Phase Registration in a Gallery Improving Gait Authentication

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Abstract

In this paper, we propose a method of inertial sensor-based gait authentication by inter-period phase registration of an owner's gallery. In spite of the importance for gait authentication of constructing a gallery of phase-registered gait patterns, previous implementations just relied on simple methods of period detection based on heuristic knowledge such as local peaks/valleys or local auto-correlation of the gait signals. Consequently, we propose to improve a gait gallery by incorporating a phase registration technique which globally optimizes inter-period phase consistency in an energy minimization framework. However, the previous phase registration technique suffers from a phase distortion problem due to ambiguities in the combination of a periodic signal function and a phase evolution function. We present a linear phase evolution prior to constructing an undistorted gait signal for better matching performance. Experiments using real gait signals from 32 subjects show that the proposed methods outperform the latest methods in the field.

1. Introduction

Electronic devices including wearable electronics, are expected to be sophisticated enough in the future to be able to interact with the owner and understand his/her needs, intentions, and health conditions [4, 5]. Inertial sensors (gyroscopes or accelerometers) are in fact increasingly being embedded in commercial portable electronic devices such as mobile phones due to their high cost performance, and inertial sensor-based owner assistance from mobile phones is an active research topic [15, 16, 18].

One of the useful sources of information for assisting an owner is his/her gait signal, because the human gait (walking) signal conveys various types of information such as personality [6], gender [2], physical condition [1], and mood [3], and can easily be captured by inertial sensors. For such systems, owner authentication is the first critical task in starting an interaction with the owner.

Because the human gait is a periodic motion, most methods of gait-based owner authentication detect periods (walking cycles) or extract frequency-domain features for constructing gait patterns. Human gait signals are, however, always varied due to many factors such as mood, physical condition, walking speed, ground condition, carrying weight, shoes and so on, and hence stable frequency-domain features during a long walking sequence are generally unavailable. Therefore, most previous studies relied on period detection [7, 8, 9, 10, 11, 12, 13, 14, 17] for constructing gait patterns, and few methods relied on frequency features [9, 15].

Although previous methods detected periods based on heuristic knowledge such as local peaks/valleys and/or auto-correlation of signals, they still have a problem with the instability of period detection when the gait signal is largely distorted by the above stated factors.

Recently, Makihara et al. proposed a robust method for the phase registration and period segmentation of a single quasi-periodic signal sequence using Self Dynamic Time Warping (Self DTW) [19]. The method is a promising solution for a quasi-periodic gait signal because it registers phases between periods of the whole signal, corrects the relative distortion between periods and constructs consistent periods. Therefore, the first contribution of this paper is the improvement on constructing an owner's gallery without any heuristic knowledge by incorporating this phase registration technique [19].

The phase registration technique [19], however, sometimes suffers from a problem of ambiguity which is a combination of a phase evolution function and a periodic signal and produces temporally distorted signals compared to their original signals. This results in unnecessary additional costs for the elastic pattern matching method (e.g. DTW) in the recognition stage as discussed in Section 3.2 in detail. Therefore, the second contribution of this paper is the incorporation of linear phase evolution prior to solving the ambiguity combination problem to construct undistorted peri-

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odic signals for a much improved gallery.

The structure of the paper is organized as follows. Section 2 provides a summary of previous work. In Section 3, we briefly summarize walking period detection from inertial signals using Self-DTW, and describe its ambiguity problem. We then try to improve the period detection by the linearization of time warping function to construct the gait pattern, which is presented in Section 4. Next, we describe the recognition method in Section 5. The experiments on our method are presented in Section 6. Finally, the conclusions and future work are outlined in Section 7.

2. Related Work

Approaches using period detection: Most recognition systems [9, 11, 13, 14] detect the walking period to make the gait pattern. One period contains the motion signals of both the steps of the left and right legs. Some authors [7, 8] tried to extract a period of the left or right leg motion signal as a gait pattern.

There are several existing techniques for walking period detection. Rong et al. [14] estimated periods by detecting local peaks of the vertical acceleration signal since it contains the clear up-down motion of the two legs. Gafurov et al. [9] detected the periods by relying on the local auto-correlation and the local peaks on the up-down acceleration. All these methods relied on characteristics such as the clarity of motion of the up-down (vertical) acceleration or the relationship of local peaks to detect the gait cycles. However, there was no guarantee that these characteristics would remain stable for large variations of data since the gait signal is changed unavoidably.

A more complicated solution to detect the periods of the resultant signal (computed from three acceleration signals) was presented by Mohammad et al. [17]. In this method, instead of computing the local auto-correlation, the authors first extracted a single sub-sequence of the signal with a fixed length, then slid the sub-sequence along the signal to compute the matching distances and find the local minimum points of this distance sequence. These local minimum points were combined with the local minimum points on resultant signal to refine the period locations. All the gait periods can then be detected. A further step is also carried out to remove the periods that are too different from the others so that wrongly detected or distorted periods are removed. There are some problems for this method such as finding a good sub-sequence, tuning many parameters and few number of periods being detected. This method also faces the instability problem of local minimum points like other methods.

In contrast, the proposed method detects the gait periods using the phase registration technique [19]. This phase registration method can be applied to any quasi-periodic signal and it does not rely on the local characteristics of the signal but globally optimizes the whole sequence. Therefore, all the periods are phase-registered and the relative distortion between periods is undistorted to regain consistency.

Approaches by frequency analysis: Other researchers used some frequency-domain features such as a histogram of intensity [9, 15] or the coefficients of Fourier transform [7]. To obtain such frequency features, we need a relatively long and stable gait signal to extract them. However, a real walking signal is very noisy and temporally distorted, and hence such a long stable gait signal is rarely available. Therefore, walking period detection-based methods outperform frequency based techniques in most situations [14].

Signal matching: It is also important to choose an appropriate signal matching technique at the recognition stage. In spite of the fact that gait signals are vulnerable to temporal distortion, most of the existing approaches use rigid signal matching techniques such as the Euclidean distance [9, 10, 11] or cross-correlation [8]. Recently, elastic signal matching techniques such as DTW have been widely used [13, 17] since they work well with temporal distortion of the signal. Note that while the existing methods use elastic signal matching technique for matching between a gallery and a probe only, the proposed method also uses it for constructing a gallery.

3. Phase Registration

Because we adopt period-based matching in the same way as previous work [7, 8, 9, 11, 13, 14], we need to extract gait periods from quasi-periodic gait signals accurately to construct a gallery. Moreover, all the periods should be phase-synchronized for consistency of the gallery. Since the conventional period detection approaches based on auto-correlation maximization or local peak detection cannot consider phase synchronization, a method of phase registration using Self-DTW is applied for this purpose. Here, we introduce only the problem statement of phase registration and, due to the page limitations, for the ambiguity combination problem, refer to [19] for technical details.

3.1. Problem statement

Given a periodic function of the multi-dimensional signal $\boldsymbol{f}(t)$ with period P that satisfies $\boldsymbol{f}(t+jP) = \boldsymbol{f}(t)\ \forall j \in \mathbb{Z}$, a time normalized by period P, is introduced as an absolute phase s and a relative phase $\tilde{s}$ as

$$s = s_P(t) = \frac{t}{P} \tag{1}$$

$$\tilde{s} = s - \lfloor s \rfloor, \tag{2}$$

where $s_P(t)$ is a phase evolution function, and $\lfloor \cdot \rfloor$ is a floor function. A normalized periodic function is subsequently introduced as

$$\boldsymbol{h}(s) = \boldsymbol{f}(s_P^{-1}(s)), \tag{3}$$

which satisfies $\boldsymbol{h}(s) = \boldsymbol{h}(\tilde{s})\ \forall s$.

Next, it is assumed that the phase evolution function $s_P(t)$ is distorted by temporal fluctuation into $s_Q(t)$ and that the periodic signal $\boldsymbol{f}(t)$ is converted to a quasi-periodic signal $\boldsymbol{g}(t)$, which is subject to

$$\boldsymbol{g}(t) = \boldsymbol{h}(s_Q(t)) = \boldsymbol{f}(s_P^{-1}(s_Q(t))). \tag{4}$$

Given the quasi-periodic signal $\boldsymbol{g}(t)$ and its phase evolution function $s_Q(t)$, the normalized periodic function is reconstructed as

$$\boldsymbol{h}(s) = \boldsymbol{g}(s_Q^{-1}(s)). \tag{5}$$

In addition, since the signal is usually sampled by observation, we redefine the above variables at sampling time t_i $(i = 0, \ldots, N)$ with subscript i (e.g. $\boldsymbol{g}_i = \boldsymbol{g}(t_i)$). Therefore, our objective is to estimate a phase sequence $\boldsymbol{S}_Q = \{s_{Q,i}\}$ from a given quasi periodic sequence $\boldsymbol{G} = \{\boldsymbol{g}_i\}$. This is referred to as the *phase registration* problem and we apply Self-DTW [19] to estimate the phase sequence $\hat{\boldsymbol{S}}_Q = \{\hat{s}_{Q,i}\}$ in this paper.

3.2. Ambiguity combination problem

In this section, we describe the ambiguity combination of the phase evolution function and the normalized periodic function which remains unsolved as reported in [19].

Given another phase evolution function $s'_Q(t)$ and another normalized periodic function $\boldsymbol{h}'(s) = \boldsymbol{h}(s'_Q(s_Q^{-1}(s)))$ that satisfies $\boldsymbol{h}'(s) = \boldsymbol{h}'(\tilde{s})\ \forall s$, a quasi-periodic function $\boldsymbol{g}(t)$ is defined in two ways as $\boldsymbol{g}(t) = \boldsymbol{h}(s_Q(t)) = \boldsymbol{h}'(s'_Q(t))$ as shown in Fig. 1. Therefore, given the quasi-periodic function $\boldsymbol{g}(t)$, the ambiguity of the combinations of the phase evolution function $s_Q(t)$ and the normalized periodic function $\boldsymbol{h}(s)$ remains.

This ambiguity is not problematic when the final goal is phase registration itself and we can adopt one of the combinations of the phase evolution functions and normalized periodic functions as a result. However, it poses a problem when the reconstructed normalized periodic signals are used for the galleries and a probe and the galleries are matched by DTW. The reason for the problem can be explained as follows.

First, the transition paths as a result of DTW matching between signals of different subjects (inter-class matching) tend to be more nonlinear than those for the same subjects (intra-class matching). This over-fitting sometimes results in confusion by making inter-class signal distances smaller than intra-class signal distances. To avoid such confusion, certain appropriate penalties for the nonlinear transitions (e.g., double-speed or half-speed transition) are usually introduced. On the other hand, if a normalized periodic function is obtained as a phase-distorted one $\boldsymbol{h}'(s)$ due to a wrong phase evolution function $s'_Q(t)$, additional elastic phase deformation is needed leading to additional transition cost in DTW matching, which also results in confusion

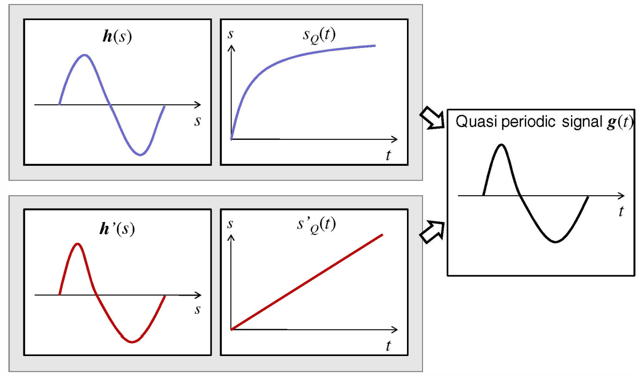


Figure 1. Ambiguity combination problem. Different combinations of normalized periodic functions and phase evolution functions may produce the same quasi-periodic signals $\boldsymbol{g}(t)$.

by making intra-class signal distances larger than inter-class signal distances. This additional cost is essentially unnecessary in the case of a phase-undistorted normalized periodic function $\boldsymbol{h}(s)$. Therefore, we introduce the phase evolution function linearization process as described in the next section for relaxing this kind of distortion derived from the ambiguity combination.

4. Linearization of the Time Warping Function

In order to relax the ambiguity combination problem, a prior of the linear phase evolution function is brought into the proposed algorithm. The procedures are mainly divided into the three parts: (1) period segmentation, (2) reconstruction of the Time Warping Function (TWF), and (3) linearization of the TWF. Each procedure is described in the following subsections.

4.1. Period segmentation

Once the phase sequence is estimated, we can obtain period segmentation boundaries in sub-sampled resolution based on the fact that the phase s and relative phase $\tilde{s}$ are integer and zero at the period segmentation boundaries, respectively. In more detail, the j-th period segmentation boundary i^j_{bound} is obtained as follows. First, we find adjacent samples which satisfy

$$(s_{Q,i} - j)(s_{Q,i+1} - j) < 0. \tag{6}$$

Next, the j-th period segmentation boundary i^j_{bound} is calculated by interpolation as

$$i^j_{bound} = (1 - w)i + w(i+1), \tag{7}$$

$$w = \frac{j - s_{Q,i}}{s_{Q,i+1} - s_{Q,i}}. \tag{8}$$

Moreover, an elapse of the j-th period is easily obtained as $P^j = i^j_{bound} - i^{j-1}_{bound}$.

4.2. Reconstruction of the time warping function

A TWF is a function to describe a relationship between linearly evolved phase $\bar{s}$ within a period and an estimated relative phase $\tilde{s}$, and that of the j-th period is denoted as $\tilde{s} = w^j(\bar{s})$. Suppose that the i-th sample belongs to the j-th period, its linearly evolved phase $\bar{s}_i$ is then expressed as

$$\bar{s}_i = \frac{i - i_{bound}^{j-1}}{P^j}. \tag{9}$$

Thus, a TWF for the j-th period is reconstructed by interpolation from a set of the linearly evolved phases and estimated relative phases $X^j = \{\{\bar{s}_i, \tilde{s}_{Q,i}\} | i_{bound}^{j-1} < i < i_{bound}^{j}\}$. Note that the normalized periodic signals at specified phase intervals are also recovered by linear interpolation in the same way.

4.3. Linearization of the time warping function

Because we rely on a prior of the linear phase evolution function, a TWF averaged over periods should ideally be linear. The average TWF is computed as: $\bar{w}(\bar{s}) = \sum_j^{N_P} w^j(\bar{s})/N_P$, where N_P is the number of periods. Suppose that a certain transformation function of the estimated relative phase $\tilde{s}$ is $\tilde{s}' = \gamma(\tilde{s})$ for linearizing the TWF. The average TWF after the transformation needs to satisfy the linear phase evolution constraint as

$$\gamma(\bar{w}(\bar{s})) = \bar{s}. \tag{10}$$

Hence, the transformed relative phase $\tilde{s}'$ and the transformation function γ are naturally expressed by the inverse function of the average TWF as

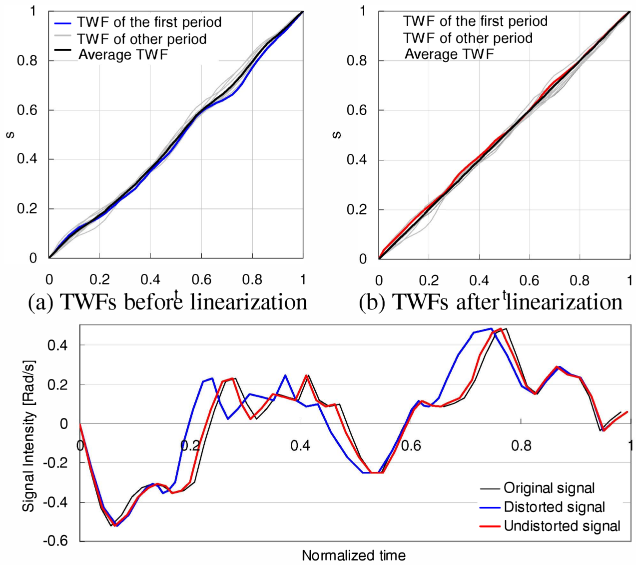
$$\tilde{s}' = \gamma(\tilde{s}) = \bar{w}^{-1}(\tilde{s}). \tag{11}$$

Finally, a new TWF is interpolated from $\tilde{s}'$ in the same way. Examples of the distorted TWFs and the linearized TWFs are shown in Fig.2(a) and Fig.2(b), respectively. After this linearization, the time-distorted periods given by Self-DTW are all undistorted so that they become close to the original periods, as shown in Fig.2(c).

5. Recognition

In this paper, we focus on the advantage of using a phase registration technique to solve this authentication problem. Therefore, we also use the same pattern matching method as the previous work [17] for comparison with previous works. Therefore, DTW is used for an elastic pattern matching technique. Here, the gait pattern is defined as the normalized gait signals of a period (or walking cycle).

First, a gallery $\mathbb{G}$ is defined as a collection of sample patterns of all conditions for the owner: $\mathbb{G} = \{\boldsymbol{g}_i\}$. For any probe pattern $\boldsymbol{p} = \{p_j\}$, the distances between it and



(a) TWFs before linearization (b) TWFs after linearization (c) Related signals of the first period

Figure 2. TWFs and their average TWF before and after linearization, and the related signals of the first period. The distorted TWF of the first period (blue line) in (a) is undistorted as shown by the TWF (red line) in (b). The distorted signal (blue line), undistorted signal (red line) of the first and their original signal (black line) are displayed on a normalized time axis in (c).

all the patterns in $\mathbb{G}$ are computed, and the min rule [20] is exploited to integrate results from multiple periods as

$$Dist(\mathbb{G}, \boldsymbol{p}) = \min_i D(\boldsymbol{g}_i, \boldsymbol{p}). \tag{12}$$

Since $\boldsymbol{g}_i$ and $\boldsymbol{p}$ are made independently, they are not phase-registered. The distance between them is computed as the minimum distance between $\boldsymbol{g}_i$ and the circularly shifted pattern of $\boldsymbol{p}$:

$$\begin{aligned} D(\boldsymbol{g}_i, \boldsymbol{p}) &= \min_k d\left(\boldsymbol{g}_i, \boldsymbol{p}^{shift_k}\right), && (13)\\ \boldsymbol{p}^{shift_k} &= \left\{p_{(j+k) \mod N}\right\}, k = 0..N-1, && (14)\end{aligned}$$

where N is the number of samples per channel of the gait pattern. The distance $d(.,.)$ can be computed as the normalized cumulative DTW score at the end of the optimal warping path as in [13, 17].

In a real application, more advanced recognition techniques, such as combining classifiers[20], k-nearest neighbor methods[21], and so on should be applied to the framework. The standard DTW to compute distance in Equ.(12) and Equ.(13) can be replaced by cyclic and continuous dynamic programming, and period detection for the probe sequence is not needed.

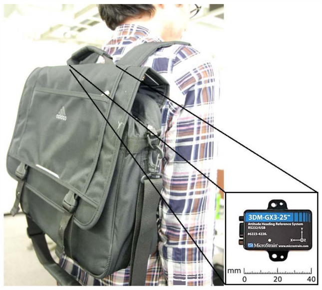


Figure 3. Our experimental sensor system consisted of an inertial sensor, fixed under the handle, connected to a small computer inside the back-bag.

6. Experiments

6.1. Experiment Setup

In the experiments, we tried to show the advantage over existing methods of using a phase registration technique in constructing the gallery for this biometric recognition problem. Our experimental system employed one of the latest inertial sensors from MicroStrain, the 3DM-GX3-25, which can capture 3D linear accelerations, 3D rotational velocities simultaneously. Our experimental sensor system is shown in Fig.3.

The sensor was fixed under the handle and placed inside a back-bag. It was connected to a small computer, a Sony Vaio type P, through a USB port. 32 healthy subjects including 7 females and 25 males, were asked to take part in the experiments. Their age varied between 21 and 40. Each subject walked normally along an indoor corridor. We captured 5 sequences (SEG_i, i=1..5), of walking data for each subject under different conditions such as different carrying weights. Here, the weight for SEG_{i+1} was heavier than that for SEG_i. Each sequence was nearly 2 minutes long and contained about 64 gait periods. Gait signals were captured with a sampling period of about 10 milliseconds.

6.2. Competitors

We compared the proposed method with the previous methods. The first proposed method used the original phase registration [19], in which the TWF linearization was not applied, and also used DTW for computing pattern distance. This method is denoted as PROPOSED_NOLIN in this paper. The second proposed method was similar to the first but applied TWF linearization, which is denoted as PROPOSED_LIN.

The benchmark competitors are four period detection-based approaches by [11] (GAFUROV_2010), [14] (RONG_2007), [13] (RONG_2007_DTW), [17] (MOHAMMAD_2010), and one frequency analysis-based approach by [9] (GAUFUROV_2006). RONG_2007_DTW and MOHAMMAD_2010 used the matching procedure as described in Section 5, while the other competitors used a similar method with the only difference being that $d(.,.)$ in Equ.(13) was computed by Euclidean distance.

Each gait pattern for period-detection based approaches was normalized to 50 samples per channel, and 3 channels of rotational velocities were used, although methods such as GAFUROV_2010, RONG_2007, RONG_2007_DTW only used up-down acceleration signals for detecting the gait period. Examples of gait patterns constructed by the proposed method and others are shown in Fig.4.

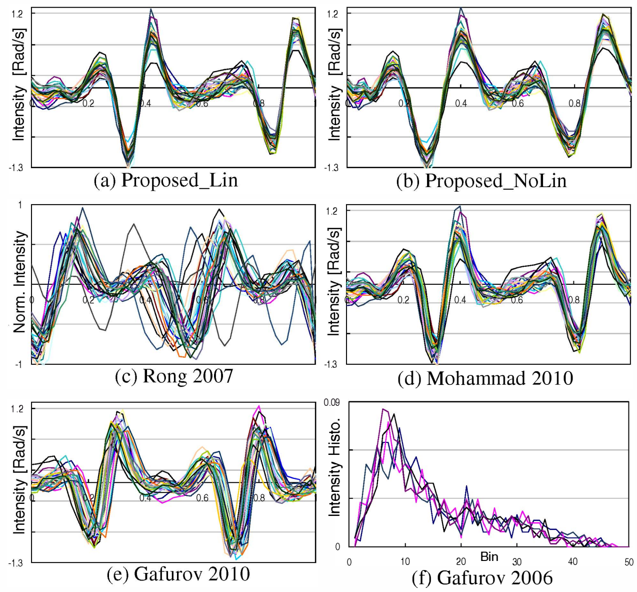


Figure 4. Examples of the constructed patterns, only for pitch ω_x, in the proposed method with linearization (a) and without linearization (b), RONG_2007 (c), MOHAMMAD_2010 (d), GAFUROV_2010 (e), and walking intensity histogram of GAFUROV_2006 (f). For RONG_2007, the signal intensity of each channel was normalized. For GAFUROV_2006, only a few patterns were detected since a long sequence (5 periods) of intensity was used to compute the histogram. Different patterns are depicted in different colors.

6.3. Evaluation Method

The Receiver Operating Characteristics (ROC) curve and Equal Error Rate (EER) were computed for the performance evaluation of each gait authentication method. The ROC curve shows the relationship between the False Rejection Rate (FRR) and False Acceptance Rate (FAR) for the authentication scenarios. The lower the EER, the better the method performs.

We carried out two procedures on the data for evaluation purposes. The first data scenario, each of 5 sequences with different carrying weights, was divided equally into 2 sub-sequences for making gallery and probe data. This data setup is denoted as HALF_HALF. In the second data scenario, we prepared data in the leave-one-out manner, and it is denoted by LOO. In summary, we had 5 situations, each of them is denoted by LOO_#i when the SEG_i was used for making the probe data and the other 4 sequences were for the gallery. In this experimental data setup, we checked the recognition methods where the probe data was captured under conditions different from the conditions for which the gallery was made. An example of the pattern differences due to different weights can be found in Fig.7.

Given a set of gallery data and probe data, each method had to extract the periods automatically for making gallery and probe patterns. Note that each probe pattern was tested independently to compute the ROC curve and EER.

6.4. Results and Discussion

6.4.1 HALF_HALF data scenario

The results of EER and FRR at 1% FAR are shown in Table.1 and ROC curves are shown in Fig.5. From these results, we can see that the proposed methods, PROPOSED_NOLIN and PROPOSED_LIN, give the best results among the competitors. We can also see that histogram method is unsuitable for our problem, where the data is captured in real environment with variations. Factors such as carrying weight significantly change the signal intensity, therefore the histogram method is not reliable. Compared to PROPOSED_NOLIN, PROPOSED_LIN managed to solve the ambiguity combination problem, therefore it produced better results. For RONG_2007 and RONG_2007_DTW, the most serious problem was its walking period detection method. In this method, the authors relied on the local minimum, maximum and zero-cross points of the up-down acceleration to detect the walking period. For the stable signals such as the data captured in their paper, these points can be relied on. Where the subject walks with some variation factors, it may, however, induce errors due to the dependency on these points. It can also clearly be seen that RONG_2007_DTW worked better than RONG_2007, because DTW was applied for matching patterns. Although, the same DTW was used for matching patterns as in the proposed methods, RONG_2007_DTW gave worse results than the proposed methods since its period detection did not work well. The problem for GAFUROV_2010 is that they apply the direct matching using Euclidean distance for phase-unregistered patterns. MOHAMMAD_2010 could also extract the periods very well, however, these periods were not phase-registered, the relative temporal distortion between them remained. That results in an additional cost when matching intra-class patterns using the DTW. The PROPOSED_LIN, applied Self DTW to extract periods so that all the periods were phase-registered, then linearization of TWF could be applied to correct the relative temporal distortion between them. Therefore, when the DTW was used for matching, additional cost for matching intra-class patterns was not as much as for MOHAMMAD_2010 method. That is why the PROPOSED_LIN outperformed MOHAMMAD_2010 in the experiments.

Table 1. EERs and FRR at 1% FAR for HALF_HALF

Method	EER	FRR at 1%FAR
PROPOSED_NOLIN	0.072	0.21
PROPOSED_LIN	0.060	0.18
RONG_2007	0.128	0.47
RONG_2007_DTW	0.087	0.31
GAFUROV_2010	0.088	0.29
GAFUROV_2006	0.227	0.91
MOHAMMAD_2010	0.073	0.23

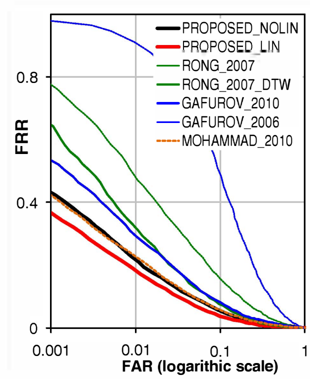


Figure 5. ROC curves for all competitors for HALF_HALF.

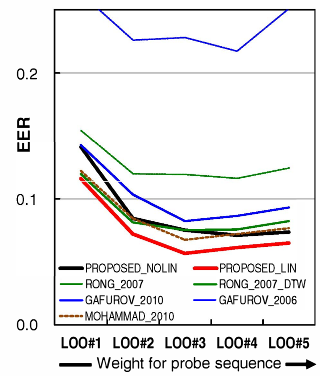
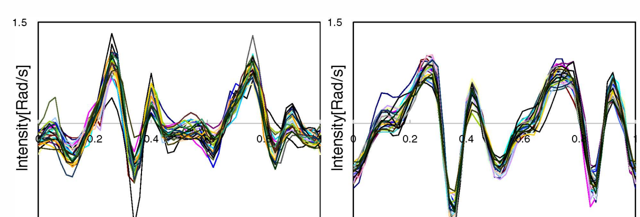


Figure 6. EERs for all situations of LOO.

6.4.2 Leave-one-out data scenario

The results for this data setup are shown in Fig.6. Results similar to the above results can be seen for each situation. The only difference is for the PROPOSED_NOLIN due to its ambiguity problem. For sequences with lighter additional weights such as situation LOO_#1, the test signal is more unstable than for heavier weights, as we can see from Fig.7, and hence the ambiguity problem is more problematic, which results in lower recognition performance. For heavier additional weights, the test signal becomes more stable, the performance of Self-DTW is statistically better



(a) Pattern for light weight (b) Pattern for heavy weight

Figure 7. Gait patterns for pitch ω_x are constructed by phase registration with linearization from sequences with light weight (a) and heavy weight (b) in the back-bag. The weight difference was about 2 kg.

and the EER evaluation of PROPOSED_NOLIN is closer to that of PROPOSED_LIN.

7. Conclusions and Future Work

The paper proposed a gait-based owner authentication method using an inertial sensor. While the existing methods rely on the relatively simple period detection method, the proposed method employed a phase registration technique to obtain better period segmentation. Moreover, the linear phase evolution prior was introduced to solve the ambiguity combination problem in the existing phase registration method. As a result, much better patterns were constructed as galleries and they improved the performance of gait authentication.

In this work, we focused on the temporal distortion aspect in gait pattern matching, for which there exist several significant factors such as walking speed changes and orientation changes of the sensor attachment. In particular, orientation changes easily occur with mobile phones in pockets, so this needs to be solved in the future studies.

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