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Accelerometer-based gait recognition via voting by signature points

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This letter presents a novel algorithm to recognize human identities via gait by body-worn accelerometers. It uses acceleration information to measure human gait dynamics. Acceleration-based gait recognition is a non-intrusive biometric measurement, which is insensitive to changes of lighting conditions and viewpoint. The proposed algorithm firstly extracts signature points from gait acceleration signals, and then identifies the gait pattern using a signature point-based voting scheme. Experiments with a data set of 30 subjects shows that the proposed algorithm significantly outperforms other existing methods and achieves a high recognition rate of 96.7% in case of five accelerometers.

Introduction: The emerging pervasive computing paradigm emphasizes that computing be thoroughly integrated into everyday activities, and services be provided in an unobtrusive manner, which requires the awareness of user identity. Many miniaturised sensors, ranging from micrometres to millimetres, are being widely used in our daily life. Especially, wearable accelerometers have been employed in various applications, such as recognition of human daily activities [1], gesture recognition. This letter addresses recognition of human identities via gait measured by wearable accelerometers in pervasive computing environments. Compared with ID card, body-worn RFID, and other biometric techniques such as face, video-based gait, and fingerprint, the accelerometer-based gait biometrics has several advantages. It is lighting-invariant, viewpoint-invariant, and nonintrusive. It cannot be lost and stolen. However, only a little work has been done on accelerometer-based gait recognition in the literature, e.g. correlation of mean cycle [2], Manhattan distance of median cycle [3], and Dynamic Time Warping (DTW) approach [4].

In this letter, a novel accelerometer-based gait recognition approach is proposed, which firstly extracts a series of salient points (called *signature points*) by searching extrema in the scale space of gait acceleration signals, and then identifies the gait pattern by a signature point-based voting scheme. The signature point extraction enables the algorithm to focus on those important local patterns that characterise the individual identity. Recognition using voting scheme makes it robust to local intra-class variation and applicable for the multi-accelerometer case.

Signature points of gait acceleration: Signature points are the fiducial positions of gait signals, which are expected to behave as the discriminative features of personal gait dynamics; that is, they should be both stable for the same person and distinctive for different persons. The idea of signature point extraction is to search extrema in the scale space of gait acceleration signals, inspired by SIFT for 2D images [5].

Suppose that the gait acceleration acquired by an accelerometer is represented by a temporal sequence $x(t)$, $t \in \{1, 2, 3, \ldots, T\}$, where T is the signal length of the gait. To be robust against accelerometer-worn position, we take magnitude of acceleration only. The σ-scale of the gait is defined as

$$y(t,\sigma) = g(t,\sigma) * x(t), \tag{1}$$

where $g(t,\sigma)$ is the Gaussian filtering kernel with variance σ^2. The differences between adjacent gait scales are calculated as

$$\begin{aligned} d_i(t) = d_i\left(t, \alpha^i \sigma_0\right) &= y\left(t, \alpha^{i+1}\sigma_0\right) - y\left(t, \alpha^i \sigma_0\right) \\ &= \left(g\left(t, \alpha^{i+1}\sigma_0\right) - g\left(t, \alpha^i \sigma_0\right)\right) * x(t). \end{aligned} \tag{2}$$

where $i \in \mathbb{Z}$, $\sigma_0 > 0$ is the base scale parameter, and $\alpha > 0$ is the geometric factor. The difference-of-Gaussian (DoG) filtered sequences form a scale difference pyramid $D = (\ldots, d_1, d_2, \ldots, d_i, \ldots)$, called the gait *scale-space*, which has good characteristics of comparability between adjacent DoG filtered sequences. A point s in the gait x is a signature point if and only if its value $x(s)$ is larger (or smaller) than its two neighbours in its current scale and the six neighbours in the upper and lower scale. We denoted all the signature points of the gait x as $\mathcal{S}(x)$. In this letter, a DoG gait pyramid with three scales is adopted. Descriptor of a signature point s can be depicted simply by its temporal neighbourhoods, denoted as a $(2h+1)$-dimensional vector

$$\Theta(s) = \left(x(s-h), \ldots, x(s), \ldots, x(s+h)\right). \tag{3}$$

Identification as voting by signature points: Before gait recognition, gait's step cycles are detected and segmented in advance. Then each step cycle is normalized to a same length L. Assume that gait x has m step cycles separated by $m+1$ points $t_1 < t_2 < \ldots < t_{m+1}$, where the ith cycle occupies the interval $\left(t_i, t_{i+1}\right]$, we define the relative location of a signature point s in step cycle period as

$$\mathrm{rloc}(s) = s - t_i, \quad \text{where } t_i \text{ subjects to } s \in (t_i, t_{i+1}]. \tag{4}$$

Given the training set $\mathcal{B} = \{(b_i, l_i)\}_{i=1}^{n}$ with n identity-known gaits, where b_i is a gait and l_i .is its identity (or label), the set of all the signature points in the training set can be written as $\mathcal{T} = \bigcup_{i=1}^{n} \mathcal{S}(b_i)$. Thus, each signature point from b_i also has the label l_i.

Suppose that a is an input gait with unknown identity. For each signature point $s \in \mathcal{S}(a)$, we predict its label by nearest neighbour method. That is, we use the label of the nearest signature point in $\mathcal{T}$ as the predicted label of s. The distance metric of two signature points s_1 and s_2 is defined for nearest neighbour finding in the space of signature point

$$\mathrm{dist}(s_1, s_2) = \begin{cases} |\Theta(s_2) - \Theta(s_1)|, & \text{if } |\mathrm{rloc}(s_1) - \mathrm{rloc}(s_2)| < \delta \\ +\infty & \text{otherwise} \end{cases}. \tag{5}$$

The temporal constraint δ in the definition makes that only those signature points near to s in a step cycle period can contribute to the prediction procedure of s, which is based on the observation that similar signature points generally appear at similar locations relative to their corresponding step cycles. It can suppress noises and reduce computational cost. The signature point s will be ignored if no neighbour at a definite distance presents.

After all labels of signature points in $\mathcal{S}(a)$ are predicted, the unknown gait a can be identified via voting by these signature points. Each signature point s of a "votes one ticket" for the predicted label of s. Finally, the identity of the gait a is assigned to the label with the most votes. This voting scheme can easily be generalized to multiple accelerometers (i.e. multiple *channels*) simultaneously worn on different body parts.

Experiments: To evaluate the algorithm, a gait acceleration data set with 30 persons was built in two one-month-separated days. Each person worn five tri-axial accelerometers on different body parts (as shown in Fig.1), including the left upper arm, the right wrist, the right side of waist, the left thigh, and the right ankle, similar to [1]. The Bluetooth-enabled Wii Remote was employed as the accelerometer device and data is collected wirelessly to a laptop computer in real time. Each person was asked to walk naturally along a 20-meter corridor six times in either day. Each time (i.e. a gait sequence) lasts about 10 seconds with 8-12 step cycles. Thus, there are 320 (6×2×30) gait sequences in the data set. The frequency of acceleration acquisition is set to 100Hz. We use one day's data as the training set and the other day's data as the test set, i.e. two-fold cross validation. We take advantage of salience of signal valleys in the ankle channel to segment step cycles. Then all the step cycles are normalized to the length of 100 sampling points prior to gait identification. The descriptor parameter h is optimal to 10, and the temporal constraint δ is set to 15.

The discriminative capability of each channel is investigated. The experimental result of identification rate for each channel and combination of all the five channels is shown in Table 1. It can be seen that upper arm channel has the best performance (74.5%) compared with the other four channels, and wrist channel has the worst identification rate. Although the performance of each channel is below 75%, combination of all the five channels achieves a high identification rate of 96.7%, which depicts that the discriminative capability of different channel can compensate each other.

We compare the proposed approach with three typical methods in previous works: correlation [2], Manhattan distance [3], and Dynamic Time Warping (DTW) [4]. In Fig. 2, we compare the identification performance of different methods using CMC (Cumulative Match Characteristics) curves. Since the three methods for comparison all work with single accelerometer of waist, here we also report the performance of our approach with the waist channel only. The result shows that our approach significantly outperforms the three existing ones. In addition, Fig. 2 also illustrates performance of the three lower-body channels (ankle, thigh, and waist). Because motion situation of hand and arm is easy to be changed by simultaneous behaviours with walking, such as holding a heavy object, while the lower body part has more stable motion. Our approach obtains the identification rate of 85.2% for the lower-body case.

Conclusion: The proposed algorithm is based on signature points, instead of the whole gait signal, to give prominence to the stable and distinctive localities. The extraction of signature point is based on extrema in the scale space. The voting mechanism with temporal constraint enhances robustness of our algorithm against intra-class variation and noise. Experimental results demonstrate that the proposed algorithm outperforms other methods significantly on our data set of 30 subjects. The performance of accelerometers worn on different body parts is also discussed. The recognition rate of 96.7% is obtained when five accelerometers are used, which shows the accelerometer-based gait biometrics is promising.

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Figure captions:

Fig. 1 Five positions for accelerometer wearing
Fig. 2 Cumulative Match Characteristics curves of different methods

Table captions:

Table 1 Discriminative capability of different channels

Table 1

Channel	*Recognition rate*
Wrist	66.8%
Upper arm	74.5%
Waist	70.1%
Thigh	67.5%
Ankle	72.9%
All the five channels	**96.7%**

Figure 1

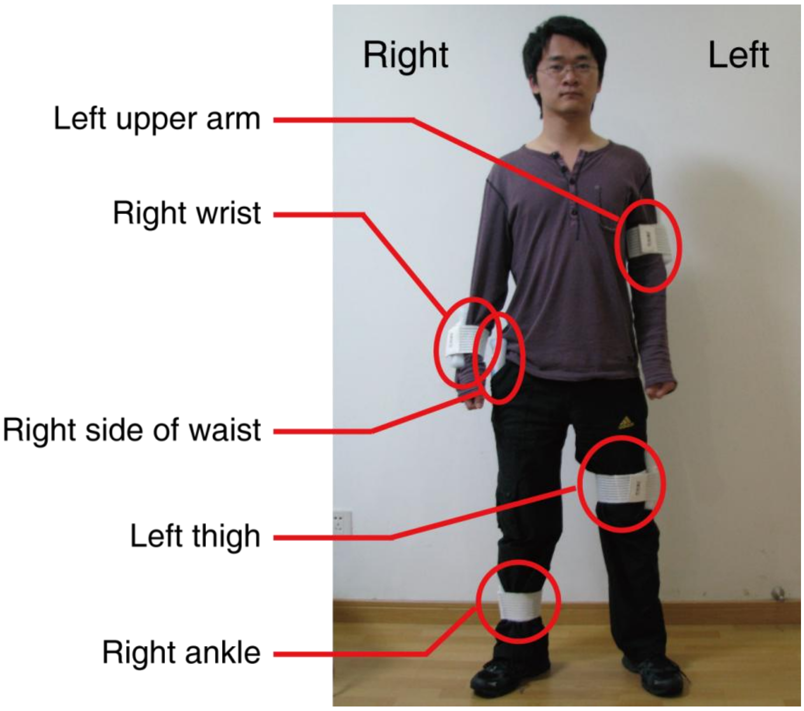

Figure 2