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.
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-constrained 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 $\mu$ and variance of $\sigma^2$ 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

$$H_0: x = n,$$
$$H_1: x = s + n. \quad (1)$$

This detector determines the true hypothesis among two hypotheses after comparing with threshold $\tau$:

$$\begin{cases} H_0 & \text{if } x \leq \tau, \\ H_1 & \text{if } x > \tau. \end{cases} \quad (2)$$

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

$$f_{x_H}(x | H_0) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} x^2\right), \quad (3)$$
$$f_{x_H}(x | H_1) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} (x-1)^2\right). \quad (4)$$

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 $\tau$.

$$P_D = P(H_1; H_1) = \int_{\tau}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} (x-1)^2\right) dx. \quad (5)$$
$$P_{FA} = P(H_1; H_0) = \int_{\tau}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} x^2\right) dx. \quad (6)$$

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 inconsistent 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.
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 (31°C) 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.
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.

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

We define the alarm duration $l_a$ 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 ($\sigma_e$).

The details of this algorithm are as follows.

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 $Nn_w*t_s$.

As shown in Fig. 5, we set the threshold given by (8) as an example. Here, $m_e$ and $\sigma_e$ 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
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, $\tau$. 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 ($\tau$) computed using the average duration ($m_l$) and its standard deviation ($\sigma_l$) 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 $\sigma_l$ for a fixed period.

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

$$\tau_l = m_l + \sigma_l.$$  (9)

B. Acquisition (Sampling and Storing)

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

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, $\tau_l$. 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.
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.

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.

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<tr>
<td></td>
<td>Total</td>
<td></td>
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<tr>
<td>Alarm duration (ms)</td>
<td>Avg.</td>
<td>424.0</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td>219.1</td>
</tr>
<tr>
<td>Window energy (ms)</td>
<td>Avg.</td>
<td>489.2</td>
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<tr>
<td></td>
<td>Std.</td>
<td>248.8</td>
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Table 3. Target alarm statistics.

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<th></th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
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<tr>
<td></td>
<td>Avg.</td>
<td>762.7</td>
<td>887.0</td>
</tr>
<tr>
<td>Alarm duration (ms)</td>
<td>Std.</td>
<td>214.5</td>
<td>137.9</td>
</tr>
<tr>
<td>Window energy (ms)</td>
<td>Avg.</td>
<td>808.7</td>
<td>836.7</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td>170.9</td>
<td>142.9</td>
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</table>

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.

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
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.

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


Table 4. Summary of performance analysis for proposed algorithms.

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<tr>
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<th>WED (P_D=10%)</th>
<th>ADD (P_F=10%)</th>
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<tr>
<td></td>
<td>given P_D</td>
<td>given P_F</td>
</tr>
<tr>
<td></td>
<td>(90%)</td>
<td>(90%)</td>
</tr>
<tr>
<td>Case 1</td>
<td>34.3%</td>
<td>50.1%</td>
</tr>
<tr>
<td>Case 2</td>
<td>25.5%</td>
<td>57.9%</td>
</tr>
<tr>
<td>Case 3</td>
<td>24.6%</td>
<td>58.8%</td>
</tr>
</tbody>
</table>


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