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Handgrip Recognition

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Abstract: Dynamic handgrip recognition is a new biometric authentication method based on the human grasping behavior. Handgrip pattern recognition seeks to analyze the dynamics inherent in grasping behavior such as how the pressure varying during the grasping process. A novel real-time biometric system based on handgrip pattern is proposed for smart gun design in this paper. An experiment was initialized and the results proved that handgrip pattern recognition is a promising biometric technology for smart gun design.

Keywords: Biometric authentication, handgrip recognition, smart gun.

1. Introduction

There are significant numbers of stolen guns in circulation. Evidence from the National Crime Victimization Survey (NCVS) indicates that there are nearly 350,000 incidents of firearm thefts from private citizens annually (Zawitz 1996). Experts estimate that approximately 500,000 guns are stolen each year based on the fact that an average of 1.5 firearms being taken in each incident (Cook 1995). NCVS and FBI data show that the majority of guns stolen are handguns. Survey shows that stolen firearms are a major source of guns used in crime (Wright 1986). If a handgun can be personalized, so that only the authorized person can operate that gun, it will significantly limit the availability of guns to criminals in the illegal gun market.

Law enforcement officers will also benefit from smart gun. An FBI study examining data found that an average of seven law enforcement officers were killed annually in the line of duty with their own firearms (FBI 1998). In addition, many incidents in which a law enforcement officer's gun is taken by a suspect or a prisoner do not result in deaths, but do result in serious injuries. Personalizing the handguns used by law enforcement officers will prevent these injuries and deaths (Wintemute 1994).

Many devices have been designed to make the gun smarter. Basically, they can be divided into two categories, "Electronic" and "Biometric". Electronic technology uses an electronic device to move away a blocking device inside the grip from its blocking position and lets the trigger be pulled when the device receives a correct signal. Examples are magnetic lock, and radio lock. The signal could be emitted from a ring worn by the authorized user. However, signal interference is possible. If the signal could not be transmitted clearly, the gun operation could malfunction. Besides, the gun would be operable if an unauthorized person has the ring. Furthermore, a gun owner may keep the ring and gun together to make it easier to find the ring when he wants to use the gun – which reduces the safety provided by the ring. An alternative uses a PIN. Example is the electromechanical lock technology. However, the user might forget the PIN or do not have time to input the PIN in some emergency cases.

Biometrics measures and analyzes a person's physiological or behavioral characteristics for identification and verification purposes. It associates an individual with a previously determined identity/identities based on how one is or what one does (Jain 2000). Since many physiological or behavioral characteristics are distinctive to each person, biometric identifiers are inherently more reliable and more capable than password based techniques in differentiating between an authorized person and an impostor.

The most well known biometric technology is fingerprint identification. Fingerprint technology is a physiologic based biometric technology. A fingerprint is made of a series of ridges and valleys on the surface of the finger. The uniqueness of a fingerprint can be determined by the pattern of ridges and valleys as well as the minutia points. Humans have used fingerprint for personal identification for centuries and the validity of fingerprint identification has been well established. Fingerprint identification can be applied for smart gun design too.

However, the fingerprint technology requires a clear scan image of the fingerprints (Xiao 1991), which in some cases is not appropriate. Guns are used in all types of weather and in many different situations. If the user has dirty hands or wears gloves, fingerprint detection is useless.

Dynamic handgrip recognition is a novel behavior based biometric technology which is especially appropriate for smart gun design. The behavioral biometric technology is based on the fact that human actions are predictable in the performance of repetitive, routine tasks (Umphress 1985). Dynamic keystroke recognition and handwritten signature verification are such examples. In 1895, observation of telegraph operators showed that each operator had a distinctive pattern of keying messages over telegraph lines (Bryan 1973). When a person types, the latencies between successive keystrokes, keystroke duration, finger placement and applied pressure on the keys can be used to construct a unique signature for that individual (Monrose 1997). For regularly typed strings, such as username can be quite consistent. Researches have also shown that a unique handwritten signature template can be built for an individual. Each time he signs, he traces out his template, not exactly identical but with small stochastic variations (Hastie 1991). These variations include the speed of writing, rotation, scale, and shear. Society has relied on the written signature to verify the identity of an individual for hundreds of years. The complexity of the human hand and its environment make written signatures highly characteristic and difficult to forge precisely. Similar to dynamic keystroke and handwritten signature, firing a gun is also a repetitive action for an experienced firearm user. The same neurophysiologic factors that make a written signature and dynamic keystroke unique are also exhibited in a user's handgrip pattern.

Dynamic handgrip recognition seeks to analyze the dynamics inherent in weapon firing process. Where are the fingertips when people grasp a gun? How hard do people grasp the gun? How does the pressure vary from the beginning to the end of the firing process? How and when does the pressure cross a threshold? There are a number of such parameters inherent within the dynamic process. By comparing those features, an authorized user can be recognized.

2. Fingertip Analysis

The physical dimensions of a human hand contain information that is capable of authenticating the identity of an individual. In fact, each human hand is unique. Finger length, width, thickness, shapes and relative location of these features distinguish every human being from every other (Miller 1971, Sidlauskas 1988).

The fingertip placement on the gun handle is affected by human hand geometry and human grasping behavior simultaneously. The hand geometry uniqueness does not guarantee the fingertip placement recognizable for everybody. Therefore, an experiment was performed to investigate the placement of a person's fingertips on the handle of a replica gun. The experiment was conducted to answer the following questions: Is the fingertip placement of one subject repeatable enough so that it can be used as a biometrics pattern? Is the difference of the fingertip placement between two subjects more than the variation of one subject?

A digital camera was used to take the picture (1600 $\times$ 1200 pixels) when a subject was asked to grasp and hold a replica handgun (Glock 17). To ensure pictures for all subjects have the same scene geometry, the camera and replica gun were both securely fixed to a flat board attached to a tripod. The tripod could be raised or lowered so the gun was held level to the shoulder of the subject. The gun and camera were aligned in parallel and separated by a distance of 49cm.

Figure 1. The measured fingertip positions

Three points on the gun handle were defined as reference points. These three points can be used as coordinates to transform a distance measured by pixel number to a distance in mm. This computation is done by comparing the pixel number and corresponding scene distance in mm for the edges of the known triangle defined by the three reference points. The approximate image scaling for the plane of the gun handle is one pixel corresponding to an area of about 0.31×0.26 mm^2 in the real scene.

The fingertip positions of each subject were measured by placing colored circular markers 6mm in diameter at the center of the fingernail for the middle, ring and pinkie as well as the thumb (blue for the middle, ring and pinkie and green or yellow for the thumb). The image coordinates of the fingertips are taken as the center of each particular detected region. Figure 1 shows the digital image of fingertip placements of one subject. The four markers as well as the detected fingertip positions can be seen as shown by the crosshairs. Every subject was asked to grasp, hold, release, and re-grasp the replica gun for a total of five times and five pictures were taken. Each picture was then sent to the image processing routing to produce the detected fingertip locations. The detected fingertip locations were visually checked and in the cases where the automatic processing step failed the fingertip positions were picked out manually. Figure 2 shows fingertip positions of five trials from one subject.

Figure 2. Fingertip positions of five trials of one subject

There were 160 subjects (70% male, 30% female) that participated in this experiment. The age of these subjects range varies from 18 to 62 years. Most of the subjects were right handed. Among 160 subjects, there were 16 police officers, with age varying from 23 to 58 years old. The police officers in this study had between 1.5 and 30 years of firearm experience. About 37% of them have around 15 years firearm experience, while the remaining proportion has an approximate uniform distribution. In addition, each officer was asked what grip pattern they preferred. About 75% of police personnel subjects use both hands while firing a weapon. The others use only one hand. And 43.8% of the officers stated they used the “cup and saucer” grip with the gun cradled in the opposite hand whilst 25% stated they held the support hand level with the weapon. Figure 3 shows the overall fingertip distribution of 160 subjects on the gun handle.

Figure 3. Overall fingertip distribution of 160 subjects

In order to make the fingertips mathematically measurable, each set of fingertip positions is represented by a single point (Xt, Yt, Xm, Ym, Xr, Yr, Xp, Yp)’ in 8D space, where X represents the fingertip horizontal position, Y represents the fingertip vertical position, t represents the thumb, m represents the middle finger, r represents the ring finger, and p represents the pinkie finger.

2.1 Cluster Analysis

The objective of cluster analysis on fingertip dataset is to investigate how similar the fingertip positions are across all subjects in the study. If the fingertip positions are reasonably separable, then it may be possible for a biometric system to use this characteristic to verify an individual or a specific group of individuals. In addition, this analysis can be used to see how repeatable a subject's grip pattern actually is.

A natural concept of clustering suggests that there should be parts of the space in which the points are very dense, separated by parts of low density (Everitt 1993). Each high dense region generally is taken to signify a different group. The density searching clustering algorithm identifies clusters by searching for regions in the data space in which the density of fingertip records is large.

The kernel density is defined as

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n_i} K\left(\frac{x_i - x_j}{h}\right) \qquad (1)$$

where $K(u)$ denotes a so-called kernel function, and h denotes the bandwidth (Silverman 1986, Scott 1992). For the uniform kernel, $K(u)=1/2\ I(|u|<1)$, and the density function is $f(x)=1/2nh$ {the number of observations fall in $[x-h, x+h]$}. The uniform kernel density search algorithm is used here for clustering.

For each observation, find the nearest neighbor with a greater estimated density. If such a neighbor exists, join the cluster, which the observation belongs with, to the cluster, which the specified neighbor belongs with (Gitman 1973, Huizinga 1978). Cascaded density estimates are obtained by computing initial kernel density estimates and then, at each observation, taking the arithmetic mean of the initial density estimates of the observations within the neighborhood. The cascaded density estimates can, in turn, be cascaded, and so on. Let f_i^k be the density estimate at x_i cascaded k times, then at times of k+1,

$$f_i^{k+1}(x) = \sum_{j \in N_i} \frac{f_j^k(x)}{n_i} \qquad (2)$$

By applying this density search algorithm, 798 samples were divided into four natural groups. The result cluster set is a best case scenario where there are no misclassified samples at all. Table 1 shows these four natural groups. The first column of Table 1 shows the cluster number. The second column shows how many samples are in this cluster. The third column shows how many subjects are in this cluster. The fourth column shows the overall proportion.

By studying the subjects in each group, we could find that most adults have similar fingertip distribution and could be classified into cluster 1. On another hand, subjects with extreme small hand size or short finger length could be classified to cluster 4 with no mistakes. Subjects with extreme big hand size or long finger length could be classified to cluster 2 or 3 with no mistakes. Since children have much smaller hand and shorter finger than adults, there is no difficulty to discriminate children from adults by looking at the fingertip placements on the gun handle. The analysis also shows that fingertip distribution of 16 police officers were very tight grouping of fingertip locations across the repeated trials. Therefore, for more experienced gun users, fingertip placement not only may be used for verification, but also may be used for identification.

Table 1. Details for the four natural clusters produced by the density search technique.

Cluster	Samples	Subjects	Proportions (%)
1	525	105	65.625
2	115	23	14.375
3	63	13	8.125
4	95	19	11.875

2.2 Fisher Linear Discriminant Analysis

Fisher linear discriminant is a classification method that projects high-dimensional data into lower dimension and performs classification in this lower-dimensional space. The projection maximizes the distance between the means of the two classes while minimizing the variance within each class. Fisher linear discriminant analysis also can be used to determine which variables in a dataset contribute more than the others to discriminate between two or more groups of objects. In this case, the objects are the fingertip sets, the variables are the eight fingertip coordinates [(x, y) for the thumb, middle, ring and pinkie] and the group for each object is defined by the cluster set produced by the K nearest neighbor cluster analysis.

Let X_i be a set of N (in this case N = 8) column vectors of dimension D. The mean of the dataset is

$$\vec{\mu}_x = \frac{1}{N}\sum_{i=1}^{N}\vec{X}_i \tag{3}$$

There are K classes $\{C_1, C_2, \ldots, C_k\}$. The mean of class k containing N_k members is

$$\vec{\mu}_{xk} = \frac{1}{N_k}\sum_{X_i \in C_k}\vec{X}_i \tag{4}$$

The between class scatter matrix is

$$S_B = \sum_{k=1}^{K} N_k (\vec{\mu}_{xk} - \vec{\mu}_x)(\vec{\mu}_{xk} - \vec{\mu}_x)^T \tag{5}$$

The within class scatter matrix is

$$S_W = \sum_{k=1}^{K}\sum_{X_i \in C_k}(\vec{X}_i - \vec{\mu}_{xk})(\vec{X}_i - \vec{\mu}_{xk})^T \tag{6}$$

After calculating the eigenvalue and eigenvector of $S_B S_W^{-1}$, we have canonical coefficients of the first eigenvector shown in Table 2. The variables are listed in order based on their importance (absolute value of canonical coefficient of the first eigenvector).

Table 2. The eigenvector coefficients

Variable	Coefficient
Xr	0.1660
Yp	-0.0926
Yt	0.0816
Ym	0.0541
Xm	0.0205
Xt	-0.0118
Xp	-0.0178
Yr	0.0042

Since more than 70% energy of $S_B S_W^{-1}$ come from the first eigenvalue and eigenvector, the other eigenvalues and eigenvectors may be ignored when we evaluate the importance of fingertip variables. From Table 2, it would appear that the horizontal variation of the ring finger position is the most important in classification. Followed by the vertical variation of the pinkie, then the vertical variation of the thumb, and finally, the vertical variation of the middle fingertip position. Informally, this result can be explained by the information about the grip each variable provides. The horizontal variation of the ring finger position provides information about the length of the hand and

(or) fingers, while the vertical variations within other fingers positions are informative about the relative dispersion of the hand as well as variations in hand placement on the gun handle.

3. Dynamic Handgrip Analysis

In order to collect valid handgrip data, a real handgun, Beretta 92FS, specially designed and manufactured for the military by Beretta Corporation, was used as the prototype of a smart gun. There were 16 sensors being installed on the gun handle. These sensors convert the pressure signals to analog voltage signals. There was another sensor connected to the trigger to provide a pulse signal when trigger pulled.

Time constraint of the pressure signal needs to be considered, because not every squeeze on the gun handle is the valid signal. Only the pressure variation during a short period before trigger pulled is the valid signal. Generally, people can click a button in 100ms or remove his/her hand from a button in 200ms when this person receives a “go” or “stop” signal. Therefore, 100ms is considered as the psychological moment. It means that if an action is done in 100ms, people will consider this action done instantaneously. Therefore, the handgrip signal during the period of 100ms before the trigger pulled is the signal needs to be studied.

Most real-time systems require a DSP microprocessor as the core equipment. DSP microprocessors are characterized by fast multiply instructions, reduced instruction sets, and specialized instructions to make DSP algorithms execute fast and efficiently (Chassaing 1989). A TMS320C31 DSP Starter Kit (DSK) was selected for this application. The C31 DSK is a relatively powerful, inexpensive stand-alone application development board. The DSK includes the TMS320C31 processor, the TLC32040 analog interface circuit (AIC), and comes with an assembler and debugger.

The TLC32040 analog interface circuit (AIC) provides C31 the interface to these 16 sensors. The AIC converts analog input signals into digital signals for C31 analysis. After the signal being processed, the output data is returned to the AIC for conversion into an analog signal. The analog-to-digital converter (ADC) and digital-to-analog converter (DAC) with 14-bit dynamic range can work at variable sample rate. Since 100ms is considered as the psychological moment, each muscle probably moves in 10ms. If the sample rate is set to 1ms each sample, it will be fast enough to catch every muscle movement. Therefore, the sample rate is set to 1000 samples/second.

The TMS320C31 DSK is incorporated into one box with 16 analog input channels and four analog output channels. The DSP box is shown in Figure 4. The four output channels were connected to a red/green LCD light and two buzzes. If the test subject is an authorized user, green light and one buzz give the “go” signal. Otherwise, red light and another buzz give the “no-go” signal.

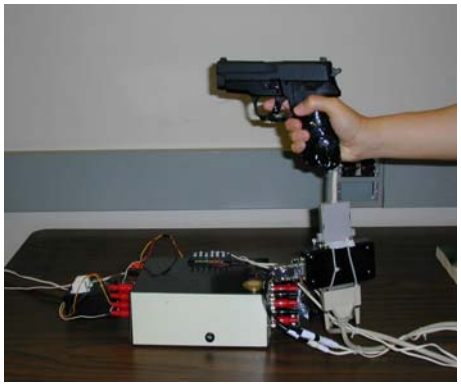

Figure 4. DSP box

In order to find the best sensor positions, five subjects, who were professional firearm users, were asked to participate in an experiment. Initially, these five subjects were asked to grasp a Beretta 92FS handgun to get their fingertip position distribution. Then, the positions of the 16 pressure sensors on the gun handle were carefully

designed based on their fingertip distribution to mostly distinguish these five subjects. The positions of the 16 pressure sensors are shown in Figures 5 and Figure 6.

Figure 5. Sensor arrangement on left side grip

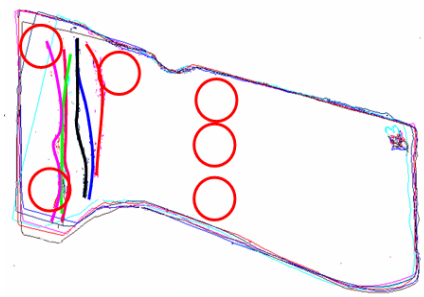

Figure 6. Sensor arrangement on right side grip

Figures 7 and Figure 8 show the data of channel 9 from five trials of two subjects. A down trend pattern for the first subject and an up trend pattern for the second subject can be found in these two pictures.

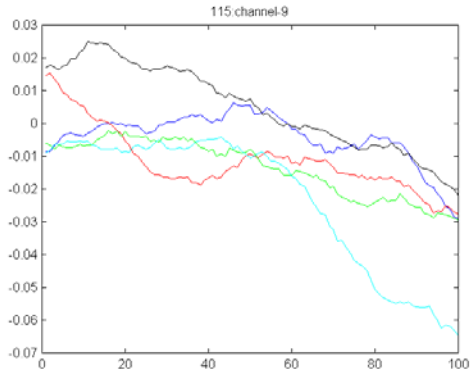

Figure 7. Pressure signal on channel 9 from one subject

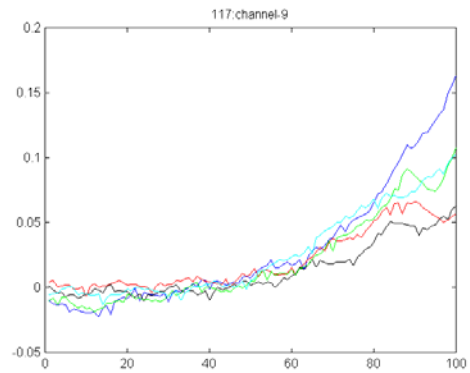

Figure 8. Pressure signal on channel 9 from another subject

Note in the next sections, the data during 128ms before the trigger being pulled instead of 100ms will be used because 128 is the nearest integer of 2^n to 100, and it is more convenient to use 2^n to do FFT or other transform in the future.

3.1 Matching In Time Domain

In order to depict the similarity between two time series, it needs to define a similarity measurement during the matching process. Given two time series $x(t)=\{x_0, x_1, \ldots, x_n\}$ and $y(t)=\{y_0, y_1, \ldots, y_n\}$, a standard approach is to compute the Manhattan distance $D(x, y)$ between time series $x(t)$ and $y(t)$. The Manhattan distance function on one channel is defined as

$$D(x,y)_{ch} = \sum_{t=1}^{T} | x(t) - y(t) | \qquad (7)$$

And the total Manhattan distance over all channels is defined as

$$D(x,y)_{total} = \sum_{ch=1}^{n} \sum_{t=1}^{T} | x(ch,t) - y(ch,t) | \qquad (8)$$

Given an unknown time series $x(t)$ and the template data $\{y_1(t), y_2(t), \ldots, y_m(t)\}$, then $x(t)$ is most similar to $y_a(t)$ if $D(x, y_a)=min\{D(x, y_i)\}$, $i=1,2,\ldots, m$, and $D(x, y_i)$ here represents the total Manhattan distance between x and y_i over all channels. If $y_a(t)$ belongs to class Y_a, then $x(t)$ belongs to Y_a.

The drawback to direct use of the Manhattan distance is the tendency of the largest-scaled distance from one channel will dominate the others. Relative distance is another method to measure the similarity. To find the relative distance, the average waveform and average intra-group distance on each channel for each subject need to be calculated. On every time point for each channel, the average waveform is defined as $y'(t)=1/n \sum y_i(t)$. The average intra-class distance is defined as

$$d' = \frac{1}{n} \sum_{i=1}^{n} \sum_{t=1}^{T} | y_i(t) - y'(t) | \qquad (9)$$

And the relative distance between input signal $x(t)$ and the template $y_j(t)$ is defined as

$$d(x, y_j) = \sum_{ch} D(x, y_j) / d'_j \qquad (10)$$

If $y_c \in Y_c$ and $d(x, y_c)=min\{d(x, y_j)\}$, then Y_c is considered as the possible class that $x(t)$ belongs to. However, there is a big problem of directly using relative distance algorithm to do the pattern recognition. For example, if subject *a* has big average variation (big average distance d_a) and subject *b* has less variation d_b. For the input signal $x(t)$

and the average waveform from subject *a* and *b*, there are $d(x, a) = D(x, a)/d_a$ and $d(x, b) = D(x, b)/d_b$. Even if $D(x, a)$ is larger than $D(x, b)$, it is possible that $d(x, a)$ is smaller than $d(x, b)$, because d_a is larger than d_b. As a result, the relative distance algorithm will mistakenly classify the test data *x* belong to subject *a*.

In summary, directly using the relative distance algorithm does not give good result. It can be used to improve the answer of total distance algorithm, as discussed in Section 4.

3.2 Matching In Transform Domain

Linear transforms, especially Fourier transform and wavelet transforms, are widely used in solving problems in science and engineering. Fourier transform and wavelet transforms, in essence, decompose or separate a waveform or function into different frequency components. In most cases, the important data is in low frequency area. Therefore, noise can be eliminated by discarding high frequency coefficients. In addition, the information that is most prominent in the original signal will appear as high amplitudes in that region of the transform domain. Setting a threshold, and discarding all values in the transform domain that are less than this threshold, can extremely reduce the data size and delete the noise.

The algorithm used for matching in time domain also could be applied in transform domain. First, the original handgrip data would be transformed to Fourier or wavelet coefficients. Then, use the same distance measure function defined before to measure the distance between the coefficients in transform domain.

Both Fourier transform and wavelet transform are helpful to handgrip pattern recognition. However, Fourier transform requires a lot of computation and is time consuming. Even though DSP is specially designed for multiplication and addition, and FFT is developed for fast Fourier transform, it still costs approximately 10ms to do the computation for each channel. Since there are 16 sensors (channels) installed, it requires approximately 160ms for Fourier transform. On the other hand, the recognition must be done in less than 100ms. Obviously, Fourier transform is not acceptable for real-time analysis.

Wavelet analysis is an alternative transform analysis tool. There are a wide variety of popular wavelet algorithms, including Haar wavelets, Daubechies wavelets, Mexican Hat wavelets and Morlet wavelets. Due to the approximation quality and the simplicity, the Haar wavelet, which requires the least computation, becomes a good choice for the real-time work.

It is interesting that the results of time domain matching and the results of transform domain matching were not same. Sometimes, time domain matching gave the correct answer and sometimes wavelet domain matching gave the correct answer. This suggests that if we could get the union of results from time domain matching and wavelet domain matching, it is more possible to get the correct pattern. On another hand, by getting the union of the results from time domain matching and wavelet domain matching, it could find more than one possible patterns and thus requires one more step to pick up the final answer from two candidates.

4. Real-time Handgrip Recognition

The handgrip pattern recognition focuses on the pressure variation over the time not the absolute amplitude of the handgrip signal, because the absolute amplitude of the handgrip signal may have big variations in different cases. The hand pressure will be much weaker when a person is sick or injured. However, the relative pressure waveform will not change much in such cases. Normalization needs to be done before to create patterns for each subject.

To normalize the data, all DC values of all samples in the template were removed first. Then, the maximum pressure value on all sensors from each sample during the 128ms before trigger pulled was calculated and set to +/- 1. The other values were normalized in the same ratio so that the pressure waveform kept same.

The patterns (average waveforms) for each subject needs to be built up before training process. Given the template data $\{y_1(t), y_2(t), \ldots, y_m(t)\}$ from subject *y* on channel *ch*, the average waveform is calculated by $avg(t)=[y_1(t)+ y_2(t)+ \ldots+ y_m(t)]/m$. This is the handgrip pattern for subject *y* on channel *ch*.

If the distance between x and y_a is the smallest among all y's, i.e., x is most similar to y_a, then it is considered user y_a is firing the gun. This method, which is done in time domain, can be applied to wavelet domain too. The Haar wavelet transform is applied to all template data. A pattern based on wavelet coefficients is built up for every subject. Distances between the input signal's wavelet coefficients and all wavelet patterns are calculated. The smallest distance suggests the most similarity existing between the input and that pattern.

As stated in the previous section, the result of time domain matching and the result of wavelet domain matching were not same. We could get the union of results from time domain matching and wavelet domain matching, which could find more accurate candidates, and then have one more step to pick up the final answer from two candidates. Therefore, the real time handgrip pattern recognition algorithm based on the input signal x can be defined as following:

1. Calculate the total distances between x and the stored patterns. If $D(x, y_a)$ is the minimum, then y_a is identified as the possible pattern.
2. Apply the discrete *Haar* wavelet transform to x to get x_h. Calculate the distances between x_h and the stored wavelet coefficient patterns. If $D(x_h, H_b)$ is the minimum, where H_b is the Haar transform for y_b, then y_b is identified as the possible pattern too.
3. If $y_a = y_b$, then it is the answer. Let *answer* = y_a and terminate the algorithm.
4. Otherwise, calculate the relative distances $d(x, y_a)$ and $d(x, y_b)$. If $d(x, y_a) < d(x, y_b)$, then *answer* = y_a, otherwise, *answer* = y_b.

There were five professional gun users participated into the experiment. Each subject was tested for five rounds. In each round, the subject aimed at different targets and fired the handgun with real bullets for 15 times. Two subjects wore the gloves to test whether wearing gloves affects the analysis result.

Table 3. Recognition results

Subject	1	2	3	4	5
1	100%	0	0	0	0
2	3.6%	80.2%	7.8%	4.2%	4.2%
3	1.6%	0.8%	88.8%	2.2%	6.6%
4	2.4%	1.8%	0.6%	92.8%	2.4%
5	2.0%	0.6%	10.8%	1.2%	85.4%

To evaluate the real-time handgrip recognition algorithm, 50 samples were randomly picked from each subject as the templates, and the other samples were used as tests. This process was repeated 20 times, with totally 2500 tests. The recognition speed is 19ms per recognition, based on the TMS320C31 DSP system. The success rates are 100%, 80.2%, 88.8%, 92.8%, and 85.4% respectively for these five subjects. The average success rate is 89.44%. The recognition results are shown in Table 3.

From Table 3, it shows that the handgrip of subject #1 is the most consistent one. No test from subject #1 was mistakenly recognized as others. The second most consistent handgrip signal is from subject #4, whose success recognition rate is 92.8%. There are 2.4% tests being mistakenly recognized as subject #1, 1.8% tests being mistakenly recognized as subject #2, 0.6% tests being mistakenly recognized as subject #3, and 2.4% tests being mistakenly recognized as subject #5. Subject #2 and #5 wore gloves in this experiment. Since subject #5 has the second highest recognition rate, it will be considered as that, wearing gloves would not affect the handgrip recognition.

The real-time handgrip recognition algorithm can be used for verification too. In the preprocessing stage, the verification algorithm works similar to the recognition algorithm. There is one more step in preprocessing stage, the mean intra-class distances and the standard deviations need be calculated for each subject. The thresholds should be decided in the preprocessing stage too. Usually, they could be defined as fractions of the standard deviations of the intra-class distances.

During the verification stage, after the user claims his/her individuality, the distances in time domain and wavelet domain between the input signal with the claimed pattern would be calculated. If either the distance in time

domain, or the distance in wavelet domain, being greater than the threshold, this person would be considered as an unauthorized user. Otherwise, the gun becomes operable.

5. Conclusions

In this research, a new biometric identification technology is proposed to recognize the authorized users of handguns. This approach is based on the fingertip distributions and dynamic handgrip pressure variations during the firing process. A real-time biometric identification system was built as the prototype. The experiment results proved that handgrip recognition is a promising technology for smart gun design.

Handgrip recognition can also be used for car driver or pilot identification/verification. A shifter or joystick can be used as the simulator. Sensors can be installed around the shifter handle or joystick handle to capture the handgrip signal. A DSP system can be used for the real-time pattern recognition.

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