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Motion Direction Identification Using Pyroelectric Infrared Sensors Utilizing Machine Learning

Jyoti Mahur, Rachna Sharma, Chandani Srivastava
Department of Computer Science & Engineering
Mangalmay Institute of Engineering & Technology, Greater Noida, India

***Abstract*— Passive infrared sensors are inexpensive gadgets that are often utilized as simple yet effective person-presence triggers. The objective of this work is to extend the conventional application of the detector from motion detection to motion identification and activity classification. Specifically, by adjusting the effective polarization of the sensing elements in a very PIR detector, it is possible to determine the relative direction of movement of an item traveling on the motion plane of the PIR sensor. In this work, we introduce a novel method that uses two pairs of orthogonally aligned PIR sensors to determine the relative direction of human movement (in eight evenly spaced directions). Six participants, each traveling in eight different directions, provided data for our newly designed data gathering equipment, which is equipped with four dual sensing element PIR sensors and new lenses. Based on the collected PIR signals, we have performed a classification study utilizing popular machine learning techniques as instance-based learning and support vector machines. Based on the data set gathered from two orthogonally aligned PIR sensors with different lenses, we were able to identify the direction of movement with an accuracy of over 97%, according to our findings. Furthermore, we found that we could use machine learning techniques to attain recognition accuracy between 88% and 94% by employing a smaller feature set consisting of three peak values for each PIR detector.**

Keywords*—*PIR, motion sensor, machine learning, occupancy sensing, SVM, motion detection.

I. Introduction

After much research, a wide range of applications utilizing occupancy detection and localization technology, made possible by the straightforward presence detection of a dense array of PIR sensors, have been developed. When someone is not directly present, a number of additional factors can influence the PIR sensor's output, including the body's distance from the device, the direction and speed of movement, and the presence of multiple persons.

In this paper, we present a novel method of police investigation a relative direction of human movement (in eight directions at 45 degree intervals, i.e., N, NW, W, SW, S, SE, E, NE) with a set of four PIR sensors, whose twin sensing components are aligned with four directions, i.e., N-S, W-E, NW-SE, and NE-SW. We have created a data collection device that is mounted on the ceiling of a room and consists of four PIR sensors with twin detecting elements, Fresnel lenses to alter their fields of view, and op-amp circuits. Six experimental individuals were given eight different routes to walk in, and we collected data from them. We have created classifiers to recognize the direction of movement using machine learning techniques such as support vector machine and instance-based learning, supported by the PIR signals recorded during walking.

Our approach shows that the data set from two PIR sensors with modified lenses with orthogonally aligned sensing components can be used to detect the eight walking directions with over 97% accuracy. We have also found that 88% to 94% recognition accuracy may be obtained by using feature sets that are reduced to three peak values for each PIR device. We are optimistic that the suggested methodology will be able to help numerous application areas, including health care and sensible energy systems, by offering more precise occupancy detection and localization in a very large structure.

The remainder of the paper is structured as follows: A variety of indoor localization and motion direction police investigation systems utilizing PIR sensors are introduced in Section II. In Section III, the operation of PIR sensors is presented along with our typical methods for observing walking directions. Section IV discusses the knowledge collection process and PIR sensor-based moving direction police investigation gadget, as well as the classifiers that we frequently employ in machine learning. Section V displays the experimental findings using the gathered knowledge set while taking into account the number of PIR sensors, their reading range, and therefore the condensed feature sets. Section VI discusses the issues that still face our methods. Section VII includes concluding observations at the end.

II. Related Studies

It has required a great deal of time and effort to build the localization technology for indoor PIR sensors with human following enabled. Gopinathan et al. created a pyroelectrical motion-following system that employed four PIR detectors to detect human motion in one of fifteen cells spread across 1.6

m2. A human identification system was proposed by Fang et al. [2] using a PIR sensor whose visibility is controlled by a Fresnel lens array and the principal components regression technique. Additionally, they provided a technique [3] for recognizing individuals who are randomly moving utilizing PIR sensors with variable visibility. Shankar et al. developed a human tracking system using a low-cost sensor cluster consisting of PIR sensors and Fresnel lens arrays to accomplish the necessary spatial segmentations [4]. They measured the speed and direction of motion over a region more than 12 meters by looking at the response characteristics of the sensor cluster. Hao et al. proposed a human tracking system using an RF transmitter, an MSP430 family microcontroller, and a radial sensor module comprising eight PIR detectors with Fresnel lens arrays arranged in a circular [5]. They showed off how the system might be used to sense the angular movement of a single moving human target in order to track it. Hao et al. introduced wireless distributed PIR sensor systems that are comparable to this. A 3D simulation research for people tracking utilizing PIR sensors was demonstrated by Luo et al. [7]. In order to deliver numerous tailored services in an office setting, Tao et al. recently published a person location method employing an infrared ceiling sensor network [8]. They identify several people at the office door by predicting their walking directions, assuming each person works in an office and has distinct living patterns (such as going to his or her own desk right away). Five people were identified with 84% accuracy using support vector machine.

As Lee noted in [9], the analog output signal of PIR sensors is more complex than simple on-off triggering, and these characteristics have been applied in numerous ways to ascertain motion direction. Zappi et al. created a low-cost PIR sensor-based wireless network system with the aim of counting the number of people passing and figuring out their direction of travel [13]. The system is installed along a hallway wall and comprises of three sensor nodes with PIR sensors and modified Fresnel lenses to narrow their field of view. It also includes a coordinator node. They demonstrated 100% correct direction of movement detection and 89% correct number of persons detection while a single person and a group were present, based on the data set collected from PIR sensors.

PIR sensors are now frequently employed in conjunction with other types of sensors in a wide range of applications for creating intelligent environments, including security, healthcare, and smart energy systems. The reduction of standby power usage for lighting devices that enable PIR devices, near lightweight devices, and lighting period modules was demonstrated by Tsai et al. [15]. They also unquestionably demonstrate a means of lowering a personal laptop monitor's standby power usage while it is in the standing sleep position [16]. In order to increase energy potency while retaining learning effectiveness, Erickson et al. built and implemented an occupancy-based energy management system backed by wireless sensor networks based on cameras and PIR devices for opportunistically dominant HVAC systems [17]. This investigation of the viability of a person's movement detection system using a variety of alternatives extracted from PIR device signal was motivated by the PIR device's primary occupancy and motion detection capabilities for various application domains.

III. UNDERSTANDING PIR SENSORS

PIR sensors are well-known and frequently utilized as a simple but effective presence trigger for alarms in systems like automatic lighting control and police investigation systems. PIR sensors are a subset of thermal IR detectors [19] and employ materials that produce electrical phenomena, such as ad lib polarized LiTaO3 in the crystal structure. Due to the fact that polarized crystals absorb incident infrared light, the temperature of the crystal is altered, which prevents electrical dipoles from spontaneously polarizing within the crystal. Later on, the air's ions balance out the imbalanced charges. Figure 1 schematically depicts a PIR sensor with two sensing components positioned in a motion plane and an output signal captured during walking. The distance between the body and the PIR sensor, the direction and speed of a moving object, and the number of people present are some of the variables that impact a PIR sensor's output. Within these elements, the primary focus of this research is determining the direction of motion for an object moving within the PIR sensors' range of view. The field of vision could be shaped and expanded by using PIR sensors in conjunction with various Fresnel lenses [20]. We can distinguish between the two signals captured according to the relative directions of walking, i.e., left to right and right to left, as shown in Fig. 1(b), and subsequently be able to obtain clear direction information of the moving object, by alternating the polarities of the sensing elements in a PIR sensor, as shown in Fig. 1(a).

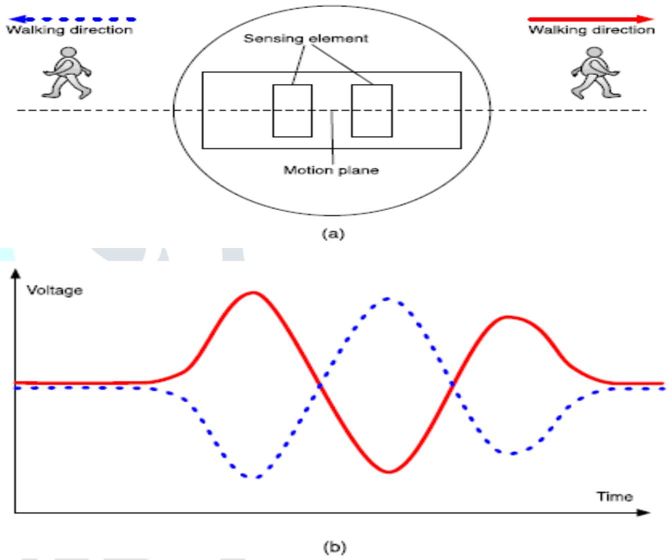

Fig. 1. (a) PIR Sensor with dual sensing element. (b) Its output Signal when walking

We may envision a method of classifying multi-directional walking based on an array of PIR sensors, each of whose (and thus the motion plane of each PIR sensor) is well aligned with the walking direction we want to detect. This method is based on the first tests and literature review. The primary outcome of this study is to provide a novel approach to recognizing walking directions using an array of PIR sensors, and to explore the experimental findings in relation to the quantity, field of view, and reduced feature sets of PIR sensors.

IV. MOVING DIRECTION IDENTIFICATION DEVICE

First, we'll go over the design of a device for detecting motion that consists of four PIR sensors and an information collecting system for recording PIR detector data. Next, we use the DAQ system we created to demonstrate the data collection process.

A. PIR Array and DAQ System

A PIR detector with its dual sensing portions aligned in an extremely motion plane, as Lee predicted in [9], will enable the creation of precise direction data for a moving object. As a result, we will envision a moving direction detecting device made up of a network of PIR sensors, each of which is familiar with the motion we are looking for, as illustrated in Fig. 2.

Even if we tend to imagine an array of four PIR sensors in the image to detect N, NW, W, SW, S, SE, and E, NE, it'll be possible to create another accurate direction detecting device using the many extra PIR sensors. In the result sections that follow, we usually show how the number of PIR sensors affects the recognition accuracy of moving direction.

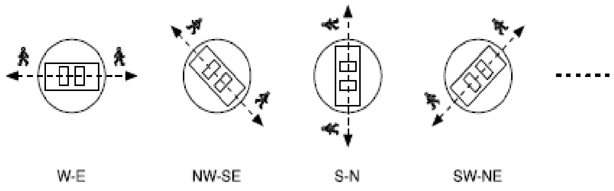

Fig. 2. Array of PIR Sensors with dual sensing elements.

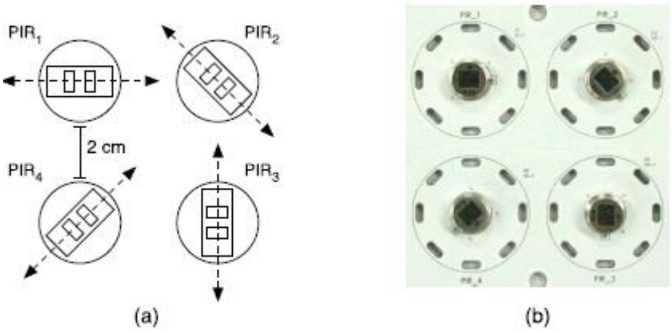

Fig. 3. (a) A schematic diagram of an array of four PIR sensors whose sensing elements are each oriented at W-E, NW-SE, S-N, SW-NE angles. (b) A top view of an array of four PIR sensors we implemented.

For our tests, we built a direction detecting apparatus with four PIR sensors, as seen in Fig. 3. A schematic design of a set of four PIR sensors with sensing components that are each familiarized at the W-E, NW-SE, S-N, and SW-NE angles is shown in Fig. 3(a), and a primary view of the set of four PIR sensors that we have implemented is shown in Fig. 3(b). PIR sensors are spaced apart by two cm when taking into account the lens system configuration that might create the PIR sensors' reading sector. We chose the IRA-E710 from Murata Manufacturing Co., whose horizontal and vertical fields of view are both 90° [21]. We have created op-amp circuits to boost the low PIR signaling because the IRA-E710 emits a low analog voltage signal.

B. *Information Assortment and Analysis*

In our investigations, PIR detector signals were recorded as test individuals entered an extremely watched region from eight different directions, as illustrated in Fig. 4. The 3.6 m x 3.6 m monitored field has a 2.6 m high ceiling. In the center of the field, a movement direction detector is mounted to the ceiling.

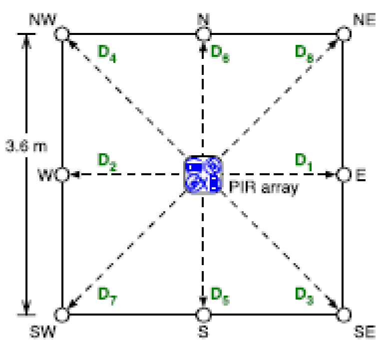

Fig. 4. A top view of the monitored field.

Six test subjects' PIR sensor signals have been gathered. The participants are instructed to go from circle to circle along the dashed lines in eight directions (D1,..., D8) as naturally as they can.

C. *Classifiers*

From the variety of machine learning algorithms that were accessible, we chose seven classification strategies: Nave Bayes, support vector machines, multilayer perception, instance-based learning (k-nearest neighbor method), decision trees (C4.5), decision tables, Bayes net, and multilayer perception. Support vector machines are among the most advanced discriminative algorithms available, and they perform well in a wide range of applications. We choose the linear kernel over the quadratic and cubic ones because of the computational cost. We chose the simple k-nearest neighbor approach from instance-based learning algorithms, and the decision tree and decision table from rule-based learning algorithms. All of the tests based on these classifiers used Weka, a tool developed by the University of Waikato's Machine Learning Group [22].

V. EXPERIMENTS AND RESULTS

We employed 10 times 10-fold cross-validation, or 10 different 10-fold cross-validation trials, with the same learning method and data set for classification analysis, averaging the 100 experimental outcomes.

A. *The Number of PIR Sensors*

In this section, we show how the quantity of PIR sensors affects the classification accuracy of walking directions. The average of the cross-validation findings for the chosen classification techniques based on PIR signals are presented in Table I. Since the average values for all classifiers are relatively similar (i.e., have very small standard deviations), we do not display the standard deviation of the findings. The k-nearest neighbor approach, which uses instance-based learning, has the best classification performance, as shown in Table I. This outcome is not unexpected because prior work in [14] used the k-nearest neighbor method to perform body distance recognition using PIR sensors and demonstrated good recognition accuracy. We must look into the aggregate confusion matrix in order to grasp the classification performance better. Based on the data set gathered using a single PIR1 sensor, Table II displays an aggregate confusion matrix for support vector machines. When two PIR sensors, PIR1 and PIR3, were used in the experiment, its confusion matrix can be examined to confirm this. Based on the data set gathered using PIR1 and PIR3 sensors, Table III displays an aggregate confusion matrix for support vector machines.

TABLE I
RECOGNITION ACCURACY (%) OF WALKING DIRECTION WITH RESPECT TO THE NUMBER OF PIR SENSORS WITH UNMODIFIED LENSES

Classifier	Recognition Accuracy (%)				
	PIR 1	PIR 1,3	PIR 2,4	PIR 1,2,3	PIR 1,2,3,4
Bayes Net	82.69	82.78	84.49	90.70	91.03
Decision Table	67.78	71.93	75.53	82.43	82.26
Decision Tree	81.76	84.14	84.72	88.78	88.64
Instance-Based Learning	**88.01**	**91.20**	**92.47**	**94.14**	**94.30**
Multilayer Perception	81.12	88.80	88.82	91.20	91.49
Naive Bayes	72.18	79.16	81.64	89.59	90.43
Support Vector Machine	75.14	90.53	90.47	92.34	92.72

TABLE II
CONFUSION MATRIX OF SUPPORT VECTOR MACHINE BASED ON TEN TIMES TENFOLD CROSS-VALIDATION FOR EIGHT WALKING DIRECTIONS WHEN USING PIR1

Classifies as:	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
D_1	521	0	0	0	0	1	0	76
D_2	0	545	0	53	0	0	0	0
D_3	1	0	543	0	43	1	0	10
D_4	0	37	0	551	0	0	10	0
D_5	0	0	0	0	**332**	**248**	19	0
D_6	0	0	21	0	**326**	**251**	0	0
D_7	0	0	0	12	14	6	516	50
D_8	136	0	0	0	0	2	71	392

TABLE III

CONFUSION MATRIX OF SUPPORT VECTOR MACHINE BASED ON TEN TIMES TENFOLD CROSS-VALIDATION FOR EIGHT WALKING DIRECTIONS WHEN USING PIR1 AND PIR3

Classifies as:	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
D_1	579	8	10	0	2	0	0	0
D_2	0	579	0	20	0	0	0	0
D_3	12	0	579	0	8	0	0	0
D_4	0	10	0	589	0	0	0	0
D_5	0	0	2	0	**500**	**77**	21	0
D_6	0	0	0	0	**58**	**541**	0	3
D_7	0	7	0	3	6	1	512	70
D_8	0	3	0	0	1	20	69	506

The overall recognition accuracy when using more than two PIR sensors is around 90%. We also know that by adding more PIR sensors to the direction-detecting device, recognition performance might be enhanced. However, the various inputs required by the classifiers due to the numerous PIR sensors result in a significant computing burden. As a result, we ought to think about reducing the quantity of PIR sensors used to generate feature sets for motion direction detection.

B. *Fresnel Lens and Field of View*

PIR sensors use Fresnel lenses to shape its field of view [20]. Fresnel lenses can be made by molding plastic materials with transmission characteristics appropriate for a specific wavelength range, such the human body (8–14 m). We have used the data set obtained from the PIR arrays using the modified single-zone lenses to conduct a classification analysis of walking directions. The average outcomes of cross-validation, which we ran ten times, ten times, and ten times on the selected classification approaches using the PIR sensor data we collected with the modified lenses, are displayed in Table IV.

Table IV shows that the support vector machine performs the best in terms of classification, with the exception of the situation of a single PIR sensor, PIR1. Actually, 99.48% recognition accuracy is demonstrated by the classification result using a support vector machine with all four PIR sensors and modified lenses. Table V presents an overall confusion matrix for support vector machines based on the data set collected with modified lenses and all four PIR sensors.

TABLE IV
RECOGNITION ACCURACY (%) OF WALKING DIRECTION WITH RESPECT TO THE NUMBER OF PIR SENSORS WITH MODIFIED LENSES

Classifier	Recognition Accuracy (%)				
	PIR 1	PIR 1,3	PIR 2,4	PIR 1,2,3	PIR 1,2,3,4
Bayes Net	81.14	94.55	98.64	97.59	97.87
Decision Table	72.72	82.68	84.08	82.53	83.70
Decision Tree	86.39	93.58	97.14	97.10	97.72
Instance-Based Learning	**88.99**	97.35	**98.62**	98.10	98.70
Multilayer Perception	84.37	97.33	98.28	98.39	98.95
Naive Bayes	74.87	91.83	96.93	94.93	97.99
Support Vector Machine	79.99	**98.24**	**98.62**	**99.03**	**99.48**

TABLE V
CONFUSION MATRIX OF SUPPORT VECTOR MACHINE BASED ON TEN TIMES TENFOLD CROSS-VALIDATION FOR EIGHT WALKING DIRECTIONS WHEN USING FOUR PIR SENSORS WITH MODIFIED LENSES

Classifies as:	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
D_1	600	0	0	0	0	0	0	0
D_2	0	600	0	0	0	0	0	0
D_3	**10**	0	**590**	0	0	0	0	0
D_4	0	0	0	600	0	0	0	0
D_5	0	0	0	0	600	0	0	0
D_6	0	0	0	0	0	**597**	0	**3**
D_7	0	0	0	0	0	0	600	0
D_8	**10**	0	0	0	0	0	0	**590**

It should be emphasized, though, that instance-based learning also performs well when only one or two PIR sensors are used, such as PIR1, PIR1 and PIR3, PIR2, and PIR4. With two PIR sensors, it specifically demonstrates about 98% recognition accuracy, leading us to draw the conclusion that, due to its simplicity, instance-based learning will also be a strong choice for classifiers.

VI. CONCLUSION

We have accomplished moving direction detection with the use of PIR sensors and machine learning techniques. In order to gather PIR sensing element signals, we designed a data collection device, mounted it on the testing area's ceiling, and connected two pairs of PIR sensors to op-amp circuits. Using a variety of machine learning algorithms, we classified police work based on the direction of movement while accounting for the number of PIR sensors, their reading range, and condensed feature sets. This analysis was bolstered by the data set collected from six experimental subjects who moved in eight different directions. Our results show that a 97% accuracy in movement direction recognition may be achieved with the data set obtained from two orthogonally oriented PIR sensors. Additionally, we found that the smaller feature set may yield 88%–94% accuracy based on machine learning techniques.

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