then be achieved by applying another PCA to the data, and discarding all the modes of variations except the $N_{\mathrm{user}} - 1$ ones with the smallest variances. This last operation is in fact a dimensionality reduction by means of the LDA (Linear Discriminant Analysis). The whole procedure of dimensionality reduction can be represented by a transformation matrix $\mathbf{F}$. After the LDA, the total covariance matrix becomes an identity matrix, while the within-class covariance matrix becomes diagonal. Both of them have a dimensionality of $N_{\mathrm{user}} - 1$ [3]. As a result, (1) can be rewritten as

$$\begin{aligned}\mathrm{S}(\mathbf{x}) = &-(\mathbf{Fx} - \mathbf{F}\boldsymbol{\mu}_{\mathrm{W}})^{\mathrm{T}}\mathbf{\Lambda}_{\mathrm{w}}^{-1}(\mathbf{Fx} - \mathbf{F}\boldsymbol{\mu}_{\mathrm{W}}) \\ &+ (\mathbf{Fx} - \mathbf{F}\boldsymbol{\mu}_{\mathrm{T}})^{\mathrm{T}}(\mathbf{Fx} - \mathbf{F}\boldsymbol{\mu}_{\mathrm{T}}),\end{aligned} \tag{2}$$

where $\mathbf{\Lambda}_{\mathrm{W}}$ denotes the resulting diagonal, within-class covariance matrix. Equation (2) shows that four entities in total need to be estimated from the training data: $\boldsymbol{\mu}_{\mathrm{W}}$, $\boldsymbol{\mu}_{\mathrm{T}}$, $\mathbf{F}$, and $\mathbf{\Lambda}_{\mathrm{W}}$.

2.2 Support Vector Machine

The SVM is a binary classifier that maximizes the margin between two classes. Attributed to this characteristic, the generalization performance (i.e. error rates on test sets) of SVM usually either matches or is significantly better than that of competing methods [9],[10].

Given a training set of instance-label pairs $(\mathbf{x}_i, y_i), i = 1, ..., l$ where $\mathbf{x}_i \in R^n$ and $y_i \in \{1, -1\}^l$, SVM requires the solution of the following optimization problem:

$$\min_{\mathrm{w},b,\xi} \quad \tfrac{1}{2}\mathrm{w}^T\mathrm{w} + C\sum_{i=1}^{l}\xi_i \tag{3}$$

$$\text{subject to } y_i(\mathrm{w}^T\phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \tag{4}$$

$$\xi_i \geq 0. \tag{5}$$

Here training vectors $\mathbf{x}_i$ are mapped into a higher (maybe infinite) dimensional space by the function ϕ. Then SVM finds a linear separating hyperplane with the maximal margin in this higher dimensional space. $C > 0$ is the penalty parameter of the error term, a larger C corresponding to assigning a higher penalty to errors. Furthermore, $K(\mathbf{x}_i, \mathbf{x}_j) \equiv \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$ is called the kernel function.

We applied SVM to the grip-pattern verification, where multiple users are involved, by using the method proposed by [11]. Specifically, the problem is formulated in a difference space, which explicitly captures the dissimilarities between two grip-pattern images. In this difference space, we are interested in the following two classes: the dissimilarities between images of the same individual, and the dissimilarities between images of different people. These two classes are the input to a SVM algorithm, and the SVM algorithm generates a decision surface separating the two classes.

The data are transformed by both PCA and LDA in exactly the same way as in the case of the LRC, prior to the classification. In SVM we used the Gaussian radial basis function kernel.

3 Experiments, Results and Discussion

We recorded the grip-pattern data from a group of police officers in three sessions, with approximately one month and four months in between. In total, 39 subjects participated in both the first and the second collection sessions with 25 grip-pattern images recorded for each subject. In the third session, however, the data were collected from 22 subjects out of the same group, and each subject contributed 50 images. The verification performance is evaluated by the overall EER of all the subjects. It is computed from the matching scores of all the genuine users and impostors.

The experimental results obtained by using the SVM and the LRC are compared in five cases. In the first case, none of the three methods of TMR, DTM and LABP described in Section 1 is in use (see Table 1). Only one of these methods is applied in the second, third, and fourth case, respectively (see Table 2, 3, and 4). In the last case, all of the three methods are implemented (see Table 5).

Table 1. Original verification results in EER(%)

Train	Test	LRC	SVM
1	3	24.09	17.55
2	3	18.95	14.73
1	2	7.94	4.36
3	2	20.16	11.64
2	1	5.53	4.00
3	1	14.70	11.45
Average		15.2	10.6

One can see from Table 1 that if none of the methods of TMR, DTM and LABP is applied, the verification results based on SVM are much better on average, than those

Table 2. Verification results in EER(%) with data preprocessed by TMR

Train	Test	LRC	SVM
1	3	18.36	10.55
2	3	18.88	13.24
1	2	5.98	5.84
3	2	17.82	15.45
2	1	3.90	4.07
3	1	12.91	10.73
Average		12.9	9.9

Table 3. Verification results in EER(%) with DTM

Train	Test	LRC	SVM
1+2	3	13.73	12.73
1+3	2	5.09	5.27
2+3	1	4.00	4.47
Average		7.6	7.4

obtained by LRC. This suggests that SVM is more capable in coping with large across-session variations of data, compared to LRC. This may be attributed to the different characters of these two classifiers. Since the SVM tries to maximize the margin between different classes, it seems to have better generalization performance compared to the LRC, which is based on the PDF estimation of data.

However, Table 2, 3, and 4 show that if one of TMR, DTM or LABP is applied, the SVM is not as much superior to the LRC as in Table 1, even though the verification results based on both classifiers become improved on average. That is, LRC benefits more from these methods than SVM. It is quite interesting to note that LRC actually outperforms SVM, if all three preprocessing methods are combined in use (see Table 5). To summarize, SVM seems to lose its superiority to LRC once the data are better modelled in the training session. What's more, the better the data are modelled, the more superiority SVM tends to lose. Since the best verification results are obtained by using LRC (see Table 5), we shall continue our future work based on LRC, instead of SVM.

Table 4. Verification results in EER(%) with data preprocessed by LABP

Train	Test	LRC	SVM
1	3	9.98	6.91
2	3	16.73	9.81
1	2	5.23	3.09
3	2	11.91	10.31
2	1	4.82	3.57
3	1	8.55	8.76
Average		9.5	7.0

Table 5. Verification results in EER(%) with TMR, DTM and LABP

Train	Test	LRC	SVM
1+2	3	4.86	7.64
1+3	2	3.64	5.82
2+3	1	2.02	3.67
Average		3.5	5.7

4 Conclusions

The grip-pattern verification has been implemented based on both classifiers of LRC and SVM, and the results have been compared under different conditions. It has been shown that SVM gives much better results than LRC, when there are considerable data variations between training and testing. That is, in the situation where data are improperly modelled during the training process, SVM seems to be able to capture the characteristics of data better than LRC. However, once the variations are reduced and thus the data are better modelled during the training process, SVM tends to lose its superiority. Besides, the better the data are modelled, the less SVM tends to outperform LRC.

Acknowledgments

This research is supported by the Technology Foundation STW, applied science division of NWO and the technology programme of the Ministry of Economic Affairs.

References

1. The national Uniform Crime Reporting Program, Law Enforcement Officers Killed and Assaulted, tech. rep., Federal Bureau of Investigation (2001)
2. Shang, X., Veldhuis, R.N.J., Bazen, A.M., Ganzevoort, W.P.T.: Algorithm Design for Grip-Pattern Varification in Smart Gun. In: ProRISC (2005)
3. Veldhuis, R., Bazen, A., Kauffman, J., Hartel, P.: Biometric verification based on grip-pattern recognition. In: SPIE (2004)
4. Shang, X., Veldhuis, R.N.J.: Registration of Hand-Grip Pattern in Smart Gun. In: ProRISC (2006)
5. Jain, A.: Fundamentals of digital image processing. Prentice-Hall, Englewood Cliffs (1989)
6. Shang, X., Veldhuis, R.N.J.: Local Absolute Binary Patterns as Image Preprocessing for Grip-Pattern Recognition in Smart Gun. In: BTAS (2007)
7. Bazen, A., Veldhuis, R.N.J.: Likelihood-Ratio-Based Biometric Verificaton. IEEE Transactions on circuits and systems for video technology 14(1) (2004)
8. Van Trees, H.L.: Detection, Estimation, and Modulation Theory. Wiley, New York (1968)
9. Vapnik, V.N.: The Nature of Satistical Learning Theory. Springer, Heidelberg (1995)
10. Burges, C.J.C.: A Tutorial on Support Vector Machines for Pattern Recognition. Data Mining and Knowledge Discovery 2, 121–167 (1998)
11. Jonathon Phillips, P.: Support Vector Machines Applied to Face Recognition. In: Advances in Neural Information Processing Systems, vol. 11. MIT Press, Cambridge (1999)