Reduction of False Alarm Signals for PIR Sensor in Realistic Outdoor Surveillance

Sang Gi Hong, Nae Soo Kim, and Whan Woo Kim

A passive infrared or pyroelectric infrared (PIR) sensor is mainly used to sense the existence of moving objects in an indoor environment. However, in an outdoor environment, there are often outbreaks of false alarms from environmental changes and other sources. Therefore, it is difficult to provide reliable detection outdoors. In this paper, two algorithms are proposed to reduce false alarms and provide trustworthy quality to surveillance systems. We gather PIR signals outdoors, analyze the collected data, and extract the target features defined as window energy and alarm duration. Using these features, we model target and false alarms, from which we propose two target decision algorithms: window energy detection and alarm duration detection. Simulation results using real PIR signals show the performance of the proposed algorithms.

Keywords: PIR sensor, target detection, false alarm reduction, window energy, alarm duration.

Manuscript received Apr. 9, 2012; revised July 23, 2012; accepted Sept. 13, 2012.

This work was supported by the Dual Use Technology program of DUTC, South Korea [Surveillance and Reconnaissance Sensor Network Development].

Sang Gi Hong (phone: +82 42 860 1795, sghong@etri.re.kr) and Nae Soo Kim (nskim@etri.re.kr) are with the IT Convergence Technology Research Laboratory, ETRI, Daejeon, Rep. of Korea.

Whan Woo Kim (wwkim@cnu.ac.kr) is with the Department of Electrical and Computer Engineering, Chungnam National University, Daejeon, Rep. of Korea.

http://dx.doi.org/10.4218/etrij.13.0112.0219

I. Introduction

Wireless sensor networks (WSNs) are being applied in several areas, including environmental and structural monitoring, instruments and measurements, military surveillance, precision agriculture, and intelligent transport systems [1]-[5]. Of these, surveillance services focus on perceiving an unknown body in motion using multiple sensors through signal processing techniques.

To provide reliability in a system, it is important to select optimal sensors for system operations and develop algorithms for wireless networking and signal processing. However, there are certain problems in operating surveillance with multiple sensors in an outdoor environment, such as false alarms.

As a sensor for measuring infrared radiation from a moving target within its field of view, a passive infrared or pyroelectric infrared (PIR) sensor is generally applied to motion detection applications. If a moving object exists in front of a sensor, then the sensor measures the difference in temperature between this object and the background environment using pyroelectric cells and generates detection signals.

While a PIR sensor can easily be used in diverse applications, it is vulnerable to sporadic sensing from changes in the environment. The main causes of false alarms include direct exposure to sunlight, headlights, and other light sources. In addition, a sudden change of temperature in the detection field from an inflow of warm or cold air from a heating ventilation or air conditioning system is also a possible cause of false alarms.

Although a PIR sensing element combined with various lens shapes is used to minimize false alarms, improve the detection performance, and provide different types of detection patterns, some limitations still exist in reducing false alarms [6]. In particular, the application of a PIR sensor outdoors is difficult owing to changes in ambient temperature and environmental conditions. Thus, it is necessary to develop a signal processing algorithm that is adaptive to environmental changes.

There have been many studies for this purpose. *A Line in the Sand*, *ExScal*, and *VigilNet* are well-known surveillance projects using WSNs to reduce environmental false alarms. These projects calculated frequency characteristics of moving objects and environmental noises and implemented algorithms for noise reduction and target detection [7]-[10]. Frequency-based processing is a general and effective way to detect and classify objects using the original signals. However, it requires relatively complex calculations to apply to a resource-constraint processor.

Recently, multisensor fusion architectures have been studied to develop low-power unattended ground sensor systems invulnerable to false alarms [11]. Nevertheless, reducing false alarms using a single PIR sensor is still fundamental to basic signal processing.

This paper proposes two PIR processing algorithms to reduce false alarms and provide reliable performance for moving-object detection outdoors. These algorithms are based on the statistical characteristics of false and target alarms featured by *window energy* and *alarm duration*. The suggested algorithms aim at light-weight processing on a resource-constrained processor widely used in wireless sensor networks.

This paper is organized as follows. Section II briefly reviews the *binary-hypothesis Neyman-Pearson detector*, generally used in signal detection research. In section III, two detection algorithms to reduce false alarms with a digital-type PIR sensor are proposed. The first one is a modified algorithm of energy-based detection that is generally used in signal processing. The second is an algorithm based on the duration characteristics of false alarms and target signals. In section IV, we show the simulation results of the proposed algorithms and their performances through Gaussian modeling. Finally, section V offers some concluding remarks and a discussion of further studies.

II. Mathematical Background

Here, we introduce the binary-hypothesis Neyman-Pearson detector, a simple but effective algorithm that is widely used to classify signals over communication channels [12], [13]. This detector is generally used as a criterion or classifier for a Gaussian distribution signal with a mean of μ and variance of σ^2 to make a decision between two hypotheses, one being noise (H_0) and the other the signal of interest (H_1). Hypotheses H_0 and H_1, respectively referred to as a null hypothesis and an alternative hypothesis, are symbolically represented as

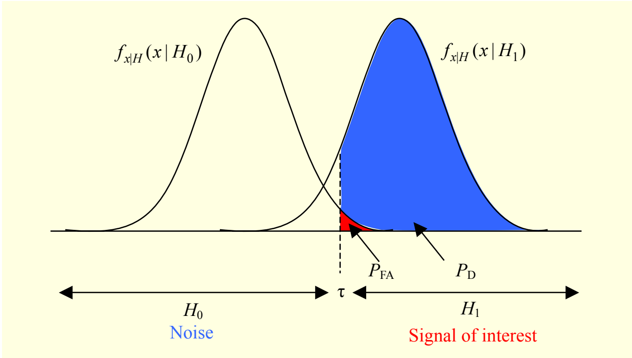

Fig. 1. Concept of binary-hypothesis Neyman-Pearson detector.

$$\begin{aligned} H_0 &: x = n, \\ H_1 &: x = s + n. \end{aligned} \tag{1}$$

This detector determines the true hypothesis among two hypotheses after comparing with threshold τ:

$$\begin{cases} H_0 & \text{if} \ \ x \le \tau, \\ H_1 & \text{if} \ \ x > \tau. \end{cases} \tag{2}$$

If we assume that noise and interest signals have Gaussian distributions (0, 1^2) and (1, 1^2), respectively, the probability density function (PDF) of each can be defined as

$$f_{x|H}(x|H_0) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}x^2), \tag{3}$$

$$f_{x|H}(x|H_1) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}(x-1)^2. \tag{4}$$

As illustrated in Fig. 1, the decision of H_1 when H_1 is true is called the probability of detection and is denoted by P_D. However, the determination of H_1 even when H_0 is true can be thought of as a false alarm. It is represented as the probability of a false alarm, and its indication is P_{FA}. We can calculate P_D and P_{FA} as in (5) and (6) by fixing the threshold to τ.

$$P_D = P(H_1; H_1) = \int_\tau^\infty \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}(x-1)^2)dx. \tag{5}$$

$$P_{FA} = P(H_1; H_0) = \int_\tau^\infty \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}x^2)dx. \tag{6}$$

In general, sensor signals are subject to change based on the environment around the sensors, and the signal statistics can also be changed. Therefore, the rate of false alarms becomes inconstant if a fixed threshold is used. To make the probability of a false alarm constant, it is necessary to apply an adaptive algorithm including feedback parameters that allow compensating for the environmental changes. This is a constant false alarm rate detector.

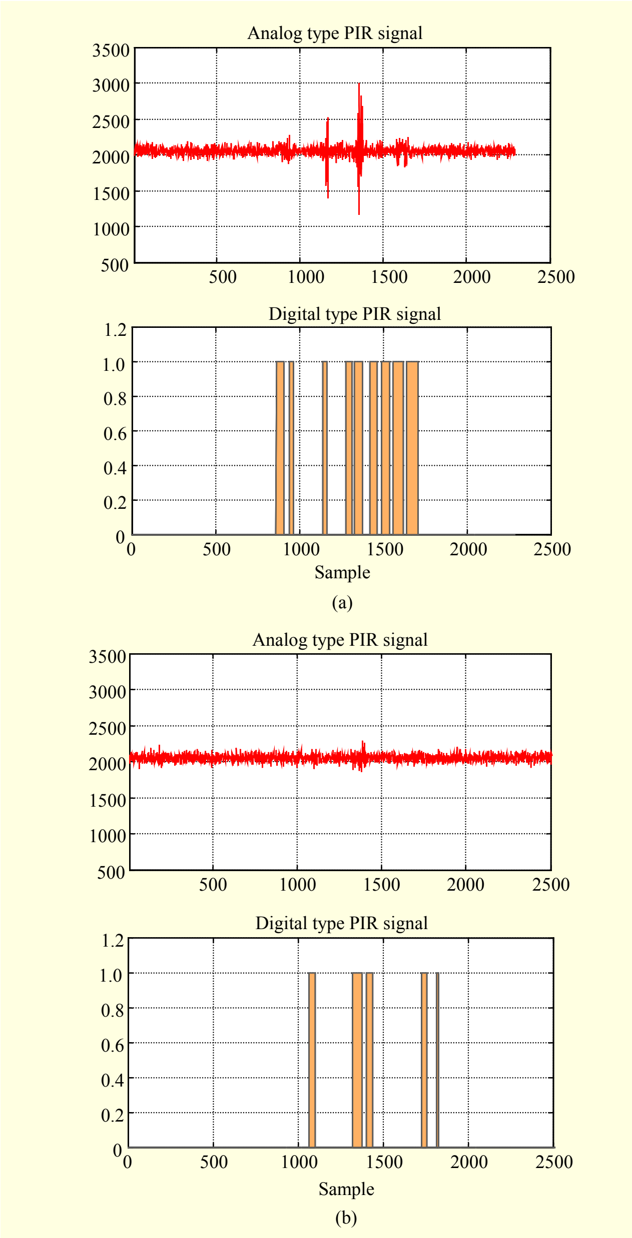

Fig. 2. Comparison of performances between analog and digital PIR sensors for detecting walking human at distances of (a) 5 m and (b) 7 m.

In addition to an adaptive algorithm, since it is impossible to improve both probabilities simultaneously, we propose an algorithm to maximize P_D for a given $P_{FA}=\alpha$ or minimize P_{FA} for a given $P_D=\beta$ in the target detection using PIR sensors.

III. Proposed Algorithms

1. Digital Output PIR Sensor

The projects mentioned in the previous section used analog output PIR sensors. Instead, we use a digital output PIR, that is, AMN44121, made by Panasonic, Inc. It includes 80 sensing cells and is able to support a 110° horizontal and 93° vertical detection range [14].

Figure 2 shows sample detection signals gathered with an analog sensor (AMN24111) and digital sensor (AMN44121) applied to a real target. We collect the sensing data of a human passing by the front of the sensors under hot (31ºC) and clear (windless) conditions.

As presented in Fig. 2, we can estimate that two types of sensors have a similar detectable distance. Generally, an analog sensor requires extra circuits or signal processing techniques to create a detection signal, but it can improve the detection performance by using additional embedded circuits, such as filters and amplifiers. On the other hand, the digital PIR sensor has a comparator circuit inside of the sensor and thus does not require additional circuits to process sensor signals for detection. As a result, the digital PIR sensor is more appropriate for a resource-constrained processor requiring lightweight processing. For this reason, we select a digital PIR sensor to employ in our study, aiming at sensor network applications.

2. Problems and Assumptions

Figure 3 shows sample signal patterns for three consecutive cars moving near sensors, which are acquired using a magnetometer and three digital-type PIR sensors. The first graph is a magnetic signal pattern of the magnetic distortion caused by three cars passing in front of the magnetometer. The second is a noiseless target signal, and the third shows a noise-only signal gathered using a PIR sensor. Finally, the last graph displays a mixed target and noise PIR signal. As shown in Fig. 3, a PIR sensor can produce three different types of target detection patterns.

The statistical sensing characteristics of a PIR sensor placed outdoors for object detection can be summarized as follows.

a) It shows changes in the false alarm rate owing to changes in the environment, such as sunlight, shadows, and light reflection, which are types of environmental noise.

b) The duration of an alarm (the length of one rectangular pulse) from a target is relatively longer than an alarm from noise.

c) The statistical characteristics during a defined period are uniform unless the environmental conditions change abruptly when there are no moving objects. When a target is passing near a sensor, the density of the energy (the average energy) in this region is higher than that of other regions.

We suggest PIR signal processing algorithms reflecting the described characteristics of a) through c). These algorithms include parameter extraction, statistical modeling, false alarm filtering, target detection, and a performance analysis.

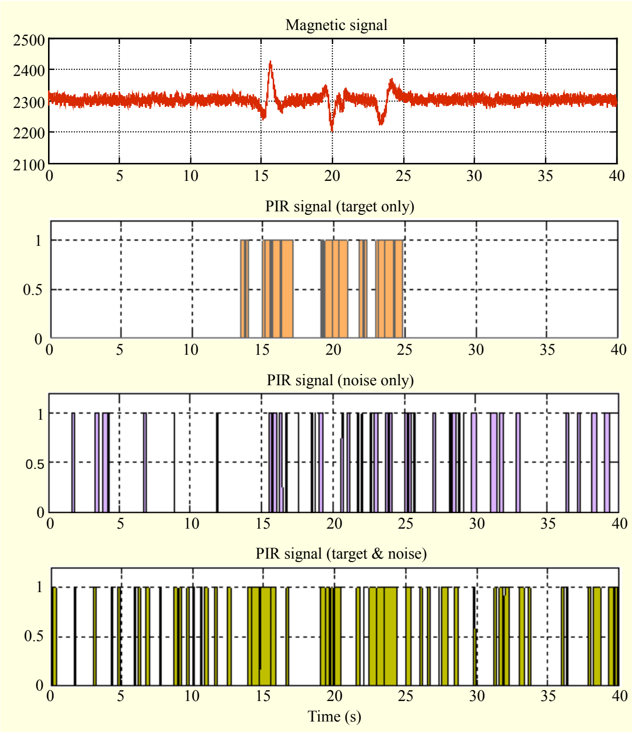

Fig. 3. Sample patterns of target detection with PIR sensor (3 cars in a row) [15].

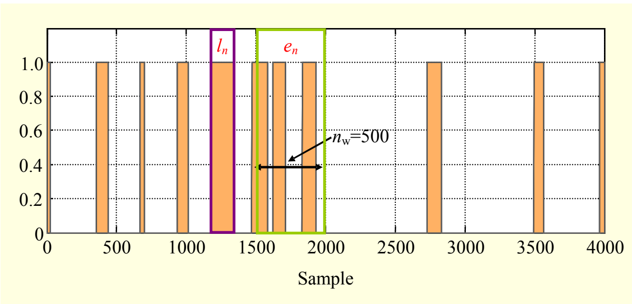

Fig. 4. Sample PIR signal and main parameters.

In this paper, we propose two main parameters, defined as window energy and alarm duration, in the suggested algorithms. The window energy denoted by e_n is defined as the total summation of PIR signal values x_i for a fixed period, window size n_w. For example, if we set the window size n_w to 500 samples, the window energy can be the total number of sensing values with 1 in each window, as shown in Fig. 4.

$$e_n = \sum_{i=(n-1)*n_w+1}^{n*n_w} x_i, \qquad n=1, 2, 3. \tag{7}$$

We define the alarm duration l_n as the length of each alarm pulse.

3. Window Energy Detection Algorithm

The energy detection algorithm is generally applied in signal processing using analog-type PIR sensors. Our modified version, the window energy detection (WED) algorithm, uses digital-type PIR sensors. As shown in Fig. 5, the algorithm determines the existence of a moving object after a comparison of the current energy to the threshold calculated using the average energy (m_e) and its standard deviation (σ_e).

The details of this algorithm are as follows.

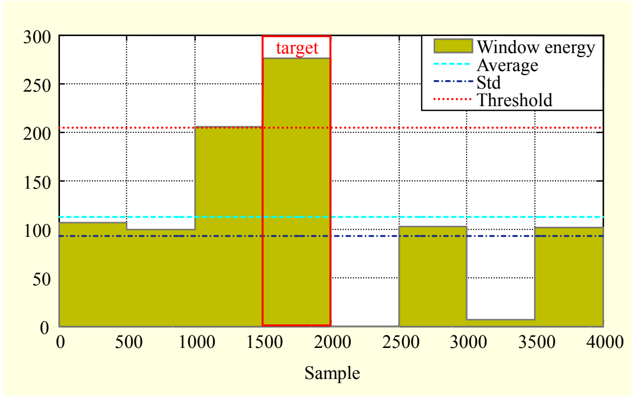

Fig. 5. Example of applying WED algorithm.

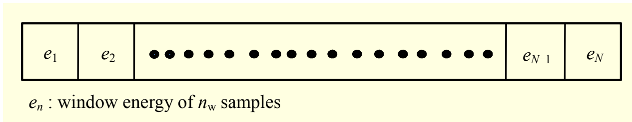

Fig. 6. Window energy queue for false alarms.

A. Initialization (Observation)

This is the first step of the proposed algorithm and is used to calculate the initial threshold value. For the initial period of time in which only false alarms exist, without the alarm signals caused by a moving object, we gather PIR signals and compute the threshold based on the proposed *window energy queue* comprised of N elements storing recent window energy values, as illustrated in Fig. 6. Each energy value is calculated after receiving n_w (window size) signals using (7). After computing and storing all elements, the average and standard deviations are calculated. At the end of the initial phase, a threshold value is determined considering the system performances. If we fix the sampling time as t_s, the total initial time becomes $N*n_w*t_s$.

As shown in Fig. 5, we set the threshold given by (8) as an example. Here, m_e and σ_e are the average and standard deviation of queue elements, respectively.

$$\tau_e = m_e + \sigma_e. \tag{8}$$

B. Acquisition (Sampling and Storing)

This process is used to obtain PIR signals for a defined period of n_w with a sampling time of t_s.

C. Processing (Parameter Extraction)

The processing step is used to extract the detection parameter (here, window energy e_n) by counting the number of samples having a value of 1.

D. Decision (Target Detection)

The decision process is used to determine whether the current window energy is caused by a moving object by comparing it to the current threshold, τ_e. If the current energy is higher than the threshold, the result is a target; otherwise, it is a false alarm.

E. Adaptation (Queue and Threshold Update)

False alarm characteristics show irregular patterns under the influence of environmental changes. For this reason, the adaptation process used to update the queue element and threshold using new statistical characteristics is necessary for maintaining consistent detection performances. This step includes a queue and threshold update.

If the decision is not a target, the oldest queue element is removed and updated with the current window energy, e_n. On the contrary, the queue is not refreshed in the case of the existence of a target.

Figure 5 shows an example of applying the WED to samples of the false alarm signals shown in Fig. 4. When we simulate the proposed algorithm using Matlab, we find that most false alarms are reduced, with the exception of partial false alarms of 1,500 to 2,000 in duration, in which the window energy is greater than the threshold.

4. Alarm Duration Detection Algorithm

The second algorithm we suggest is the alarm duration detection (ADD) algorithm. Unlike other frequency domain approaches, we propose time domain approaches considering the statistical characteristics of the alarm duration.

Figure 7 shows a sample illustration of false alarm reduction when applying the proposed algorithm. This algorithm determines the presence of a moving object after a comparison of current alarm duration with the threshold (τ_l) computed using the average duration (m_l) and its standard deviation (σ_l) acquired from each pulse.

The procedure of this algorithm is described below.

A. Initialization (Observation)

The initialization step is used to compute the initial threshold using false alarm signals caused by environmental noises only, without the existence of a moving target, through calculating m_l and σ_l for a fixed period.

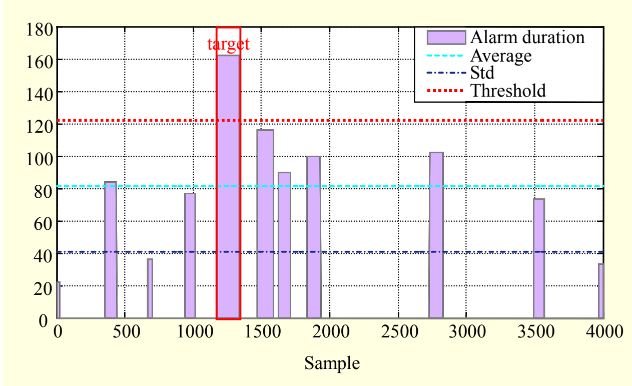

Fig. 7. Example of applying ADD algorithm.

For instance, as shown in Fig. 7, we set the threshold given by

$$\tau_l = m_l + \sigma_l. \tag{9}$$

B. Acquisition (Sampling and Storing)

This process is used to get PIR signals with a sampling time of t_s.

C. Processing (Parameter Extraction)

The processing step is used to extract the detection parameter (here, alarm duration l_n) by counting the number of samples within a pulse.

D. Decision (Target Detection)

The decision process is used to determine whether the current alarm duration l_n is representing a moving object by comparing it with the current threshold, τ_l. If the current duration is longer than the threshold, it is a target alarm; otherwise, it is a false alarm.

E. Adaptation (Threshold Update)

The characteristics of the alarm duration show irregular patterns under the influence of environmental changes. For this reason, an adaptation process to update the threshold with new statistical characteristics is necessary for maintaining consistent detection performances.

Figure 7 shows the results from carrying out the ADD algorithm for samples of false alarm signals. When we simulate the proposed algorithm with Matlab, we find that most false alarms are reduced except those between 1,000 and 1,500 in duration.

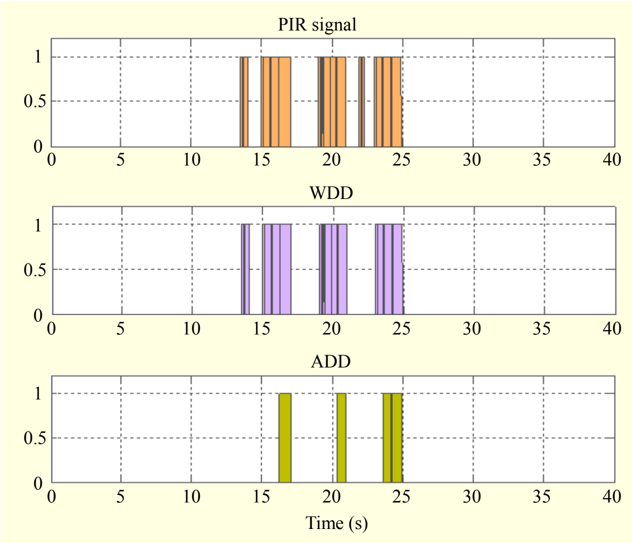

Fig. 8. Results of proposed algorithms applied under target-only condition.

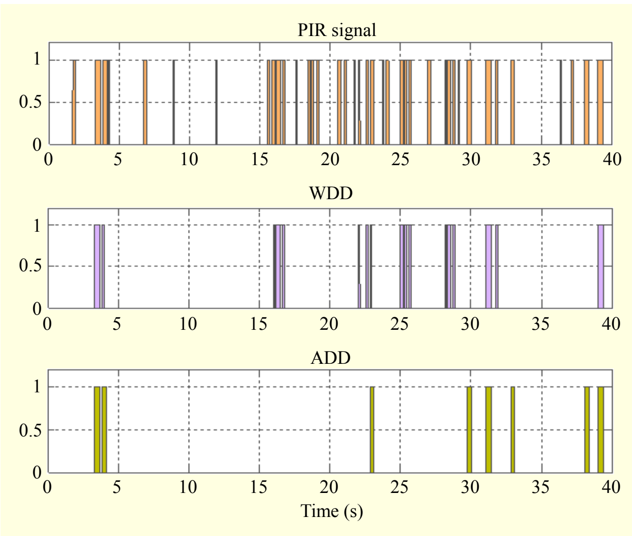

Fig. 9. Results of proposed algorithms applied under noise-only condition.

IV. Results and Performance Analysis

1. Results

The results from the proposed algorithms applied to filter false alarm signals for the three cases are illustrated in Figs. 8 through 10. Figure 8 shows a case in which only target alarms are caused by three consecutive cars moving past the PIR sensor. The second case is a situation in which only false alarms are produced by environmental changes, as described in Fig. 9. The results shown in Fig. 10 are the product of the coexistence of target and false alarms.

A summary of the performance comparison of the two algorithms derived from the above results is presented in Table 1.

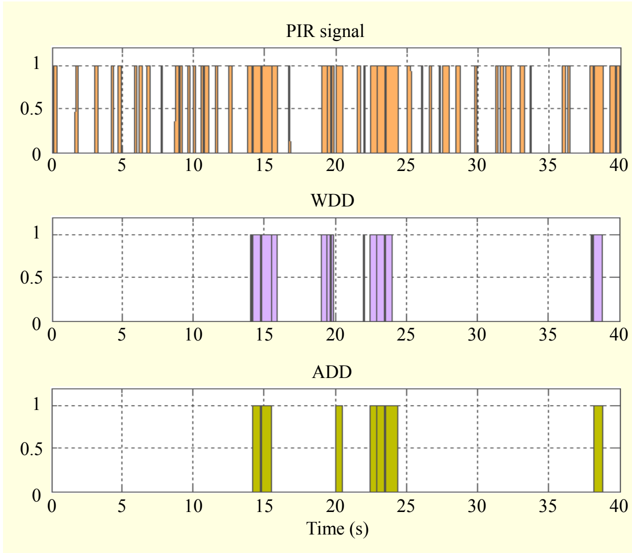

Fig. 10. Results of proposed algorithms applied under mixed condition.

Table 1. Performance comparison between two algorithms.

	WED	ADD
Strong points	-Disappearance of few or no target alarms within the target period -Better performance in detecting targets within the target period	-Better performance in reducing false alarms outside of the target period -Requires less resources, such as memory and computing power
Weak points	-Requires more memory for the energy queue -Poorer performance in reducing false alarms	-Disappearance of several target alarms within the target period -Poorer performance in detecting targets within the target period

2. Data Acquisition and Modeling

To create a statistical model with false and target alarms, we first gather real PIR signals in an outdoor sensor field and analyze the sensor data. We separately execute data acquisition experiments for the false alarms and target detection data using the system in [16].

The experimental conditions used to acquire false alarms are described next. We place sensor nodes in front of bushes at one-meter intervals (from 1 m to 5 m) on a cloudy, windy day and collect the data.

The results of a statistical analysis using the false alarm data are summarized in Table 2. As shown in Table 2, the alarm duration and window energy have a mean of 424.0 ms and 489.2 ms and a standard deviation of 219.1 ms and 248.8 ms,

Table 2. False alarm statistics.

		Total
Alarm duration (ms)	Avg.	424.0
	Std.	219.1
Window energy (ms)	Avg.	489.2
	Std.	248.8

Table 3. Target alarm statistics.

		Case 1	Case 2	Case 3
Alarm duration (ms)	Avg.	762.7	887.0	917.5
	Std.	214.5	137.9	211.7
Window energy (ms)	Avg.	808.7	836.7	839.4
	Std.	170.9	142.9	140.1

respectively.

We run the experiment three times for the target data outdoors and collect data for a human adult walking in parallel with a PIR at distances of 2 m, 5 m, 7 m, 10 m, and 15 m at normal speed. The respective weather conditions for each experiment are summarized as follows. The condition of the first case is a hot (31ºC) and windless day, the second is a clear (23ºC) and breezy day, and the last is a cool (12ºC) evening with a light wind.

Table 3 shows a summary of the statistical analysis based on the data from moving targets.

3. Performance Analysis

We apply the binary-hypothesis Neyman-Pearson detector to analyze the performance of the proposed algorithms using real PIR sensor data gathered in outdoor environments.

First, we establish the Gaussian probability distribution by calculating the statistical characteristics for the alarm duration and window energy of false alarms and those of moving objects, as described in Tables 2 and 3, respectively. We also compute the performance parameters, P_D and P_{FA}, from the cumulative distribution functions (CDFs) for the given conditions. The results of the performance are displayed in Figs. 11 and 12 and summarized in Table 4.

Table 4 shows the performance values from the proposed algorithms for two kinds of conditions with a fixed P_D of 90% and a P_{FA} of 10% for each experiment.

When we apply the WED algorithm to PIR signals, we can obtain a detection rate performance of about 57.9%, given a 10% false alarm rate, and a false alarm performance of about 25.5%, given a 90% detection rate. We can respectively improve the performances to 90.7% and 9.6% by applying the ADD algorithm.

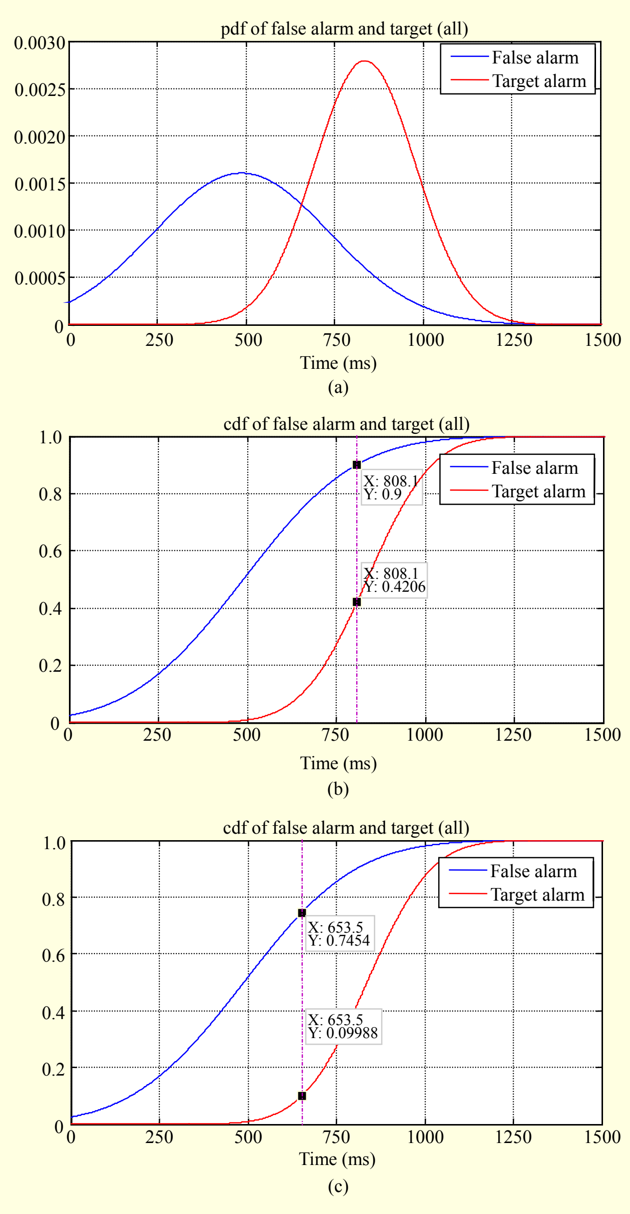

Fig. 11. Performance analysis of WED representing (a) PDFs for window energies, (b) probability of target detection for P_{FA}=10%, and (c) probability of false alarm for P_D=90% [15].

V. Conclusion

The practical uses of WSN technologies have increased in the areas of automated surveillance and security. In particular, detecting and classifying an unidentified object with multiple sensors are core technologies in this application field. To improve the reliability of such a system, it is essential to

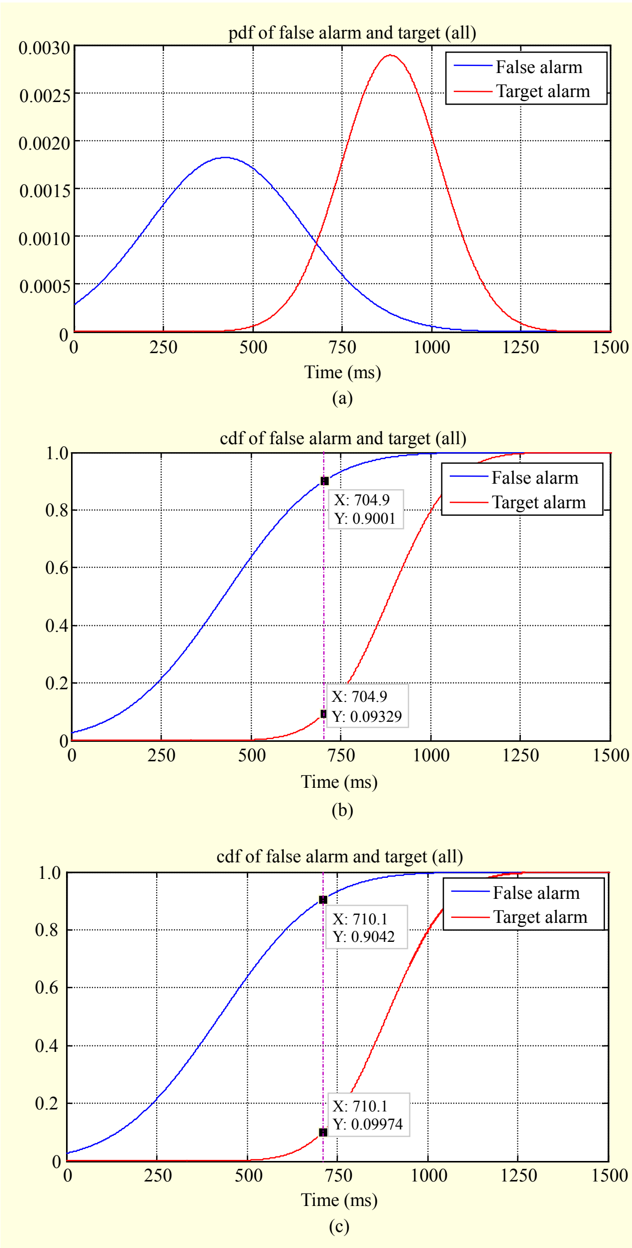

Fig. 12. Performance analysis of ADD representing (a) PDFs for alarm durations, (b) probability of target detection for P_{FA}=10%, and (c) probability of false alarm for P_D=90%.

increase the detection performance. In other words, enhancing the target detection rate and reducing the false alarm rate are key techniques for this purpose. However, environmental changes around a sensor produce false alarms such that the reliability of the performances declines.

In this paper, improved algorithms for detecting a moving target and reducing false alarms were proposed and their performances analyzed. We discussed the operation principles of a PIR sensor and its characteristics and explained various signal processing algorithms to reduce false alarms caused by environmental changes. We proposed two kinds of signal processing algorithms for detecting moving targets and reducing false alarms; one is the WED algorithm, and the other is the ADD algorithm. We analyzed PIR signals gathered under various environmental conditions, created statistical modeling, and computed the performances from the suggested algorithms. By applying the WED algorithm, we could obtain a detection rate of about 57.9%, given a 10% false alarm rate, and a false alarm rate of about 25.5%, given a 90% detection rate. In particular, we could increase the target detection rate to 90.7% and drop the false reduction rate to 9.6% by applying the ADD algorithm.

Table 4. Summary of performance analysis for proposed algorithms.

	WED		ADD	
	given P_D (90%)	given P_{FA} (10%)	given P_D (90%)	given P_{FA} (10%)
	P_{FA}	P_D	P_{FA}	P_D
Case 1	34.3%	50.1%	42%	58%
Case 2	25.5%	57.9%	9.6%	90.7%
Case 3	24.6%	58.8%	17.4%	82.4%

Nevertheless, since environmental conditions around sensors are changeable, we must study an adaptive threshold method that can be implemented in a resource-constrained processor more efficiently. In addition, as described in this paper, the two proposed algorithms each have weak and strong points. Therefore, to obtain further improved performances, we will also find ways to integrate the two algorithms.

References

[1] J.D. Lundquist, D.R. Cayan, and M.D. Dettinger, "Meteorology and Hydrology in Yosemite National Park: A Sensor Network Application," *Proc. IPSN, LNCS*, vol. 2634, 2003, pp. 518-528.

[2] A. Mainwaring et al., "Wireless Sensor Networks for habitat monitoring," *Proc. 1st ACM Int. Workshop Wireless Sensor Netw. Appl.*, Atlanta, GA, USA, Sept. 2002, pp. 88-97.

[3] N. Xu et al., "A Wireless Sensor Network for Structural Monitoring," *Proc. ACM Conf. Embedded Netw. Sensor Syst.*, Baltimore, MD, USA, Nov. 2004, pp. 13-24.

[4] S.J Hsu et al., "Development of Telemedicine and Telecare over Wireless Sensor Network," *Proc. Int. Conf. Multimedia Ubiquitous Eng.*, Busan, Rep. of Korea, Apr. 2008, pp. 597-604.

[5] Y. Zhang, X. Huang, and L. Cui, "Lightweight Signal Processing in Sensor Node for Real-Time Traffic Monitoring," *IEEE Int. Symp. Commun. Inf. Technol.*, Sydney, Australia, Oct. 2007, pp. 1407-1412.

[6] Fresnel Technologies Inc., "XX 1.2 GI 12 VX," product literature. http://www.fresneltech.com/pdf/XX1.2GI12VX.pdf
[7] A. Arora et al., "A Line in the Sand: A Wireless Sensor Network for Target Detection, Classification, and Tracking," *ACM J. Computer Netw.*, vol. 46, no. 5, Dec. 2004, pp. 605-634.
[8] A. Arora et al., "ExScal: Elements of an Extreme Scale Wireless Sensor Network," *Proc. IEEE Int. Conf. Embedded Real-Time Computing Syst. Appl.*, Hong Kong, China, Aug. 2005, pp. 102-108.
[9] T. He et al, "VigilNet: An Integrated Sensor Network System for Energy-Efficient Surveillance," *ACM J. Trans. Sensor Netw.*, vol. 2, no. 1, Feb. 2006, pp. 1-38.
[10] L. Gu et al., "Lightweight Detection and Classification for Wireless Sensor Networks in Realistic Environments," *ACM SenSys.*, San Diego, CA, USA, Nov. 2005, pp. 205-217.
[11] J.A. Hanson, K.L. McLaughlin, and T.J. Sereno, "A Flexible Data Fusion Architecture for Persistent Surveillance Using Ultra-Low-Power Wireless Sensor Networks," *Proc. SPIE*, vol. 8047, May 2011, 80470M.
[12] S.M. Kay, *Fundamentals of Statistical Signal Processing: Detection Theory*, Upper Saddle River, NJ: Prentice Hall, 1993.
[13] H.C. Lee and D.R. Halverson, "Design of Robust Detector with Noise Variance Estimation Censoring Input Signals over AWGN," *ETRI J.*, vol. 29, no. 1, Feb. 2007, pp. 110-112.
[14] Panasonic Corporation, "MP Motion Sensor (AMN2, 3, 4)," industrial literature. Available: http://pewa.panasonic.com/ assets/ pcsd/catalog/napion-catalog.pdf
[15] S.G. Hong et al., "Window Energy Detection for Unmanned Surveillance with PIR Sensor," *Proc. IEEE Int. Conf. Trust, Security Privacy Comput. Commun.*, June 2012, pp. 1543-1547.
[16] S.G. Hong et al., "Wireless Sensor Network Testbed for Real-time Sensor Monitoring," *3rd IARIA Int. Conf. Sensor Technol. Appl.* (*SENSORCOMM*), Athens, Greece, June 2009, pp. 486-489.

Sang Gi Hong received his BS and MS in electronic engineering from Pusan National University, Busan, Rep. of Korea, in 1997 and 1999, respectively. He is currently working toward his PhD in electronics engineering at Chungnam National University, Daejeon, Rep. of Korea. Since 2001, he has been with ETRI, Daejeon, Rep. of Korea, where he has been working on IT convergence technologies. His current research interests include sensor signal processing and IoT architecture.

Nae Soo Kim received his BS and MS in mathematics from Hannam University, Daejeon, Rep. of Korea, in 1985 and 1989, respectively. He received his PhD in computer engineering from Hannam University in 2001. After having worked for the Agency for Defense Development (ADD), Rep. of Korea, from 1976 to 1990, he joined ETRI, Daejeon, Rep. of Korea, in 1990 and was involved with the satellite communication and broadcasting system development projects until 2004. He worked as a project manager of several projects and also as a team leader. Since 2005, he has worked on RFID and wireless sensor networks at ETRI. He is currently the team leader of the IoT Architecture Research Team, which is researching and developing IoT/USN technologies.

Whan Woo Kim received his BS in electronics engineering from Seoul National University, Seoul, Rep. of Korea, in 1977, his MS from the University of Utah, Salt Lake City, UT, USA, in 1979, and his PhD from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Rep. of Korea, in 1988. Since 1980, he has been with the Division of Electrical and Computer Engineering at Chungnam National University, Daejeon, Rep. of Korea, where he is a professor. His current research interests include cable, digital broadcasting, and OFDM systems.