Gait Analyzer based on a Cell Phone with a Single Three-axis Accelerometer

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ABSTRACT

We propose a fuss-free gait analyzer based on a single three-axis accelerometer mounted on a cell phone for health care and presence services. It is not necessary for users not to wear sensors on any part of their bodies; all they need to do is to carry the cell phone. Our algorithm has two main functions; one is to extract feature vectors by analyzing sensor data in detail using wavelet packet decomposition. The other is to flexibly cluster personal gaits by combining a self-organizing algorithm with Bayesian theory. Not only does the three-axis accelerometer realize low cost personal devices, but we can track aging or situation changes through on-line learning. A prototype that implements the algorithm is constructed. Experiments on the prototype show that the algorithm can identify gaits such as walking, running, going up/down stairs, and walking fast with an accuracy of about 80[%].

Categories and Subject Descriptors

I.5.4 [**Computing Methodologies**]: Siganl Processing

General Terms

Algorithm, Experimentation

Keywords

gait analysis, ubiquitous service, context, sensor, accelerometer, cell phone, wavelet packet, self-organizing map.

1. INTRODUCTION

Gait analysis is important for mobile services such as presence services and health care services. When the user is found to be running, a presence service would automatically activate the voice mail mode rather than the text mode. In another example, when the user is in a train, silent mode would be activated. For health care, automatically recording the user's gait is not only convenient for him but also necessary for more accurate health advice. This is because daily medical checks are very important to protect against life-style related diseases such as diabetes and heart disease based on stress. Regular medical checks are very cumbersome because the user must go to a hospital. Determining a metabolic baseline is fraught with uncertainty since only the user's statements are available. Moreover, it is not realistic to continually wear sensors on specific parts of the body. In order to resolve these issues, we propose a gait analyzer based on a cell phone with a three-axis accelerometer. This is because cell phones are becoming indispensable in daily life and are carried everywhere due to their sophisticated functions. Moreover, as cell phones have become personal assistants, they are well placed to identify user behavior.

Many related works place small sensors on mobile devices to extract gait for a variety of purposes such as context extraction[8], [5], activity recognition[1], [9], [3], personal positioning[4] and person identification[6]. However, since most papers adopt the wearable computer approach, they require several sensors to be fixed to specific parts of the user's bodies to achieve a high degree of accuracy. Their methods are not realistic because wearing many sensors is very cumbersome. To extract features from the sensor data, they use FFT-based approaches or the statistics of the sensor data such as peak-to-peak cycles and mean values. This makes it virtually impossible to identify the localized wave data present in the sensor data because Fourier transform has lower time-frequency resolution than wavelet transform. Consequently, most systems proposed so far can detect only walking and running. Moreover, since they use knowledge-based approaches such as if-then rules to detect gait, their systems do not offer enough robustness to handle fluctuations in gaits. Krause[5] used a self-organizing algorithm that used the transition probabilities between contexts for gait detection, however, many sensors must be placed on parts of the user's body. Another related work[7] proposed a method of extracting context that is independent of sensor position. Unfortunately, their method has limited context extraction performance because feature extraction is based on the magnitude of three-axis sensor data. Crossan[2] studied the relations between user's tapping accuracy and user activities such as walking and sitting. This raises feasibility concerns since the user must tap a target on a mobile device for gait analysis.

In order to realize gait analysis via a cell phone, we should

MobileHCI'06, September 12–15, 2006, Helsinki, Finland.

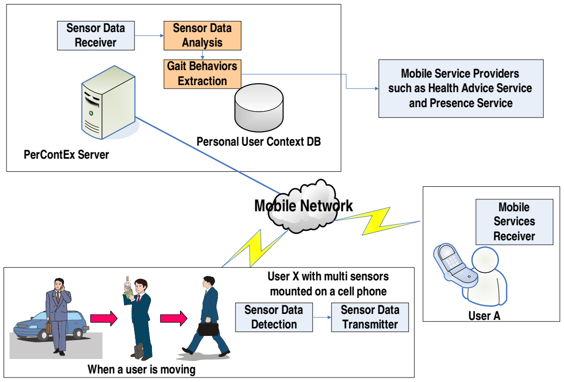

Figure 1: PerContEx System

(a) A three-axis accelerometer mounted on a cell phone

(b) Gait analysis browsing by Java applications

Figure 2: Cell Phones for PerContEx system

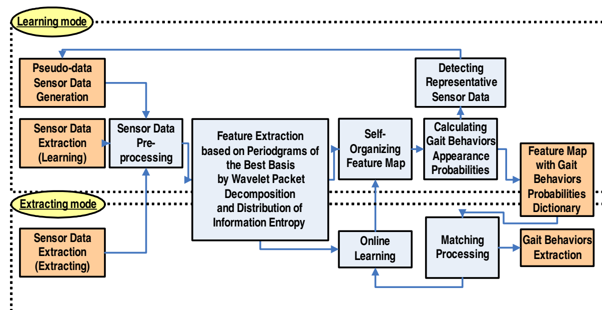

Figure 3: PerContEx Algorithm for Gait Analysis

consider low electric power consumption, robustness to the style of carrying the phone, and adaptation to the various gaits possible. Our solution, proposed here, is to analyze gait using only the data collected by a three-axis accelerometer mounted on a cell phone. It has four features;

- low cost personal devices: the only sensor is a three axis accelerometer,
- adaptation to gait variety: achieved by using periodogram and information entropy based on wavelet packet decomposition for feature extraction,
- robustness to the style of carrying the cell phone: gait patterns are learning using pseudo sensor data,
- adaptation to aging or situation changes: on online learnt is used to update gait appearance probabilities.

The next section describes our algorithm: we then introduce our experiments. Finally, we draw several conclusions and describe future works.

2. GAIT ANALYZER BASED ON PERCONTEX

2.1 System Architecture

Our proposed system is based on "PerContEx"(Fig. 1) which uses sensors mounted on a cell phone to extract personal user context (see Fig. 2). It is composed of a cell phone with a three-axis accelerometer and a PerContEx (Personal Context Extractor) server (see Fig. 1(a)). Sensor data collected by the cell phone are sent to the PerContEx server via the mobile network. The user's gait can then be monitored by Java applications in real time (see Fig. 2 (b)). The PerContEx server extracts the user context such as gait and provides them to mobile services such as health advice services. For gait analysis, the PerContEx server has a learning mode and an extraction mode (see Fig. 3). The learning mode has two steps; one is training using real sensor data labeled with gait, the other is training using pseudo data generated by rotation transformation from sensor data that is representative of gait. In the extraction mode, gaits are extracted by using feature maps; the appearance probabilities of which are acquired in the learning mode. Their appearance probabilities are continually updated through on-line learning to realize adaptation to aging or situation changes. We describe our algorithm implemented on the PerContEx server in the following sections.

2.2 Feature Extraction for A Variety of Signal Patterns

In order to handle the variety of gaits possible, our feature extraction process uses wavelet packet decomposition (WPD) for wave analysis. This is because FFT, a typical signal processing approach, provides only limited in analysis resolution. WPD provides finer analysis in each frequency range through the use of localized orthogonal basis functions with a splitting algorithm that downsamples not only the scaling components but also the wavelet components. Moreover, by using information criteria, we can obtain decomposed signals that can efficiently represent the features of signal patterns. We extract two feature vectors $\vec{X}_s^{(i)}$ and $\vec{M}^{(i)}$ $(i = x, y, z)$ from the decomposed signals as follows;

$$\vec{X}_s^{(i)} = (X_s^{(i)}(1), \ldots, X_s^{(i)}(n), \ldots, X_s^{(i)}(N_{max})) \quad (1)$$

$$\vec{M}^{(i)} = (M^i(1), \ldots, M^i(k), \ldots, M^i(K_{max})) \quad (2)$$

where

$$X_s^{(i)}(n) = \frac{1}{2\Delta T} \sum_{t_s} |u_i^{(p,q)}(t_s) exp(-j\omega_n t_s)|^2 \quad (3)$$

$$M^{(i)}(\vec{X}_d^{(i)}) = \sum_n (n - M^{(i)}(1))^k X_d^{(i)}(n) \quad (4)$$

$$X_d^{(i)}(n) = \frac{|\sum_{t_s} |u_i^{(p,q)}(t_s)|^2 \log |u_i^{(p,q)}(t_s)|^2|}{2^{p_{max}-p}} \quad (5)$$

$$M^{(i)}(1) = \frac{\sum_n nX_d^{(i)}(n)}{\sum_n X_d^{(i)}(n)} \quad (6)$$

and

$$\omega_n = \omega_{max} 2^{-p_{max}} n \quad (7)$$

$$2^{p_{max}-p} q \leqq n = n(p,q) \leqq 2^{p_{max}-p}(q+1) - 1 \quad (8)$$

$\vec{X}_s^{(i)}$ and $\vec{M}^{(i)}$ represent periodograms of the best basis and the momentum of the information entropy distribution of the best basis, respectively. Thus, the above formula does not contain $X_s^{(i)}(0)$, the DC component, because basically it contains the center of gravity. Moreover, AC components, not DC components, contain effective features for determining gaits. Thus, $\vec{X}_s^{(i)}$ is the feature vector used to detect similar sensor data while $\vec{M}^{(i)}$ is used for analyzing the attribution of sensor data. $X_d^{(i)}$ and ω_n represent information entropy distribution and frequency, respectively. $u_i^{(p,q)}(t)$ is the q-th part of the decomposed data at level p. ΔT and t_s are frame length and time, respectively.

2.3 Gait Classification with Robustness to Sensor Positions

In order to achieve robustness with regard to sensor position, we use feature maps learnt from not only observed training data but also pseudo-data, which are generated from the best representative sensor data by rotational transformation. We use the Kohonen self-organizing map (KSOM) because it can provide not only robustness to noise and signal fluctuations, but also flexibility in terms of the number of clusters. However, KSOM is weak for deciding cluster borders on the learnt feature map because of the existence of uncertain cells. In order to overcome this problem, we apply a probabilities-based technique after learning the feature map. Under our proposal, we can prepare dictionary data whose labels are kinds of gaits.

Based on the information about the number of times each gait appears, we make a probability map by calculating gait appearance probabilities in each cell. We define gait appearance probabilities $P(C_{n_c}|\vec{X}_{n_c})$ based on Bayesian theory as follows;

$$P(C_{n_c}|\vec{X}_{n_c}) = \frac{P(\vec{X}_{n_c}|C_{n_c})P(C_{n_c})}{\sum_{k_c} P(\vec{X}_{n_c}|C_{k_c})P(C_{k_c})} \quad (9)$$

where C_{n_c} and $\vec{X}_{n_c}$ represent the appearance of gait n_c and the selected cell on the feature map nearest to input vector $\vec{X}$, respectively. $P(\vec{X}_{n_c}|C_{n_c})$ and $P(C_{n_c})$ are the conditional probability of appearance C_{n_c} given $\vec{X}_{n_c}$ and the prior probability of C_{n_c}, respectively. By using the probability information based on gait appearances discovered in the learning mode, we can obtain the sensor data that is most representative of each gait. After obtaining the best representative sensor data, we transform them using a rotation matrix to create a variety of pseudo sensor data. Subsequent training with each pseudo-data in angle sets following the approach given yields as many feature maps as there are angle sets.

In order to extract gait, we use all feature maps with the possibilities trained by both observed and pseudo sensor data. The gait can be extracted by finding the most suitable cell $\vec{X}_{bm}$ according to the below conditions;

$$\begin{cases} \vec{X}_{bm} = \arg\min_{\vec{X}_c}\{\|\vec{X} - \vec{X}_c\|\} \\ \|\vec{X}_{bm} - \vec{X}_c\| < Th_{bm} \ \ and \ \ Corr(\vec{M}_{bm}, \vec{M}_c) > Th_{corr} \end{cases} \quad (10)$$

where $\vec{M}_{bm}$ and $\vec{M}_c$ are the feature vectors of the information entropy distributions of $\vec{X}_{bm}$ and $\vec{X}_c$, respectively. $Corr(\vec{M}_{bm}, \vec{M}_c)$ means the normalized cross correlation between $\vec{M}_{bm}$ and $\vec{M}_c$. Th_{bm} and Th_{corr} are thresholds to judge feature vector similarity.

2.4 Online Learning: Adaptation to Changes in User's Style

In order to adapt to changes due to the user's aging and situation currently being experienced, our proposed system has an online learning algorithm which can update gait appearance probabilities according to changes in the user's actions. We use the online learning algorithm as follows.

step 1 store sensor data as a candidate of training data for online learning if the gait extracted satisfies the below conditions

$$P(C_{n_c}|\vec{X}_{N_c}) > Th_p \ \ and \ \ Corr(\vec{M}_{bm}, \vec{M}_c) > Th_{corr} \quad (11)$$

where Th_p and Th_{corr} are thresholds to judge whether $\vec{X}_{n_c}$ is representative of a gait.

step 2 run online learning using the sensor data stored as training data.

step 3 select a better feature map by comparing the gait discrimination ability before online learning to that after online learning.

3. EXPERIMENTAL RESULTS

3.1 Experimental Conditions

We validated our proposal using a prototype system. The experiments targeted five gaits associated with movement: walking, going up/down stairs, walking rapidly, and running. Two subjects carried a cell phone with a single three-axis accelerometer in their breast/hip pocket and took almost the same routes in learning mode and extraction mode. In the learning mode, we used 15 minutes of sensor data captured by the three-axis accelerometer for each gait individually per subjects. Their frame-length and overlap-time were $3[sec]$ and $1.5[sec]$, respectively. Pseudo data were then generated by rotational transform of the 15 minute sensor data using rotations from $0[deg]$ to $45[deg]$ in $15[deg]$ steps around x-, y- and z- axis (to account for symmetry). In the extraction mode, the subjects used the same environments as in learning mode. The system basically outputs gait behavior appearance probabilities, however, in the evaluation of gait behavior extraction, we identified the gait behavior that had the maximum probability.

3.2 Results and Discussions

Figure 5 shows the results of extracting features for "walking at normal speed" and "going up stairs". As both movements contain the behavior of "walking", we can see similar wave patterns at best basis levels 2 and 3. Thus, the other best bases are useful for discriminating between "walking at normal speed" and "going up stairs" and noise.

After feature extraction, we made a feature map of gait appearance probabilities by using real data and pseudo sensor data as described above. Figure 4 shows the resulting map. We can see that each gait has a distinctive feature map.

According to Figure 6, our proposed algorithm can extract and discriminate the above gaits independent of cell

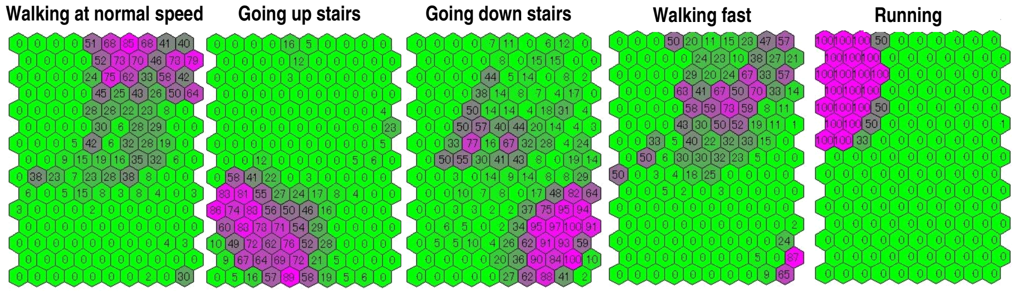

Figure 4: Learnt Feature Map with Probability Information

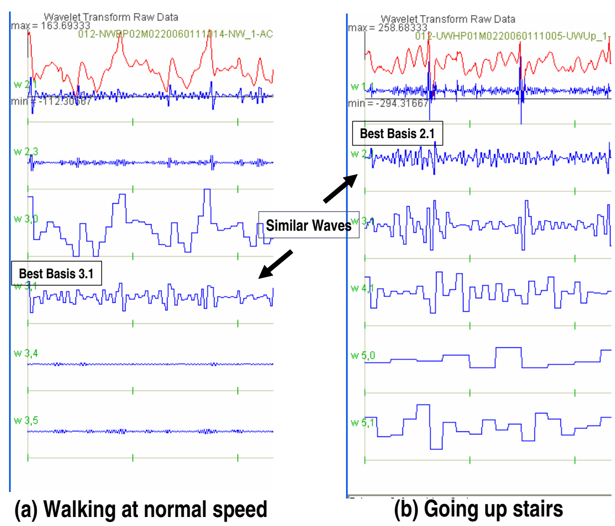

Figure 5: Sensor Data Decomposed by Wavelet Packet

phone position. Moreover, the results show that the proposed algorithm can discriminate not only walking(WN) and running(RN) but also going up/down stairs(US/UD) and walking fast(WF). The most difficult gait to identify was DS("going down stairs"). We think that DS imposes much weaker constraints on body movement than the other gaits such as US("going up stairs") and RN("running"). Many DS events were misidentified as "walking at normal speed" or "walking fast". We need to enhance the algorithm to provide a more detailed analysis of the sensor data for more accurate gait identification.

4. CONCLUSION

We proposed an algorithm that can extract gait from the data collected by a single three-axis accelerometer mounted on a cell phone as non-wearable approach; it uses feature extraction based on wavelet packet decomposition and KSOM with gait appearance probabilities. Experiments on a prototype system showed that a freely positioned cell phone with the sensor could identify gaits such as walking, running, walking fast, and going up/down stairs at the accuracy of about 80[%]. The results prove that the algorithm can not only reduce the constraints placed on users but also support ubiquitous services that require gait input.

Future work includes realizing a more comprehensive analysis of sensor data in each gait by feature extraction based on wavelet packet decomposition in order to accurately identify gaits in more complicated situations such as when the cell phone is carried by hand. We will then apply the algorithm to ubiquitous services such as presence and health care services and evaluate it in mobile environments.

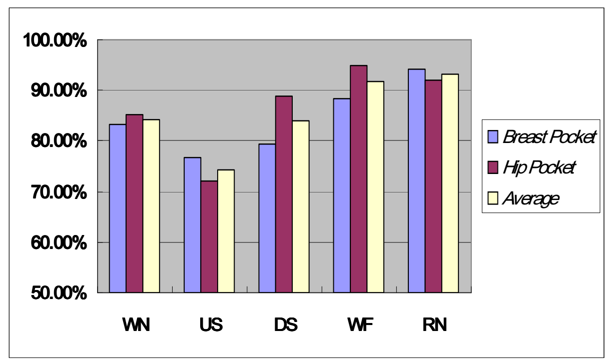

Figure 6: Accuracy of Gait Extraction

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