

Registration of Hand-Grip Pattern in Smart Gun

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Abstract— Secure Grip¹ focuses on the development of a hand-grip pattern recognition system, as part of a smart gun. It is intended for use by the police. We collected the hand-grip data from police officers in three sessions in a row with time intervals in between. If data for training and testing come from different sessions, however, the verification performance is not satisfactory. This is caused by the variations in data collected from different sessions of the same subject. Among others, one type of across-session variation is the hand shifts of subjects. Therefore we applied template-matching registration (TMR) as a data-preprocessing step. This has helped to reduce the Equal-Error Rate (EER) of the system by 1.7%. Besides, we discovered that the hand shifts of the same subject are on average smaller than those between different subjects. This has inspired the implementation of a new classifier, based on both the grip patterns and the hand shifts. With the new classifier the EER of the system has been further reduced by 3.0%.

Keywords— grip-pattern recognition, smart gun, image registration

I. INTRODUCTION

The Secure Grip project focuses on the development of a prototype recognition system, as part of a smart gun (see Figure 1), where the hand-grip pattern recognition ensures that a gun can only be fired by its rightful user. This application is intended for use by the police. We collected the hand-grip pattern data from police officers in three sessions with approximately one month and four months in between. Data were processed for verification by using the reference algorithm described in [1]. Simulation results indicate that if data for training and testing come

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from the same session the reference algorithm works fairly well, with the Equal-Error Rate (EER) lower than 1%; otherwise it gives unsatisfactory results, i.e., approximately 13% EER on average. Since in practice there will always be a time interval between data enrollment and data verification of each user, results of the across-session simulations make more sense. Therefore, the across-session verification performance of the system must be improved.



Fig. 1. Prototype of a smart gun.

After an analysis it has been discovered, that the same subject happens to produce the grip-pattern data with large variations in across sessions. It has been proved that these variations have caused the unsatisfactory across-session verification results [2]. Among others one type of variations results from the hand shifts of subjects in different sessions (see Figure 2). Accordingly we applied template-matching registration (TMR) [4] as a data-preprocessing step before verification. For comparison a novel registration approach, based on the maximal matching scores obtained from the reference algorithm, has been implemented. The TMR was found to have improved the verification results; while the maximum-matching-score registration (MMSR) not. However, the MMSR has proved to be useful in producing discriminative values of two types of shifts. Specifically, we discovered that after the MMSR the across-session shifts of a genuine user are on average much smaller than those between this user and the im-

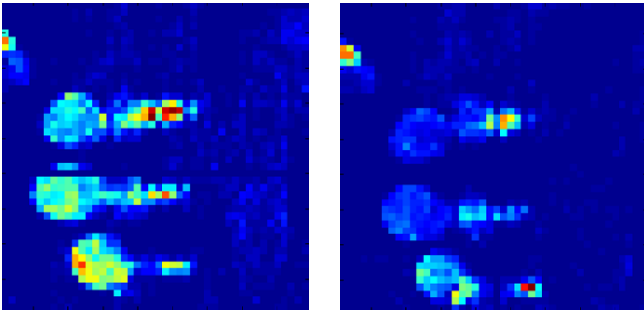


Fig. 2. Hand shifts exist between grip-pattern images of the same subject in different sessions.

posters. This has inspired the design of a new classifier based on both the grip patterns and the hand shifts. The new classifier has brought further improvement in verification performance of the system.

This paper presents and analyzes the effects of these two registration methods on the system's verification performance. Section 2 introduces the MMSR approach. Simulation results of the verification experiment using different registration methods are compared in Section 3. Subsequently, Section 4 describes the new classifier and presents the simulation results based on it. Finally, conclusions are given in Section 5.

II. MAXIMUM-MATCHING-SCORE REGISTRATION

The reference verification algorithm [1] used in the system makes a decision of classification based on a type of matching score: the likelihood ratio [3] between a grip-pattern measurement and the recognition template of a user stored in the gun. If the matching score is higher than a preset threshold the gun is authenticated to be fired. Otherwise, the grip pattern is assumed to be from an imposter. The idea of the maximum-matching-score registration (MMSR) is to align an image so that a maximal matching score is obtained. According to our observation, in the grip-pattern image registration only translation is relevant. Specifically, we shift the original image pixel by pixel in both horizontal and vertical directions. After each movement a new matching score is computed based on the new shifted image. This procedure continues until the original image has been translated to all possible positions, within a predefined scope in both directions. The shifted image with the maximal matching score is then selected as the final registration result.

Compared to other registration methods the MMSR is special, in the sense that the registration of an image is purely based on the verification algorithm. This implies that when a certain verification algorithm is in use, no other registration method results in an aligned image with a

higher matching score. In other words, an image is aligned so that its matching score is increased to the highest degree. Like other registration methods, whether the verification performance after the MMSR improves or not depends on whether the matching scores of genuine users increase on average more than those of imposters. In that sense the characteristics of images in concern also play an important role.

III. VERIFICATION PERFORMANCE AFTER REGISTRATION

In this section simulation results of the verification experiment using different registration methods are presented and analyzed. Two kinds of registration methods are concerned: the template-matching registration (TMR) and the maximum-matching-score registration (MMSR). In the TMR the across correlation of one sample image and its registration template is computed. The position of the pixel with the highest value in the resulting image determines the shifts of the sample image. The TMR has been applied to the training data to build up a stable after-registration model. The test data has been preprocessed by either the TMR or the MMSR. The simulation results are presented in Table I with different sessions taken for training and testing, respectively. The verification performance is evaluated by the overall EER. It has been computed by taking into account all the likelihood ratios, of both the genuine users and the imposters. For comparison the simulation results without any data registration processes are also shown. One can see that an improvement in the verification performance of the system has been obtained, if the TMR is applied to the test data; while the verification results become even worse if the test data is preprocessed by the MMSR.

Train	1	2	1	3
Test	2	1	3	1
<i>Original</i>	7.94	5.53	24.09	14.70
<i>TMR</i>	6.34	5.13	21.09	13.00
<i>MMSR</i>	8.00	5.75	27.70	17.73

TABLE I
SIMULATION RESULTS IN EER(%) WITH AND WITHOUT
DATA REGISTRATION.

Further information about the changes of the False-Acceptance Rate (FAR) and the False-Reject Rate (FRR) in different conditions is indicated in Figure 3. As an example, we take the data from the first session for training and that from the second session for testing. When either registration method is in use, the FRR decreases and

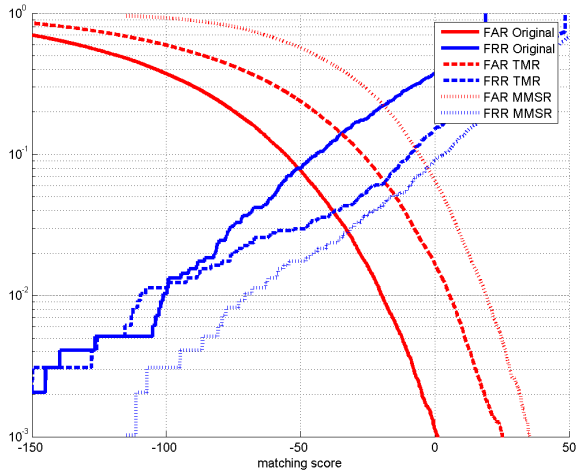


Fig. 3. Comparison of FAR and FRR curves obtained in different conditions.

the FAR increases in comparison with their counterparts without any registration step. However, in the case of the TMR the FRR decreases more than the FAR increases; while in the case of the MMSR it is the other way around.

The different effects of these two registration methods on the verification results are determined by both their working principles, and the characteristics of the grip-pattern images. As shown in Figure 2, there exist large variations in intensity distributions between one sample image and the template image to which the sample image is compared. Since the MMSR tries to maximize the matching scores between these two images, it is very likely that the sample image is shifted in the end to such a position, that those areas with relatively large intensities in these images overlap with each other. Due to the irregularity of the intensity distribution in each image, it is difficult to tell in advance whether the final verification result would become better or not. The increase in EERs in our case might be explained from the view point of statistics. If the MMSR is in use, images from both genuine users and imposters are given a more or less equal chance to obtain their maximal matching scores to the highest degree. Since before registration the matching scores of images from the imposters are relatively low in comparison with those from the genuine users, the increase in the matching scores from the imposters is then on average larger than that from the genuine users. In contrast to the MMSR, the TMR is less sensitive to variations in intensity distributions between one sample image and its template image. This is because that in computation of the across correlation, the resulting image tends to have the pixel with the highest value in its center. Therefore, the TMR helps to improve the verification performance of the system.

IV. CLASSIFIER BASED ON BOTH GRIP PATTERNS AND HAND SHIFTS

Having further analyzed the simulation results we discovered, that after registration the across-session shifts of a genuine user are generally smaller than those between this user and the imposters. That is, the within-class across-session shifts are on average smaller than the between-class across-session shifts. This special characteristic of the grip-pattern data has inspired the implementation of a new classifier, based on both the grip patterns and the hand shifts. In particular, the two types of shifts have proved to be much more discriminative obtained after the MMSR than the TMR. Specifically the hand shifts from imposters obtained after the MMSR are on average larger than those after the TMR; while the hand shifts from genuine users have similar distributions after these two methods. As an example, Figure 4 and Figure 5 present the histograms of the hand shifts when training on data from the first session and testing on data from the third session. One can see that the hand shifts from imposters in Figure 4 are generally of small values, yet those in Figure 5 are much more widely distributed.

As was mentioned in Section 3, in the MMSR it is very likely that an image is shifted so that the areas with relatively large intensities in this image and the template image overlap with each other. As one can imagine, regarding a certain template image, the intensity distributions in images from the imposters are on average more irregular than in those from the genuine user. This results in large between-class across-session shifts after the MMSR. In use of the TMR the between-class across-session shifts are also generally larger than the within-class across-session shifts. However, the difference between these two types of shifts is not as much as that in the case of the MMSR, because the TMR is less sensitive to variations in intensity distributions between one sample image and its template image, as was mentioned previously.

Therefore, we have implemented a new classifier as a combination of another two classifiers. One of them is based on the grip patterns by using the reference algorithm, with the TMR applied to both the training and the test data. The other one is based on the Euclidean distances obtained from the hand shifts in both vertical and horizontal directions by applying the MMSR to the test data. A measurement is verified as from the genuine user if and only if the verification results given by both classifiers are positive (see Figure 6) [5], [6]. Table II shows that the verification performance of the system has been further improved by using the new classifier. O_c represents the old classifier and N_c represents the new classifier. As a reference,

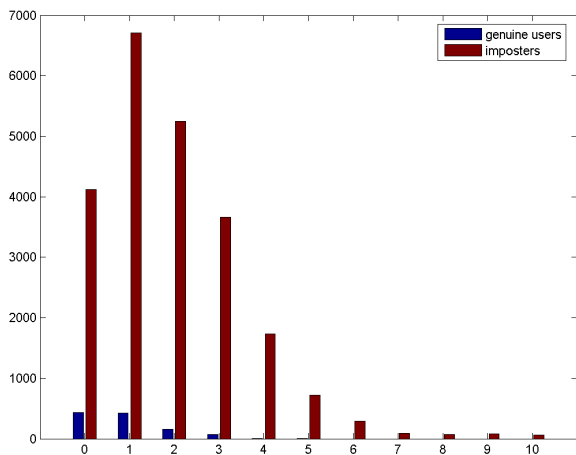


Fig. 4. Histograms of hand shifts after TMR.

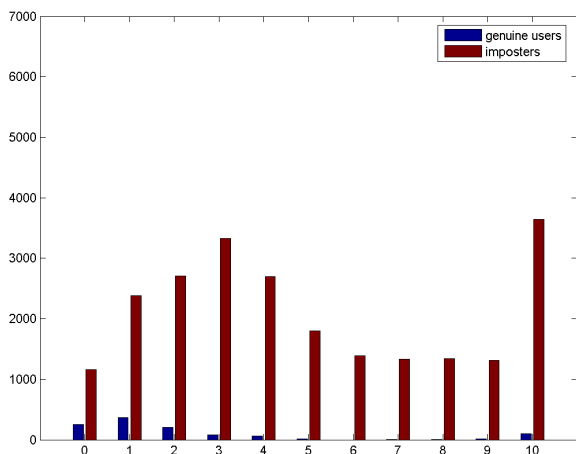


Fig. 5. Histograms of hand shifts after MMSR.

the simulations results without data registration are also presented.

V. CONCLUSIONS

In the recognition system of a smart gun, to reduce the across-session variation in the grip-pattern data caused by hand shifts of users, two registration methods have been applied: the TMR and the MMSR. Both methods have proved to be useful for improvement in the verification performance.

First of all, the EER of verification has been reduced by about 1.7% if the TMR is used as a data-preprocessing step. Furthermore, we discovered that the across-session shifts of a genuine user are on average smaller than those between this user and the imposters. Particularly, the MMSR has proved to produce discriminative values of these two types of shifts. Inspired by this a new classi-

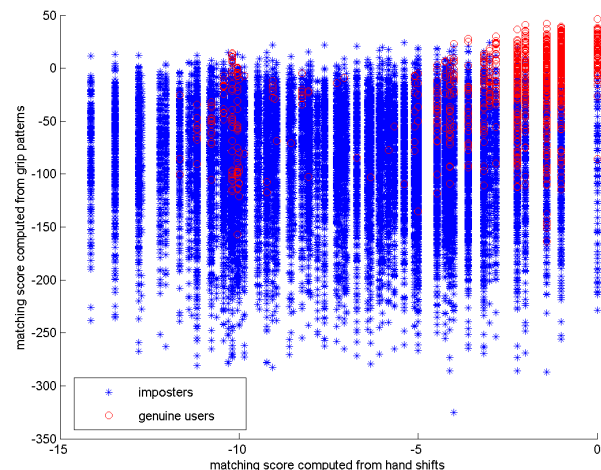


Fig. 6. Scatter graph of matching scores computed from both grip patterns and hand shifts.

Train	1	2	1	3
Test	2	1	3	1
<i>Original</i>	7.94	5.53	24.09	14.70
<i>TMR, Oc</i>	6.34	5.13	21.09	13.00
<i>TMR, Nc</i>	5.60	4.20	16.40	7.50

TABLE II

SIMULATION RESULTS IN EER(%) WITH OLD AND NEW CLASSIFIERS WHEN TMR IS USED.

fier has been implemented based on both the grip patterns, and the hand shifts obtained after the MMSR. This has improved the verification performance of the system with a further reduction in the EER by 3.0%.

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