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A Novel Pedestrian Dead Reckoning Solution Using Motion Recognition Algorithm with Wearable EMG Sensors

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Abstract

Navigation applications and location-based services are currently becoming standard features in smart phones with built-in GPS receivers. However, a ubiquitous navigation solution which locates a mobile user anytime anywhere is still not available, especially in Global Navigation Satellite System (GNSS) degraded and denied environments. Different motion sensors and angular sensors have been adopted for augmenting the positioning solutions for such environments. An electromyography (EMG) sensor, which measures electrical potentials generated by muscle contractions from human body, is employed in this paper to detect the muscle activities during human locomotion and captures the human walking dynamics for motion recognition and step detection in a Pedestrian Dead Reckoning (PDR) solution. The work presented in this paper is a consecutive step of our pilot studies in developing a novel and robust PDR solution using wearable EMG sensors. The PDR solution includes standing and walking identification, step detection, stride length estimation, and a position calculation with a heading angular sensor. A situation of standing still is identified from the EMG signals collected from a walking process, which has standing and walking dynamics, via a hidden Markov model classifier fed by sample entropy features. Such pre-classified processing reduces the misdetection rate of step detection. After step detection, two stride length estimation methods are investigated for the PDR solution. Firstly, a linear stride length estimation method based on statistic models is investigated to improve the accuracy of the PDR solution. Secondly, five different walking motions are recognized by a motion recognition algorithm based on some particular EMG features, and a fixed stride length is then set for each walking motion to propagate the position. To validate the effectiveness and practicability of the methods mentioned above, some field tests were conducted by a few testers. The test results indicate that the performance of the proposed PDR solution is comparable to that of a commercial GPS receiver in outdoor test under an open-sky environment.

Keywords: <pedestrian dead reckoning, electromyography, wearable sensors, motion recognition>

1. Introduction

Personal navigation applications and location-based services currently are becoming standard features in today's intelligent mobile devices (e.g. smart phones). The Global Positioning System (GPS) based pedestrian navigation serves as the main solution for locating mobile users. However, locating a mobile user anytime anywhere is still a challenging task, especially in GPS degraded and denied environments such as urban canyons and indoor environments. As such, it is essential to augment the GPS-based solution with other positioning techniques such as wearable Dead Reckoning (DR) sensors, pseudolites, Wi-Fi, UWB, and RFID to obtain a seamless indoor/outdoor positioning solution. Self-contained approach with wearable sensors based on DR principles is preferable for pedestrian navigation, because it does not require any supports from ambient environment.

Conventional Pedestrian Dead Reckoning (PDR) solutions (Beauregard et al., 2006, Sun et al., 2009, Ladetto et al., 2000, Toth et al., 2007) measure the acceleration from accelerometers to calculate the step count, estimate the step length and propagate the position with the heading from angular sensors such as a magnetic compass or a gyroscope. However, the signals applied for these solutions are sensitive to alignment of sensor units, inherent instrumental errors and disturbances from the ambient environment (Chen et al., 2010a).

Unlike the approaches mentioned above, an electromyography (EMG) signal, as a typical kind of biomedical signal, measures the electrical potentials generated by muscle contractions without any other references to the ambient environment. The raw EMG signal is an oscillating wave, whose amplitude increases during muscle activation (Saponas et al., 2008). The EMG based technologies, which provide researchers with a significant opportunity to capture human locomotion by directly sensing and decoding muscular activity, are widely applied in medical diagnosis, rehabilitation (Frigo and Crenna, 2009) and human-computer interaction (Asghari and Hu 2007). When a pedestrian is walking, the EMG signals measured from the pedestrian’s legs are changing periodically and can be used to count the number of step (Chen et al., 2011a, Chen et al., 2011b). Moreover, the strength of leg muscle contraction determines stride length, because there is a positive correlation between the amplitude of the EMG signals and the stride length, which makes it possible to estimate the stride length using EMG signals. The EMG signal can also be used to recognize different walking motion patterns including walking on flat, stairs and slope, which contributes to a more robust EMG based PDR solution and wider applications in context awareness, especially for indoor or urban applications where the environment usually restricts the pedestrian’s activity and locomotion. Because within a defined area, the user dynamics and walking motions are limited, which provide additional opportunities to augment the positioning solution (Chen et al., 2010c).

Considering the capacity of the EMG signal to obtain the information of pedestrian walking activities and its potential applications in context awareness and mobile interactions, we have firstly introduced this signal into the pedestrian navigation and have successfully demonstrated the feasibility of estimating the stride length by EMG signal measured from Gastrocnemius of right leg in our preliminary studies (Chen et al., 2010b, Chen et al., 2011a). Based on the wearable EMG measurement system, the work in this paper is the consecutive step of our pilot studies in further developing a more practical and robust PDR solution.

In this paper, a novel PDR algorithm is proposed using wearable EMG sensors to measure walking steps. The major advance presented in this paper is that we take the motion into account when processing the EMG signals. Firstly, walking motions are discriminated from standing still or other irregular motions to avoid false step detection; secondly, different kinds of walking motions including walking on flat, walking up along a slope, walking up/down with stairs are recognized to estimate the stride length, and thus a more robust EMG based PDR solution can be built for a more complex environment. The rest of the paper is organized as follows. Section 2 introduces the proposed PDR solution in detail. In Section 3, experimental results on several field tests are presented to demonstrate the feasibility and effectiveness of the EMG based PDR solution. Finally, the conclusions are summarized in Section 4.

2. Methods

In this section, the EMG based PDR solution is introduced according to the processing stages including data collection, standing and walking identification, step detection, stride length estimation with motion recognition and position calculation as the grey blocks shown in Figure 1.

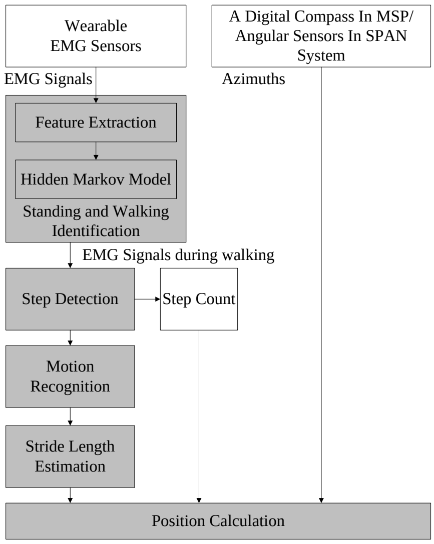


Figure 1.The diagram of the proposed EMG based pedestrian dead reckoning solution.

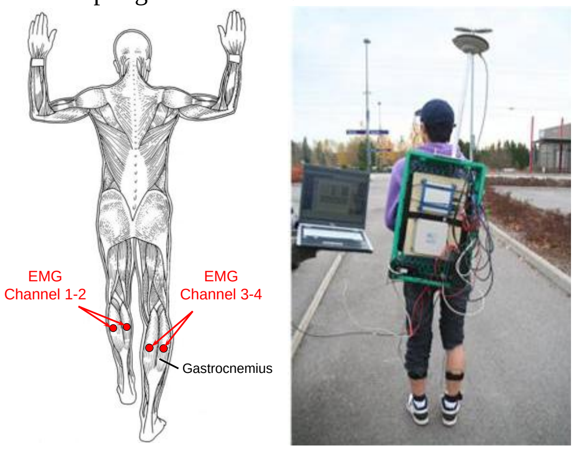
2.1 Data Collection

Three instruments are applied for collecting data in field tests; they are wearable EMG sensor, Multi-Sensor Positioning (MSP) system and Synchronized Position Attitude Navigation (SPAN) system.

A).Wearable EMG Sensors and Setup

In this study, The EMG data is recorded by a wearable surface EMG measurement system, which supports up to 16 wireless active EMG sensor modules. An EMG sensor module (or called channel) is embedded with a pair of line-shaped differential electrodes with 1 mm × 10 mm contact area and 10 mm inter-electrode distance. Each EMG sensor module, weighing less than 20 grams and measuring 38mm × 20mm × 10mm, includes built-in amplifiers with typical gain of 60 dB, a microcontroller with a 12-bit analog/digital converter, a 2.4GHz radio frequency transceiver and a 250mAh lithium battery. It is convenient to place multiple distributed modules on the skin of proper body parts which collaborate to collect multi-channel EMG signals simultaneously.

To collect muscles activities during walking, several EMG sensors are attached to muscles of both left and right legs. From the anatomical point of view and some experimental results in the literatures (Ivanenko et al., 2004, Campanini et al., 2007), the EMG signal measured from the calf (Gastrocnemius) is much more obvious than that from other muscles, when a pedestrian is walking. Therefore, two EMG sensors (CH1-2 for the left and CH3-4 for the right) are required to be attached to both the medial head and lateral head of the Gastrocnemius muscles in both legs as shown in Figure 2. The sampling rate is 1 kHz.



(a) (b)

Figure 2. EMG sensors attached on the left and right leg (The background of (a) is obtained from http://www.answers.com/topic/muscle)

Figure 3 shows typical raw EMG data collected when a pedestrian is standing and then walking during a time period of 16s. It is easily observed from Figure 3 that the contractions of muscles are cyclic during walking. The EMG signals measured from the medial head and the lateral head of the Gastrocnemius are extremely synchronous. Hence, two channel EMG signals from the same leg are averaged into one EMG stream (denoted as CHL for the left and CHR for the right) to reduce the computational complexity of further processing as shown in Figure 3.

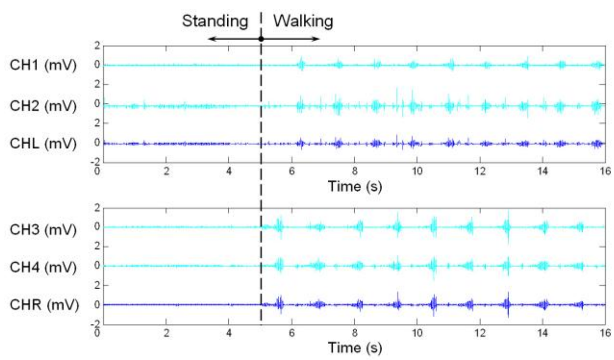


Figure 3. Typical raw EMG data collected when a tester is standing and then walking.

B). Multi-sensor positioning system with GPS receiver

MSP system developed by the Finnish Geodetic Institute (FGI) is also used in this study to measure the heading information of a pedestrian and to provide a GPS reference trajectory. The MSP includes a GPS chip (Fastrax iTrax03), a 3-axis accelerometer (VTI SCA3000), and a 2-axis digital compass (Honeywell HMC6352). For more details about the MSP, please refer to (Chen et al., 2009). The MSP was horizontally mounted on the tester's abdominal area during the tests, with a GPS antenna fixed on top of a cap for maximum satellite visibility.

C). SPAN High Accuracy GPS-IMU System

SPAN technology is a tightly couple solution of precision Global Navigation Satellite System (GNSS) receivers with robust Inertial Measurement Units (IMUs) from NovAtel to provide reliable, continuously available measurements including position, velocity and attitude even though short periods of time when no GNSS satellites are available. Such technology that integrates the GNSS data and the inertial data offers better functionality and reliability than that a traditional stand-alone GPS receiver can support. The SPAN system can operate either in Real-Time Kinematic (RTK) mode or Virtual Reference Station (VRS) mode for real-time and post-processing applications to get trajectories with centimetre level of accuracy.

Table 1: The specifications of SPAN's IMU

Gyro Input Range	±1000 deg/s
Gyro Rate Bias	1.0 deg/s
Gyro Rate Scale Factor	150 ppm
Angular Random Walk	0.125 deg/hr
Accelerometer Range	±50 g
Accelerometer Linearity	500 ppm
Accelerometer Scale Factor	300 ppm
Accelerometer Bias	1.0 mg

The GPS receiver of the SPAN is a NovAtel DL-4plus, containing the NovAtel OEM-G2 engine. A dual-frequency NovAtel GPS-702 antenna is applied during the test. The applied inertial measurement unit is a tactical-grade, ring laser gyro based IMU manufactured by Honeywell, and the specifications of the IMU are given in the Table 1. The position accuracy is approximately 2 cm for VRS mode outdoors which is used for EMG test. The data collected by SPAN is used as a reference trajectory to evaluate the performance and the improvement of the proposed stride length estimation based on a motion recognition algorithm.

2.2 Standing and Walking Identification and Step Detection

In the proposed PDR algorithm, the step count is determined and every stride length is estimated based on the walking information of the Gastrocnemius muscle activities carried by multi-channel EMG signals. However, the Gastrocnemius muscles are involved not only in walking motions but also in standing still situation. Obvious EMG signals can also be detected when a pedestrian is standing still (See Figure 3). Therefore, Hidden Markov Models (HMMs) are proposed to discriminate walking motions from standing still situations before step detection to avoid misdetection.

A). Feature Extraction

Because of the random nature of the raw EMG signal, which is often analysed as a non-stationary stochastic process, the information about the general characteristics of the muscular activity pattern is inevitably hidden in the raw EMG signals. If the raw EMG data are used directly as inputs to the identifier, the standing and walking identifier frequently produces poor results. Therefore, it is essential to use some pre-processing methods to obtain several appropriate features, which can be employed to accurately recognize EMG signal patterns. In this study, the raw EMG signal stream is blocked into frames via a sliding window of 128 samples (time interval of 128ms), and 64 of which overlap with consecutive ones. Such feature extraction processing based on sliding windows with 50% overlap has been successfully applied in previous work (Englehart et al., 2001), where the overlapped windowing schemes are demonstrated to keep the continuity of the EMG stream.

Various kinds of features for identification of the EMG have been considered in the literatures (Asghari and Hu 2007, Englehart et al., 2001, Kosmidou and Hadjileontiadis, 2009) for myoelectric control and human-computer interaction. These features have included a variety of time-domain, frequency-domain, and time-frequency-domain features. However, since in the proposed algorithm, the objective of standing and walking identification is to select useful EMG data for the step detection, it is sufficient to distinguish between walking and standing. Therefore, sample entropy of each EMG frame from both legs is used to form feature vectors in this work. The sample entropy of time series data measures the negative logarithm of the conditional probability that two sequences that are similar for m points, remain similar at the next point, within a tolerance r, where self-matches are not included in calculating the probability (Kosmidou and Hadjileontiadis, 2009).

In order to compute the sample entropy (SampEn), the EMG time series $EMG_i(t)$, $1 \le t \le N$ (here N=128 as described above) of the i-th frame from either left or right legs, is first embedded in a delayed m-dimensional space, where the vectors are constructed as:

$$x(p) = \left[EMG(p+k) \right]_{k=0}^{m-1}, \quad p = 1, 2, \ldots, N-m+1 \qquad (1)$$

The probability $B^m(r)$ that two sequences match for m points is computed by counting the average number of vector pairs, for which the distance is lower than the tolerance r. Similarly, $A^m(r)$ is defined for an embedding dimension of m+1 (Kosmidou and Hadjileontiadis, 2009). The sample entropy (SampEn) is then calculated as:

$$SampEn_i\left(EMG_i(t), m, r\right) = -\ln\left(A^m(r) / B^m(r)\right) \qquad (2)$$

It is suggested that the tolerance r is chosen as 0.2 × SD (the standard deviation of the time series). Throughout this work, the parameter m is set as 2 and the tolerance r is kept constant to the value of 0.03 for fast calculation. Figure 4 illustrates the SampEn feature streams extracted from the EMG data from both the left and right legs respectively when the tester is walking and standing. For standing and walking identification, the features of the current frames and the (T-1) previous frames are connected together, and the two-dimensional feature vector sequence with length of T can be formed as the input of HMMs. The frame number T is chosen as 15. Therefore, each feature vector sequence $\mathbf{O}_i = \{\mathbf{o}_{i-T+1}, \ldots, \mathbf{o}_{i-1}, \mathbf{o}_i\}$ fed into HMMs covers a time interval of (15+1) × 64ms = 1.024s, which is used to sufficiently capture cycles of the leg movements.

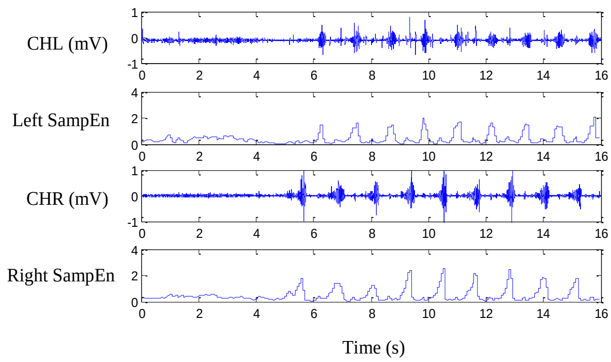


Figure 4. The sample entropy feature streams of the left and right legs respectively.

B). Hidden Markov Model

HMM is a sufficient tool for the recognition of sequences. An HMM process represents a stochastic process which takes time series data as observation evidence. The output of HMM is the probability that the observation evidences, here the observed feature sequence data $\mathbf{O}_i$, is generated by that model. HMM has been applied successfully to speech and gesture recognition (Rabiner and Jaung, 1993, Mitra and Acharya, 2007).

There are three basic problems of interest which must be solved for the model to be used in a real application: the evaluation, the decoding, and the learning problems. The first and the third problem are relevant for recognition tasks. In this work, a continuous HMM with 4 states and 3 Gaussian mixture components are proposed to recognize the two classes of activities including walking and standing. The evaluation and the learning problems are solved by standard Forward-Backward and Baum-Welch algorithms (Rabiner and Jaung, 1993).

C). Step Detection

Taking advantage of human physiological characteristics during walking, many previous researchers employed various effective algorithms for detecting the step based on the data from accelerometers, such as zero-crossing, peak detection, autocorrelation, stance-phase detection, etc. Figure 5 shows that the amplitude of EMG signals periodically changes in accordance with the step occurrence, and that the cyclic pattern of sample entropy feature streams is more obvious and easier to detect than that of the raw EMG data. A gait cycle is defined as a basic unit to describe the gait during walking, which starts when a heel of one foot strikes the ground and ends when the same foot contacts the ground again. One gait cycle includes two phases which are synonymous to a left step and a right step. For the left step, the right foot strikes on the ground until it leaves the ground to produce force for making a left pace, in which time, EMG signals vibrate strongly.

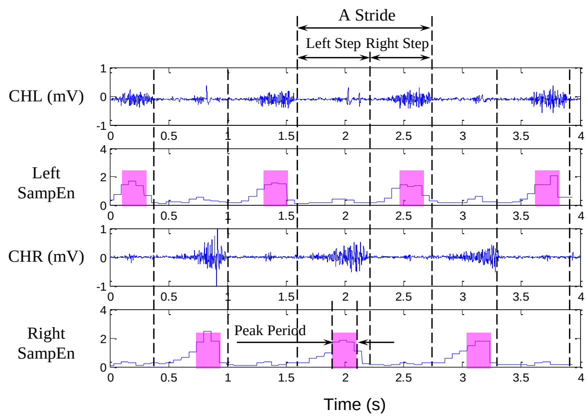


Figure 5. Illustration of step detection.

When the output of HMMs indicates the pedestrian is walking, a peak detection algorithm is applied on the left and right sample entropy feature streams respectively to determine peak periods. Considering the unique pattern of the EMG signal, the peak period is defined as the time duration of two consecutive frames (equivalent to 192ms) whose sample entropy feature summation is the highest than that of the adjacent frames. In order to avoid false detection, the peak detection algorithm used in this study includes two main constraints: 1) the summation of the sample entropy features of two consecutive frames should be larger than a threshold; 2) the time interval between two adjacent peak periods should be larger than a timing threshold. Each peak period indicates a detected step as marked in Figure 5 for illustration.

2.3 Stride Length Estimation

In INS (Inertial Navigation System), the displacement is normally calculated by double integrating the acceleration signal. However, limited by the physical nature of the EMG signal, there are no existing mathematic methods to calculate the displacement or velocity of a pedestrian with EMG signals directly. DR algorithm is feasible considering the similarity between the acceleration signal and the EMG signal. Thus, that how to estimate the stride length becomes an important component for the EMG based PDR and two stride length estimation methods are investigated in the paper to build a more robust solution.

A). Linear Stride Length Estimation Based on Statistic Models

To improve the accuracy of PDR, many previous studies (Sun et al., 2009, Ladetto et al., 2000, Toth et al., 2007, Godha et al., 2006), constructed statistics models to estimate stride length for deriving the speed, utilizing the good correlation between the speed and various parameters extracted from the sensor signals, such as stride frequency, peak value and variance of the acceleration per stride, etc. From the physiological view of pedestrian walking, the stride length has a positive correlation with the contraction strength of leg muscles. Hence, it is possible to extract some parameters from the EMG signal which can be used to construct a statistics model for stride length estimation. In our pilot work (Wang et al., 2010), several EMG features were investigated to construct different stride length estimation models, and found the most effective one is as follows.

$$SL_K = A \quad F_K + B \;\; MADV_K + C \qquad (3)$$

Where *A, B and C* are coefficients, which can be obtained by training of amounts of samples, F_K is the stride frequency at epoch *k*, and *MADV* is an EMG feature, which can be calculated by the following formula:

$$MADV = \frac{1}{T_p - 1} \sum_{t=1}^{T_p - 1} \left| s_p(t+1) - s_p(t) \right| \qquad (4)$$

where $s_p(t)$ denotes the EMG data series at time *t*, and T_p is the time duration of peak period, here T_p=192.

B). Stride Length Estimation Based on Motion Recognition Algorithm

The linear stride length estimation method based on statistic models has its limitations. The coefficients to estimate stride length are obtained by a training processing and it works well for some applications that uncomplicated environment is involved such as a flat playground. As for a more complex environment with slopes and stairs, another estimation method based on motion recognition is also investigated for such more practical case.

Because the pedestrian activity and locomotion are usually restricted by environment, the stride length can be seemed as a constant as for a particular walking motion. Five walking motions are recognized based on the followed algorithm.

The reason that such fixed stride length method is investigated is that we can focus solely on evaluating the performance contributed by motion recognition algorithm in a complex environment where the statistic models based stride length estimation may not properly work.

The walking motion recognition algorithm is based on the following assumptions. (Chen et al., 2011c)

- Because the exerted force by the muscle has positive relation with amplitude of the EMG signal and the activity of the muscles defines the motion type, the motion type has relation with the EMG signal
- The step mode is different between free walking and walking with stairs.

The pre-processing methods for motion recognition algorithm of EMG signal are similar as the methods applied before. For precise information please refer to (Chen et al., 2011a).

The $\overline{P}_{EMG}$ is the average power index of the EMG signals, and this smoothed square signal using a sliding window with the window size of m is calculated as

$$\overline{P}_{EMG}(t) = \frac{1}{m}\sum_{i=t-m+1}^{t} s(i)^2 \qquad (5)$$

Where $s(i)$ is the measurement from the measured EMG channel at epoch i. Since the EMG signal fluctuates intensively, the size m of the sliding window has been chosen as 600 (equivalent 0.6 second) by taking the practice and performance into account.

while the thresholds for the $\overline{P}_{EMG}$ are set as 450000 and 50000 to calculate M_f. And the M_f is the first motion recognition discriminator, which is used to describe how strong force the measured muscle exerts and it is calculated as

$$M_f(i) = \begin{cases} 0 & \text{if } \overline{P}_{EMG}(i) < 50000 \\ 1 & \text{if } 50000 \le \overline{P}_{EMG}(i) < 450000 \\ 2 & \text{if } \overline{P}_{EMG}(i) \ge 450000 \end{cases} \qquad (6)$$

The thresholds of 50000 and 450000 are empirically selected. In Figure 6, the red dots indicate the epochs that the tester walks up along a slope and the green dots indicate the epochs that the tester walks horizontally, and the blue dots indicate the standing still epochs.

Figure 6. The classification result of M_f based on the average power of EMG signals

M_s is the second motion recognition discriminator, which is used to describe whether pedestrian walks freely or with stairs and it can be calculated with following criterions:

$$M_s(P) = \begin{cases} 0 & \text{if } \mathrm{Std}(S_P) < 0.015 \\ 1 & \text{if } \mathrm{Std}(S_P) \ge 0.015 \end{cases} \qquad (7)$$

Where the $Std(S_P)$ is the variance of the *p-th* stride, which is calculated based on the stride period series using a sliding window of seven samples. The threshold value of 0.015 for $Std(S_P)$ is empirically selected also.In Figure 7, the green dots denote to the stepping down or stepping up strides with stair and the blue dots denote the free walking strides. For each walking motion, a fixed and dedicated stride length is set as equation (8).

$$SL_K = \begin{cases} 1.35 \text{ if } \mathrm{M}_H(K) = 4 \\ 1.30 \text{ if } \mathrm{M}_H(K) = 3 \\ 0.80 \text{ if } \mathrm{M}_H(K) = 2 \\ 0.60 \text{ if } \mathrm{M}_H(K) = 1 \\ 0.0 \text{ if } \mathrm{M}_H(K) = 0 \end{cases} \qquad (8)$$

Where the $\mathrm{M}_H(K)$ denotes the kind of motion type of pedestrian at k -th stride, and it can be determined based on the M_f and M_s discriminators mentioned before.

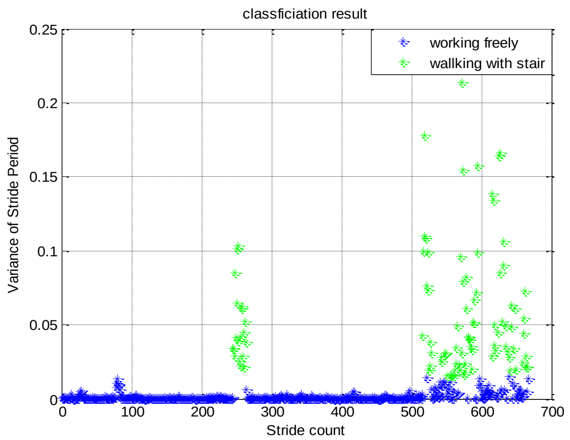


Figure 7. The classifcation result of M_s based on the variance of stride period

2.4 Position Calculation

When the pedestrian is walking, the PDR solution proposed in this paper is to process the EMG data to detect step occurrence, count stride number and estimate the stride length, which is integrated with the azimuths measured by an angular sensor to calculate the position. Assuming the beginning position of the pedestrian, the present position is calculated with:

$$\begin{cases} N_{k+1} = N_k + SL_k \cdot \cos\alpha_k \\ E_{k+1} = E_k + SL_k \cdot \sin\alpha_k \end{cases} \tag{9}$$

where N_k and E_k are the coordinate of the North and the East on the map, which represent position when the k-th stride occurs, SL_k and α_k are the corresponding stride length calculated by equation (3) or (8) and azimuth measurement of the k-th stride from the embedded digital compass on the MSP or the gyroscope of the SPAN.

3. Field Tests and Results

To validate the performance of the proposed PDR solution, a few field tests were carried out in both China and Finland. There were two sessions in the test:

- The first experimental session was carried out on the west campus of University of Science and Technology of China (USTC), which was designed to evaluate the standing and walking identification, the step detection and the statistic models based linear stride length estimation algorithm with EMG signals. Firstly, a male tester was recruited to wear EMG measurement system on his legs to collect 12 different groups of data. For each group, the tester was required to stand on the start point of a straight line of 130.50 meters for about 10 seconds, then to walk along the straight line to reach the end point at an even speed, and finally to stand on the end point for about 10 seconds. The tester's walking speeds varied in different groups (3 groups at a low speed, 4 groups at a normal speed, and 5 groups at a fast speed). Then, both the wearable surface EMG measurement system and the MSP were worn by the tester. The tester was required to walk along a prescribed long-range trajectory around the campus (Figure 9.a). And the trajectory mainly consisted of horizontal roads. The reference trajectory was collected by the MSP rather than the SPAN in these test cases.

The second experimental session was carried out at FGI in order to evaluate the performance and feasibility of the stride length estimation method based on motion recognition algorithm on a complex environment. A male tester wore EMG measurement system on his legs and carried a backpack platform where the NovAtel SPAN and the MSP were rigidly installed. The tester started the experiment from the Masala railway station, walked along a long flat platform, stepped down from a stair, passed thought two tunnels, walked along a slope, stepped up with a stair and finally arrived the main entrance of FGI. The reference trajectory achieved by the NovAtel SPAN is presented in Figure 8.

Figure 8. the reference trajectory from Novatel SPAN for the outdoor-indoor field test

3.1 Results of Step Detection

Based on the proposed standing and walking identification, 12 groups of EMG data collected from the first experimental session were processed to determine when and how long the pedestrian was walking. The decision time lags were less than 0.7s when the tester changed his activities from standing to walking and less than 1.0s when the tester changed his activities from walking to standing. The experimental results indicate it is sufficient to identify pedestrian activities using the method mentioned above.

Table 2 lists the step detection results with and without the standing and walking identification for 12 groups of EMG data (labelled as TG01 - TG12). The overall error

Table 2: Results of the step detection with and without the standing and walking identification

Testing Group	True Steps		Detected Steps without Activity Classification			Detected Steps with Activity Classification		
	left	*right*	*left*	*right*	*error (%)*	*left*	*right*	*error (%)*
TG01	87	88	88	89	1.14	87	88	0
TG02	92	92	95	94	2.72	92	92	0
TG03	88	89	90	90	1.69	88	90	0.56
TG04	79	81	80	80	1.25	77	81	1.25
TG05	78	80	78	80	0	78	80	0
TG06	81	80	84	82	3.11	81	80	0
TG07	79	81	80	81	0.62	79	81	0
TG08	75	75	74	73	2.00	75	75	0
TG09	73	73	73	72	0.68	73	73	0
TG10	72	73	74	73	1.38	73	73	0.69
TG11	72	72	72	72	0	72	72	0
TG12	73	73	76	74	2.74	73	73	0
Overall	949	957	964	960	1.47	948	958	0.21

rate of step detection can be reduced significantly from 1.47% to 0.21% after the standing and walking identification, as shown in Table 2. The results demonstrate the effectiveness of the standing and walking identification method to avoid false step detection and the practicability for using EMG to detect walking steps.

3.2 Positioning Results of the PDR Solution with Linear Stride Length Estimation

An additional GPS outage test was designed to simulate the situation when the GPS signal is not available because of the blockage nearby to investigate a case of personal navigation in urban canyons. A simulated GPS outage gap is intentionally introduced into the trajectory of the long-range test in USTC, China. When the tester walked into the gap, the GPS signals were assumed to be blocked. Then, the positions of the gap were calculated via the PDR solution only (Chen et al., 2011b). Figure 9 shows experimental results of the simulated GPS outrage gap. In Figure 9, (a) is the reference trajectory of the long-range test, marked with the start point and the walking direction; (b) shows the PDR route of the simulated GPS outrage gap and the GPS route get from

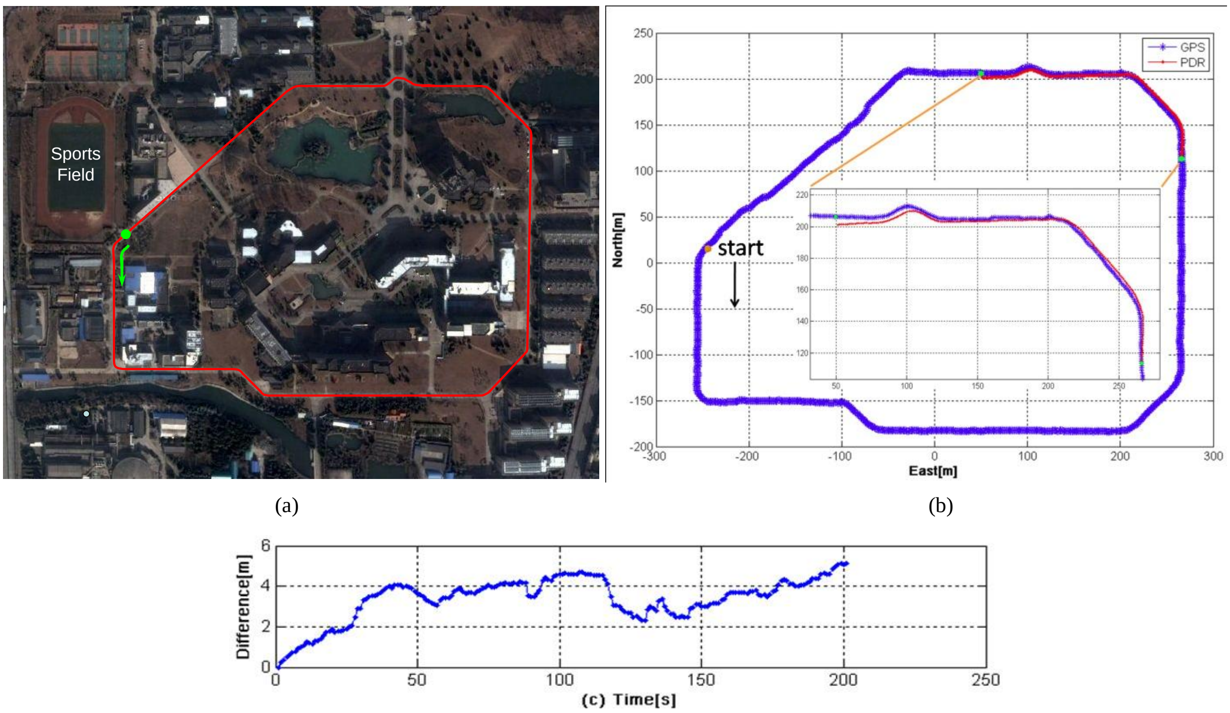


Figure 9. Positioning results of the simulated GPS outrage gap: (a) the true route of the long-range test; (b) the PDR route of the simulated GPS outrage gap against the GPS reference route; (c) Horizontal difference of the simulated GPS gap between the GPS and PDR solutions for about 200 seconds.

the MSP as reference; (c) shows the horizontal position difference between the PDR route and GPS route. The trajectory is propagated based on the linear stride length estimation and the applied azimuth is the measurements from the embedded digital compass on the MSP. The results indicate that the deviation of the PDR route is less than 5 meters compared with the GPS reference route when the tester walks 270.8 meters long during more than 200 seconds. Our proposed PDR solution based on the walking strides measured from EMG sensors and the heading from a 2-axis digital compass can achieve an acceptable performance, which is comparable to that of GPS solution. The statistic models based stride length estimation algorithm and its training method works in such environment. It is easily observed that the proposed PDR algorithm provides an effective and complementary solution to GPS-based personal navigation.

3.3 Positioning Results of the PDR Solution with Stride Length Estimation Based on Motion Recognition Algorithm

The position accuracy of EMG based PDR solution is comparable to the commercial GPS solutions for a period of 9 minutes outdoor test based on the EMG data collected from the second experimental session, which is equivalent to a walking distance of 663.1 meters in a complex outdoor route. The following walking motions are contained during the test. They are

- normal walking,
- stepping down with stairs,
- stepping up with stairs
- walking up along a slope,
- walking down along a slope,
- and several intentional stops

The proposed PDR solution with stride length estimation based on motion recognition algorithm and the heading from the SPAN can achieve an acceptable performance for pedestrian navigation in a complex environment, which offers a comparable solution to a commercial GPS receiver (Fastrax iTrax 03/16 within MSP handset) as Figure 10 shows. In Figure 10, the EMG based PDR using motion recognition algorithm solution coincides with the SPAN reference trajectory. In some GPS unfriendly parts alone the trajectory, for example, in two tunnels along the route and on a road with dense forest in its south side, the EMG solution demonstrates more robust performance against the GPS stand-alone solution, as Figure 10 presents.

To honestly evaluate the performance of proposed motion recognition algorithm, a trajectory of the EMG based PDR with fixed stride length is also be calculated, and a fixed stride length of 1.35 meter is used to calculate the position of the pedestrian. The result is presented in Figure 11. The trajectory of EMG solution coincides with the reference SPAN trajectory in the beginning. Because the route from Masala railway station to the first tunnel at the first right turn is primarily flat. After passing the first tunnel and entering a more complex environment which contains tunnels, slopes, stairs and the road with dense forest nearby, the motion recognition solution proved its robustness by comparing Figure 10 with Figure11.

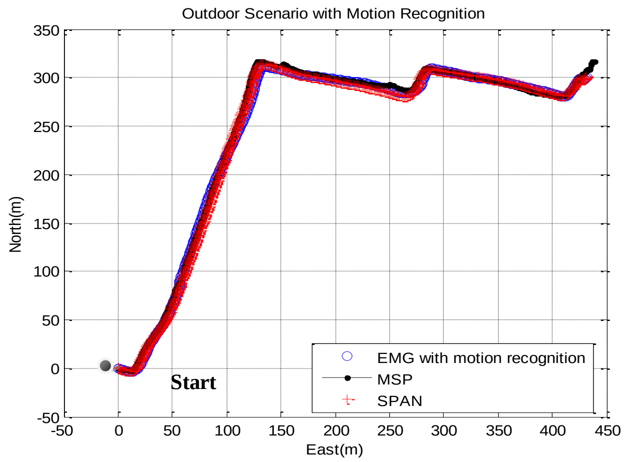


Figure. 10. The trajectory of EMG PDR with motion recognition vs commercial GPS receiver (with reference trajectory of SPAN) for outdoor scenario in a local coordinate.

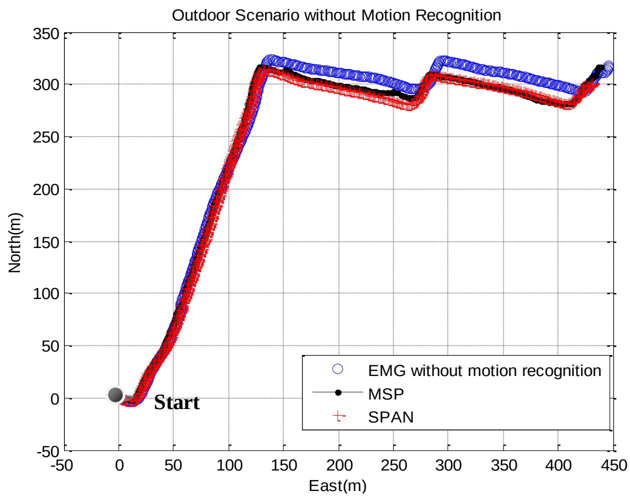


Figure 11. The trajectory of EMG PDR without motion recognition vs. commercial GPS receiver (with reference trajectory of SPAN) for outdoor scenario in a local coordinate.

4. Conclusions and Future Work

This paper has successfully introduced the EMG signal for pedestrian navigation. As a consecutive step of studies in this field, a novel PDR algorithm using wearable EMG sensors to measure walking steps and classify walking motions is proposed in this paper. Our PDR solution focuses on the EMG-based standing and walking identification, step detection, and stride length estimation. The major advances of the proposed PDR solution include: the standing and walking identification for avoiding step misdetection and the motion recognition among different situations of walking on flat, stair, and slope for estimating the stride length. Several field tests carried out demonstrate the effectiveness and practicability of the algorithm proposed. The performance of the EMG based PDR solution in several field tests is comparable to that of the GPS solution under open-sky environments.

However, the algorithm only used EMG signal from one channel of each leg, therefore the motion recognition result is limited. Actually, when a person is walking, there are multiple muscles from different parts of the body contract simultaneously; multi-channel EMG signals can be used to improve the motion recognition rate as well as to expand the recognized motion set. The classification of such pedestrian motions based on EMG signal will be investigated for more accurate algorithms for step detection and stride length estimation. In addition, the digital compass utilized to determine the walking heading in this study is vulnerable to magnetic disturbances, especially in indoor environments. Exploring the information fusion of digital compass and EMG sensors to measure the turning remains a part of our future works.

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