A Walking Velocity Update Technique for Pedestrian Dead-Reckoning Applications

Chi-Chung Lo*, Chen-Pin Chiu*, Yu-Chee Tseng *,
Sheng-An Chang†, and Lun-Chia Kuo†
*Department of Computer Science, National Chiao-Tung University, Hsin-Chu 300, Taiwan
†Industrial Technology Research Institute, Hsin-Chu 310, Taiwan
Email: {ccluo, cpchiu, yctseng}@cs.nctu.edu.tw; {changshengan, jeremykuo}@itri.org.tw

Abstract—**Inertial sensors for pedestrian dead-reckoning (PDR) have been attracting considerable attention recently. Since accelerometers are prone to the accumulation of errors, a "Zero Velocity Update" (Z-UPT) technique [1], [2] was proposed as a means to calibrate the velocity of pedestrians. However, these inertial sensors must be mounted on the bottom of the foot, resulting in excessive vibration and errors when measuring speed or orientation. This paper proposes a self-calibrating PDR solution using two inertial sensors in conjunction with a novel concept called "Walking Velocity Update" (W-UPT). One inertial sensor is mounted on the lower leg to identify a point suitable for calibrating the walking velocity of the user (when its pitch value becomes zero), while another sensor is mounted on the upper body to track the velocity and orientation. We have developed a working prototype and tested the proposed system using actual data.**

Keywords: body sensing, inertial measurement unit, location tracking, pedestrian dead-reckoning, wireless sensor network.

I. INTRODUCTION

A large number of location-based services (LBS) [3], [4], such as navigation and tracking, have recently been proposed, and a central issue in all such applications is location tracking. Currently, GPS remains the most widely used technology for positioning in outdoor environments; however, due to shadowing effects, GPS is not always available or reliable. To overcome these limitations, considerable effort has been dedicated to the development of alternative positioning techniques. These techniques can be classified into six categories: AoA-based [5], ToA-based [6], TDoA-based [7], signal loss-based [8], pattern-matching [9], [10], [11], and pedestrian dead-reckoning [1], [2], [12], [13], [14] techniques.

This work focuses primarily on PDR systems that rely on inertial sensors, such as accelerometers, electronic compasses, and gyro sensors mounted on the human body. These devices are used to measure acceleration, orientation, and angles of rotation to track the location of users. The simplest PDR system is the pedometer, which counts steps; however, walking motion actually comprises of a series of *strides*, which are far more effectively characterized by triaxial accelerometers and e-compass sensors. In [12], a pattern matching method was used to derive strides from vertical accelerations. In [13], step events were detected through the cooperative efforts of a vertical accelerometer and the angular rate at the axis of

the user's ankle. Empirical evidence supports the claim that angular rate data is more reliable than acceleration data. In [14], regression analysis was used to detect walking frequency and the variance in signals from an accelerometer during a single step, from which a conversion equation between stride length and step duration was derived. Nonetheless, each of these systems produce a high degree of error when users deviate from their normal walking patterns.

A fundamental issue in reducing measurement error in PDR systems is identifying the most effective method with which to calibrate the system. This is primarily due to the fact that accelerometers tend to accumulate a considerable number of errors when data is converted to speed or displacement. To overcome error drifting problems, a technique known as Z-UPT (Zero Velocity Update) employing a foot-mounted inertial sensor was proposed [1], [2]. Readings taken by these sensors are reported to be very close to zero when the sole of the foot touches the ground. This event represents a suitable moment from which to calibrate the system, i.e., the velocity of the walker is reset to zero when the system detects the occurrence of such an event. The main drawback of Z-UPT is that the inertial sensor must be mounted on the bottom of the foot, leading to excessive vibration and error in the measurement of orientation and displacement.

Our objective in this study was to develop an approach to eliminate both accumulated and orientation based errors. We propose a novel concept called "Walking Velocity Update" (W-UPT), using an inertial sensor mounted on the lower leg and a second sensor on the upper body. The lower sensor determines the timing aspect of walking velocity and continuously forwards this information to the upper sensor. The upper sensor calculates the velocity of the user according to measurements of acceleration calibrated against data from the lower sensor. The upper sensor also provides information related to the orientation of the user. Our results are based on the following observations concerning walking motion. First, the angular velocity of the lower leg with respect to the ground can be used to determine the walking velocity of an individual when the thigh and lower leg form a straight line. Second, when the aforementioned straight line is perpendicular to the ground (i.e., its pitch value = 0), the angular speed can be accurately converted to body speed. Third, for the purpose of
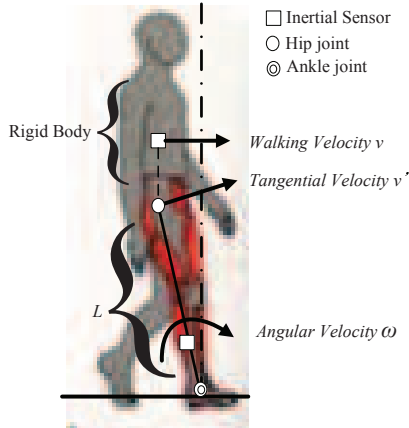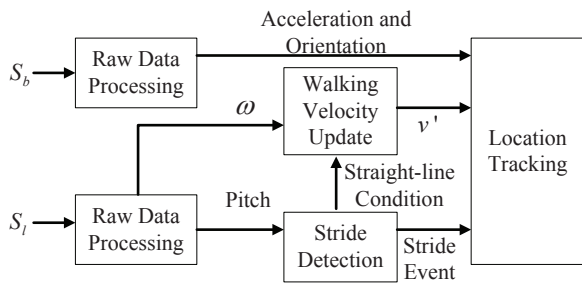
Fig. 1.   System model of of W-UPT.

Fig. 2.   Workflow of the W-UPT method.

Fig. 3.   (a) Five poses of a stride from two users and; (b) walking posture versus pitch angles.

trajectory tracking, mounting an inertial sensor on the upper body incurs fewer positioning errors than mounting one on the lower leg. A prototype was developed to verify these claims.

The remainder of this paper is organized as follows. A model of the proposed system is presented in Section II. A number of implementations and experimental results are presented in Section III. Conclusions are drawn in Section IV.
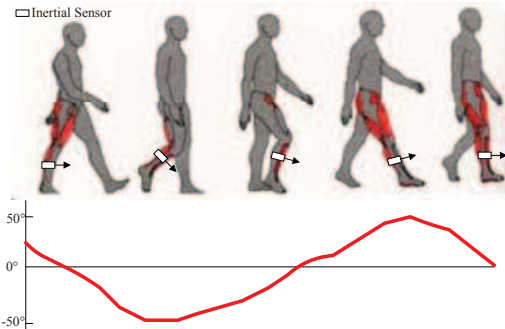
II. SYSTEM MODEL

An inherent limitation of most PDR solutions is the problem of error drifting. Z-UPT deal with this problem by resetting the velocity of the user to zero, when it detects slippage of the sole on the floor. This approach requires that the sensor be mounted on the bottom of the foot, which inevitably leads to excessive vibration and error in the measurement of orientation. To alleviate this problem, we propose a W-UPT solution, involving the use of two inertial sensors S_l and S_b mounted on the lower leg and upper body of the user, respectively. S_b measures the velocity of the user and is re-calibrated every stride according to the angular velocity measured by S_l.

Our system model is shown in Figure 1. Sensor S_b is attached to the user's upper body and sensor S_l attached to the user's lower leg. In every stride, the sole touches the ground for a short period of time. During this period, we observe that
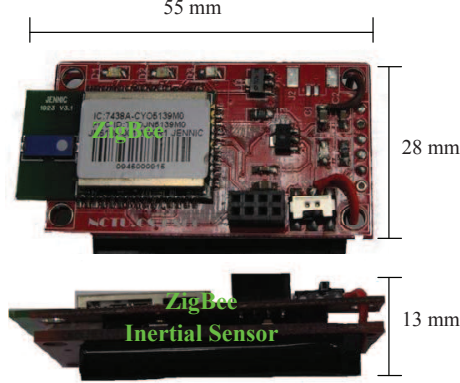
the thigh and lower leg gradually form a straight line, which we call the *straight-line condition*. When this condition is met, the horizontal component of the tangential velocity over the hip joint is equal to that of the body (because at this point they merge into a single rigid entity). Let L be the length of the leg, v be the velocity of the upper body, v' be the tangential velocity of the hip joint, and ω be the angular velocity of the lower leg. According to Newton's Second Law, we assume that the following equality holds when the thigh and the lower leg from a straight line:
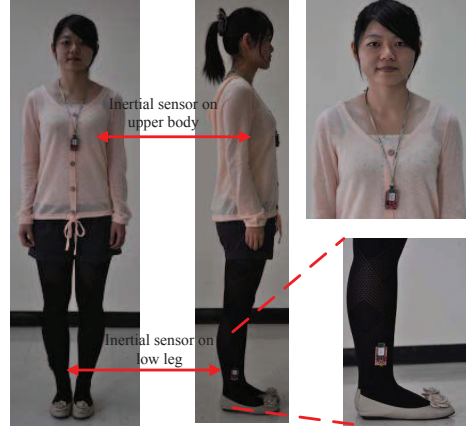
$$v' = \omega \times L. \tag{1}$$

Note the tangential velocity and the angular velocity only refer to their magnitudes (i.e., no direction is involved). Because L is given and ω can be measured by S_l, it is possible to derive v'. The projection of v' on the ground is equal to v. It follows that when the pitch value is zero, we have

$$v = v'. \tag{2}$$

Therefore, we use v' to calibrate the value of v measured by S_b when the pitch value of S_l is zero for every stride. (Note that v is indirectly derived by the accelerometer of S_b.)

Fig. 4. (a) Inertial sensor; (b) sensors mounted on the upper body and the lower leg.

Figure 2 shows the workflow of W-UPT. S_b comprises a triaxial accelerometer, a triaxial e-compass, and a triaxial gyro sensor. S_l consists of a triaxial e-compass and a triaxial gyro sensor. The Raw Data Processing block for S_b extracts information related to acceleration and orientation from the sensing data of S_b. The Raw Data Processing block for S_l extracts pitch and angular velocity ω from the sensing data of S_l. The Stride Detection block uses pitch to identify two events: stride events and straight-line conditions. Upon the occurrence of a straight-line condition, the Walking Velocity Update block computes current v' and report this velocity to the Location Tracking block. The Location Tracking block then calibrates its v as v' and computes the length and direction of the stride by integrating the acceleration sensed from S_b over time, until the next stride event is reported. At the end of this process, the sum of each stride length and its orientation is considered the trajectory of the user.

A. Stride Detection Block

The most critical issue in W-UPT is the identification of a suitable point from which to calibrate the walking velocity of the user. Consider the snapshots of five postures in the strides of two users in Figure 3(a). In both cases, during the fifth posture, the pitch angle gradually decreases from a positive value to a negative value. At the point when this value becomes zero, the straight-line condition becomes true. This is also evidenced by our real measurements in Figure 3(b). (Note that reference [13] also describes how angular rates can more accurately capture strides than the use of accelerations.) When the straight-line condition is detected, a trigger is sent to both the Walking Velocity Update block and the Location Tracking block.

B. Walking Velocity Update Block

When a report of straight-line conditions is sent to the Walking Velocity Update block, the angular velocity ω of S_l is used to determine v' by Eq. (1). Note that to obtain a smooth

value of ω, a number of filtering techniques may be used. In this case, we adopted a Low-Pass filter [15] to achieve this goal.

C. Location Tracking Block

When a stride event is reported to the Location Tracking block, it begins computation of the length and direction of the following stride, by integrating the acceleration and orientation of S_b during the current stride, until the next stride event is reported. Let a_t be the acceleration measured by S_b at time t, t_i be the time when the ith stride is reported, and t_{i+1} be the time when the $(i + 1)$th stride is reported. Then the walking velocity v_T of the user at time T, $t_i < T < t_{i+1}$, on the x-axis can be derived by

$$v_T^{(x)} = v_{t_i}^{(x)} + \int_{t_i}^{T} a_t^{(x)} dt. \tag{3}$$

Here we use superscript (x) to indicate the component on the x-axis. Note that v_{t_i} is updated by the value of v' when the ith stride is detected. The displacement d_T of the user at time T, $t_i < T < t_{i+1}$, on the x-axis can be derived by

$$d_T^{(x)} = \int_{t_i}^{T} v_T^{(x)} dt. \tag{4}$$

Similarly, the walking velocity of the user at time T, $t_i < T < t_{i+1}$, on the y-axis can be derived by

$$v_T^{(y)} = v_{t_i}^{(y)} + \int_{t_i}^{T} a_t^{(y)} dt. \tag{5}$$

The displacement d_T of the user at time T, $t_i < T < t_{i+1}$, on the y-axis can be derived by

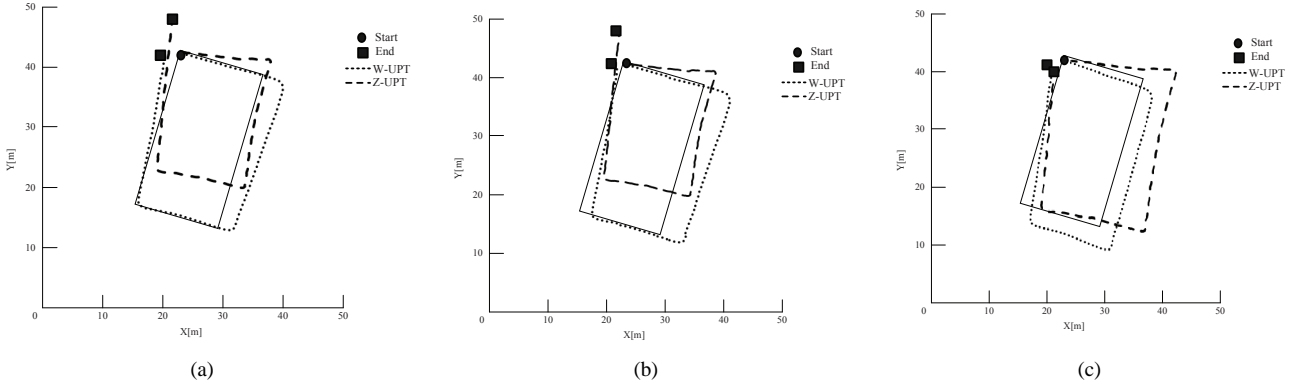$$d_T^{(y)} = \int_{t_i}^{T} v_T^{(y)} dt. \tag{6}$$

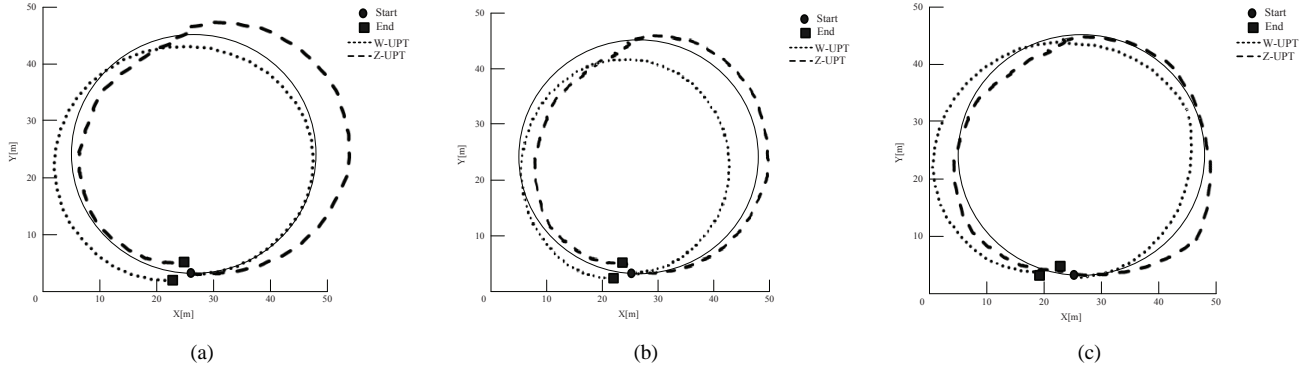Fig. 5. The trajectories along the rectangular path from (a) user A, (b) user B, and (c) user C.

Fig. 6. The trajectories along the circular path from (a) user A, (b) user B, and (c) user C.

For the $(i+1)$th stride, its displacements on the $x-$ and the y-axis can be measured as

$$D_i^x = \lim_{T \to t_{i+1}} d_T^{(x)}, \tag{7}$$

$$D_i^y = \lim_{T \to t_{i+1}} d_T^{(y)}. \tag{8}$$

The sum of n displacement vectors is considered the user's trajectory $\left(\sum_{i=1..n} D_i^{(x)}, \sum_{i=1..n} D_i^{(y)} \right)$. Note that the accelerations measured by S_b can be decomposed into z (vertical) and xy (horizontal) components. They are relative to the sensor itself. Therefore, it is necessary to transform relative accelerations into absolute accelerations. Let ψ, θ, and ϕ be the yaw, pitch, and roll values, $[a_x, a_y, a_z]$ be the accelerations in the x, y, and z directions, and $[a_n, a_e, a_d]$ be the accelerations in the north, east, and ground directions. We have the following relationship:

$$\begin{bmatrix} a_n \\ a_e \\ a_d \end{bmatrix} = R_x(\phi) R_y(\theta) R_z(\psi) \times \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix}, \tag{9}$$

where the rotation matrices are defined as

$$R_x(\phi) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi & \cos\phi \end{bmatrix}, \tag{10}$$

$$R_y(\theta) = \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{bmatrix}, \tag{11}$$

$$R_z(\phi) = \begin{bmatrix} \cos\phi & -\sin\phi & 0 \\ \sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{12}$$

III. SYSTEM IMPLEMENTATION AND EXPERIMENTAL RESULTS

A. Implementation of the System

In this study, users are equipped with two inertial sensors fabricated in our laboratory, as shown in Figure 4(a). The dimensions of the inertial sensors were 64 mm × 90 mm × 25 mm, with a weight of 60 grams. The inertial sensors provide triaxial accelerations in the range of ±5 g, the triaxial magnetic fields are in the range of ±1.2 Gauss, and the rate of rotation is in the range of 300° per second. The sampling rate of these readings was set no higher than 350 Hz. The sensors also provide orientation in Euler angle (pitch, roll, yaw) but

	User A	User B	User C
W-UPT with the rectangular path	2.38	1.90	2.61
W-UPT with the circular path	3.57	2.85	5.95
Z-UPT with the rectangular path	6.67	6.19	3.54
Z-UPT with the circular path	1.78	2.14	3.09

TABLE I
END DISTANCE ERRORS IN METERS.

at a frequency not exceeding 100 Hz. The inertial sensors communicated with the handheld device via an RS-232 or RS-485 interface. The optional communication speeds were 19.2, 38.4 and 115.2 kBaud. The inertial sensors communicated with each other via a UART interface and ZigBee protocol. Figure 4(b) shows an inertial sensor mounted on the lower leg of the user and another sensor mounted on the upper body.

B. Experimental Results

To verify our results, we performed several experiments in a sensing field $50m \times 50m$. In every case, the speed of the user was set around 1 m/sec. The first roaming path was a rectangle $28m$ in length and $15m$ in width. The second roaming path was a circle with a diameter of $40m$. Figure 5 and Figure 6 show the trajectories of three users using the W-UPT and Z-UPT methods. The dots indicate the initial positions and the small squares indicate the end positions. The W-UPT method was closer to the original shape than the Z-UPT method. Table I compares the total distance errors of W-UPT with those of Z-UPT following various roaming paths. Although the end positions of Z-UPT method are closer to the initial position than W-UPT method in the circular path, the trajectories of W-UPT method are closer to the original shape.

IV. CONCLUSIONS

This paper proposed a self-calibrating approach to PDRs using two inertial sensors mounted on a pedestrian. Sensor S_b is attached to the upper body and sensor S_l is attached to the lower leg. We also introduced a novel concept called "Walking Velocity Update", in which sensor S_l is used to determine a suitable point at which to calibrate the walking velocity of the user. The other sensor, S_b, tracks the velocity and orientation. For each stride, the W-UPT extracts pitch and angular velocity ω from the sensing data of S_l, using the pitch value to identify two events: stride events and straight-line conditions. Upon the occurrence of the straight-line condition, the W-UPT calibrates its walking velocity according to angular velocity. It also computes the stride length and direction by integrating the acceleration data from S_b to the point at which the following stride event is reported. Finally, the sum of each stride length and its orientation is considered the trajectory of the user. In our experiments, the W-UPT method proved superior to the Z-UPT method.

ACKNOWLEDGEMENT

REFERENCES

[1] E. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," *Computer Graphics and Applications, IEEE*, vol. 25, no. 6, pp. 38 – 46, 2005.

[2] L. Ojeda and J. Borenstein, "Personal dead-reckoning system for gps-denied environments," in *Safety, Security and Rescue Robotics, 2007. SSRR 2007. IEEE International Workshop on*, 2007, pp. 1 –6.

[3] S.-P. Kuo, S.-C. Lin, B.-J. Wu, Y.-C. Tseng, and C.-C. Shen, "GeoAds: A Middleware Architecture for Music Service with Location-Aware Advertisement," in *IEEE Int'l Conf. on Mobile Ad-hoc and Sensor Systems (MASS)*, 2007.

[4] C.-C. A. Lo, T.-C. Lin, Y.-C. Wang, Y.-C. Tseng, L.-C. Ko, , and L.-C. Kuo, "Using intelligent mobile devices for indoor wireless location tracking, navigation, and mobile augmented reality," in *IEEE VTS Asia Pacific Wireless Commun. Symposium (APWCS)*, 2010.

[5] D. Niculescu and B. Nath, "Ad Hoc Positioning System (APS) Using AOA," in *IEEE INFOCOM*, vol. 3, 2003, pp. 1734–1743.

[6] M. Addlesee, R. Curwen, S. Hodges, J. Newman, P. Steggles, A. Ward, and A. Hopper, "Implementing a Sentient Computing System," *Computer*, vol. 34, no. 8, pp. 50–56, 2001.

[7] A. Savvides, C.-C. Han, and M. B. Strivastava, "Dynamic Fine-Grained Localization in Ad-Hoc Networks of Sensors," in *ACM/IEEE MOBICOM*, 2001, pp. 166–179.

[8] J. Zhou, K.-K. Chu, and J.-Y. Ng, "Providing location services within a radio cellular network using ellipse propagation model," in *Advanced Information Networking and Applications, 2005. AINA 2005. 19th International Conference on*, vol. 1, march 2005, pp. 559 – 564 vol.1.

[9] P. Bahl and V. N. Padmanabhan, "RADAR: An In-building RF-based User Location and Tracking System," in *IEEE INFOCOM*, vol. 2, 2000, pp. 775–784.

[10] J. J. Pan, J. T. Kwok, Q. Yang, and Y. Chen, "Multidimensional Vector Regression for Accurate and Low-Cost Location Estimation in Pervasive Computing," *IEEE Trans. on Knowledge and Data Engineering*, vol. 18, no. 9, pp. 1181–1193, 2006.

[11] S.-P. Kuo and Y.-C. Tseng, "A Scrambling Method for Fingerprint Positioning Based on Temporal Diversity and Spatial Dependency," *IEEE Trans. on Knowledge and Data Engineering*, vol. 20, no. 5, pp. 678–684, 2008.

[12] C.-M. Su, J.-W. Chou, C.-W. Yi, Y.-C. Tseng, and C.-H. Tsai, "Sensor-aided personal navigation systems for handheld devices," in *Proceedings of the 2010 39th International Conference on Parallel Processing Workshops*, ser. ICPPW '10. Washington, DC, USA: IEEE Computer Society, 2010, pp. 533–541. [Online]. Available: http://dx.doi.org/10.1109/ICPPW.2010.78

[13] X. Yun, E. Bachmann, H. Moore, and J. Calusdian, "Self-contained position tracking of human movement using small inertial/magnetic sensor modules," in *Robotics and Automation, 2007 IEEE International Conference on*, 2007, pp. 2526 –2533.

[14] S. Shin, C. Park, J. Kim, H. Hong, and J. Lee, "Adaptive step length estimation algorithm using low-cost mems inertial sensors," in *Sensors Applications Symposium, 2007. SAS '07. IEEE*, 2007, pp. 1 –5.

[15] A. Jimenez, F. Seco, C. Prieto, and J. Guevara, "A comparison of pedestrian dead-reckoning algorithms using a low-cost mems imu," in *Intelligent Signal Processing, 2009. WISP 2009. IEEE International Symposium on*, aug. 2009, pp. 37 –42.