# Active Compressive Sensing via Pyroelectric Infrared Sensor for Human Situation Recognition

Rui Ma, Fei Hu, *Member, IEEE* and Qi Hao, *Member, IEEE*

***Abstract*—Conventional pyroelectric infrared (PIR) motion sensors use paired elements for moving target detection. This method makes them incapable of measuring thermal signals from *static* targets. We need an *active* sensor that can detect static thermal subjects. This paper presents our design of *active* PIR sensors. The proposed PIR sensing systems can actively detect static thermal targets by using three methods that are suitable to different applications: (1) a sensor that can be rotated by a self-controlled servo motor for the detection of moving or static thermal subjects nearby; (2) a sensor that is equipped with a mask for low-complexity posture recognition; (3) a sensor that can be worn on the wrist for the recognition of surrounding subjects (this sensor is especially useful for blind users). Compressive sensing (CS) theory indicates that *random* down-sampling method can capture more accurate information of the original signal than the evenly spaced sampling. Based on CS theory, we have developed the random sampling structures for the active PIR systems, and have built a statistical feature space for human scenario recognition. The experimental results demonstrate that the active sensing system can efficiently measure the static thermal targets, and the random sampling scheme has a better recognition performance than the even sampling scheme.**

***Index Terms*—Active sensing, PIR sensor, Situation recognition, Compressive sensing, Random sampling.**

## I. Introduction

HUMAN situation recognition systems have attracted many attentions due to their applications in healthcare, intelligent control, smart house, etc. The situation understanding can be achieved by using the information of locations and motions of the subjects. Generally situation recognition is different from motion recognition. The latter focuses on the individual's motions, while situation recognition is more concerned about the scenario context such as the size of the group, locations and postures of human subjects, and so on. The identification of such information does not require very accurate motion capture since our interest is to extract the intrinsic patterns of the motion signals instead of analyzing each action's snapshot images. In situation understanding, the targets can be measured at a distance despite the subject's cosmetic conditions. The system can use low-resolution sensory data for accurate context identification, and it can be non-intrusive since the subject may be unaware of the deployed sensors nearby.

Regarding human situation recognition, the video camera is perhaps the most widely used device. However, it consumes large communication bandwidth and storage space, and it can be easily influenced by the illumination and background conditions. For example, it cannot accurately capture the subject that is in dark environment or is hidden behind other objects.

Pyroelectric Infrared (PIR) sensors have been employed for human detection, tracking and identification due to their low cost, small size, and operation stability under varying temperatures. The existing systems employ the *passive* PIR sensor that uses dual elements to form a differential measurement, so that it can detect the thermal change of the environment (rather than the absolute temperature). This configuration enables it to detect the moving thermal source, but also limits its application for *static* targets.

In daily lives, many ordinary scenarios involve *static* humans. During the process of indoor scenario perception, one or several human subjects may not generate any detectable motions within a certain period. For example, people are sitting or reading books. Therefore, it is necessary to develop *active sensing* for PIR sensors. Active PIR sensors can detect the static human subjects by moving the sensor or the mask (attached in the front of the sensor) to actively generate thermal changes.

In this paper, we present the hardware and software implementations of active PIR sensing systems. Particularly we will present 3 innovative designs that can complement with each other to form an active compressive PIR sensing system:

The first one has an active thermal sensor that can be rotated by the motor. It can scan the room to count the number of people via simple software. The rotation of sensor generates thermal changes for the detected target(s).

The second one uses rotating multi-mask based on compressive sensing theory for human posture recognition. The rotating multi-mask is composed of four small masks which rotate around the sensor. And the rotation of the mask can also generate active thermal changes for the detected scene.

The third one has a special watch-like design, and can be worn around the wrist. Active sensing can be achieved by waving the arm randomly. This mechanism mimics the mouse's whiskers as shown in Fig. 1. The mouse has poor vision and simply uses its whiskers to sense the surrounding environment. This wearable sensor enables many interesting applications. For example, it can be used for the blinded to distinguish between human and non-human thermal sources surrounding them. Active PIR sensors can serve as the extension of the walking stick/cane without interfering with other people. Disabled people can also utilize this sensing system to assist with their social behaviors, such as avoiding obstacles, perceiving concealed fellows, etc.

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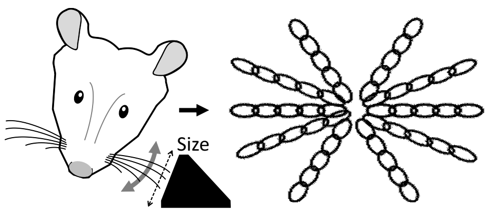


Fig. 1. The biological sensor and sampling mechanism of mouse's whiskers.

The data measured by PIR sensors has the sparsity nature due to the similarity among the data samples collected by the PIR sensor. The PIR sensing system uses much less sensors than the MRI and computer vision, but it many PIR sensors may form a wireless sensor network for large building monitoring. The energy consumption and computing load may still be large for these small wireless sensors. Applying the CS technique largely reduces the number of sensors needed to achieve the same sensing resolution. Conventional or general PIR sensors are not able to achieve scenario recognition without the random sampling technique (random modulated mask or random sensor deployment). So the use of CS for the recognition is critical.

Traditional even-spaced sampling method takes equal number of samples from the sensing space, and thus it has poor efficiency in terms of removing the data redundancy during the information acquisition from these compressed analog signals. To solve this problem we propose to use binary sensing and pseudo-random sampling in our PIR active sensor design:

(1) In binary sensing, the sensor's sensing space, called field of view (FOV), is divided into small regions. If the signal is detected in a region, it means that the human subject walks across that region, and the sensor generates a binary signal '1'. Otherwise, it generates '0' for that region. With this method, the binary sensor signal can describe the geometric information of the targets since the target may occupy multiple regions. Binary data has stronger resistance to noise than analog data due to easily differentiated high and low signals. Since only bits 1 or 0 are used in the sensing results, it reduces the data throughput and communication overheads.

(2) Compared to evenly spaced sampling, the pseudo-random sampling structure based on compressive sensing principle acquires more information of the target, and thus has better recognition performance. Based on Buffon's Needle model from integral geometry theory, we extract the binary statistic features to estimate the target size, and achieve the recognition of static human postures. Such geometric information cannot be acquired through analog signals or traditional algorithms.

The contributions of our work are three-fold:

(1) Design of active sensing schemes through a new rotating motor unit. Such a motor only adds a 2x2x2 inch volume to the tiny PIR wireless sensor board. The sensor and its masks can be periodically rotated to detect static thermal subject (such as a sitting person or sleeping pet).

(2) Pseudo-random sampling based on multi-mask hardware: We utilize compressive sensing principle to create a multi-mask lens with pseudo-random sampling structure. Such a multi-mask can generate rich signal patterns for any thermal target to be detected. Without such a multi-mask, the incoming sensing signals just have simple sinusoidal-like curves without much dominant features. Those rich patterns can be used for more accurate scenario recognition.

(3) Three-dimensional sampling for wearable PIR sensors: We have also designed a watch-like PIR sensor with 3-D sampling method. It can be worn in hand wrist to detect surrounding subjects.

We will provide the detailed hardware and software design principle below for our new invented sensor platform. Significant experiments have been conducted to verify the efficacy of the sensor hardware design as well as its sampling method.

The rest of the paper is organized as follows. Section II reviews the related work. In Section III we will introduce the sensing system setup and sensing theory. Then Section IV details the sensor design and sensing method. In Section V we present the experimental results. Section V concludes the entire paper.

## II. Related Work

Video cameras and sensors are the main approaches to human scenario information acquisition. Below will summarize the related work in those areas.

Video camera and computer vision have been long used for human activity and behavior recognition. Oliver et al. used video camera and Hidden Markov Models (HMM) to model and recognize the human interactions [1]. Brdiczka et al. proposed a 3-D video tracking system with multi-modal observations for daily human activity derivation in smart homes [2]. Tang et al. used multiple cameras to count the number of people [3]. Hou et al. proposed a method for human counting in crowded situation [4]. Microsoft Kinect is a popular camera which can detect the depth information of the targets. But the conventional video camera or MS Kinect can be disturbed by the background objects, especially in indoor scenarios with much furniture. It causes high computation overhead due to the algorithms of background image subtraction and subject segmentation from the furniture items.

Wearable sensors have been used for scene detection for a long time. Olguin et al. presented a system which can measure the human interactions, conversational time, physical proximity to other people for organizational behavior identification [5]. Baek et al. built a posture monitoring system for context awareness [6]. Hache et al. used accelerometers in smartphone platform to detect the daily mobility events [7]. Elhoushi et al. employed multiple inertial sensors to recognize the indoor stationary humans or moving actions for navigation purpose [8]. These wearable sensors for human scenario measurement need the awareness and cooperation of the targets. In other words, it is intrusive. For example, an accelerometer needs to be worn by the target, and the device and the target need to be registered in the sensing system. Otherwise, the signal of the target cannot be correctly collected. Wearable inertial sensors often only focus on individual motion measurement, thus cannot count the number of people, and are not good at group activity recognition either.

PIR sensors with low cost and the ability of motion detection are widely applied to different applications. Those sensors can form a distributed sensor network to monitor a room or other spaces. Wahl et al. used distributed PIR sensors for people counting [9], and Erden et al. used a single PIR sensor as the assistance of the video camera for the same purpose [10]. Luo and Kim et al. proposed the wireless PIR sensor systems for indoor human localization and monitoring [11], [12]. Zappi and Yun et al. presented PIR sensor arrays for human motion direction and tracking systems [13], [14]. Sun et al. presented a distributed PIR sensor network for moving human scenario recognition [19]. A research group at Duke University has conducted a series of studies on distributed PIR sensor network for human tracking and gait identification [15]–[18]. Their work used passive PIR sensors. The analog signal serves as the input of their algorithms. It is unstable and may change through time.

These works on PIR sensors have demonstrated their efficiency for motion detection. But they are all applied as passive sensors. In other words, they cannot detect static thermal objects. More research on the sampling method of PIR sensors can be explored to enhance their capability of human information acquisition. In addition to PIR senors, other existing non-intrusive sensor systems also have difficulty when the targets are stationary.

There are some pioneering works in PIR systems using choppers which have similar functions as our systems. Hashimoto et al. presented a PIR sensor system with 8-element array and oscillating mechanical chopper to count the number of people passing through a wide door [20]. Kobayashi et al. used the liquid crystal as the chopper of PIR sensor for human detection [21]. But these PIR systems with choppers are different from our proposed systems in several ways: (1) In many conventional systems, the purpose of using choppers in PIR sensors is to obtain a continuous output as the alternative of using dual pyroelectric elements for differential detection. By using choppers for a single sensor (instead of dual sensors), the sensor can recognize the existence of surrounding thermal objects. However, unless such a chopper is also equipped a rotating motor as our system does, it does not aim to detect "static target as our system does. Due to its non-mask, single-sensor architecture as well as its simple software, it typically can only detect the existence (yes or no) of the thermal target without the capability of distinguishing among different scenarios (such as people or animal, sitting or walking, etc.). Our system aims to detect the static target through a masked sensor array architecture with rotating motor as well as intelligent machine learning algorithms, and can thus recognize the shapes, types, and scenarios of the thermal targets. (2) Another major difference is the use of the compressive sensing based mask (lens) in our PIR system. Conventional pyroelectric choppers use mechanical [20] or optical [21] mechanisms and only modulate the thermal signal in the binary format (such as detected or not detected for thermal sources). Thus they cannot recognize complex scenarios (such as two people talking). Our masks on the other hand provide rich modulation patterns via particular compressive sensing masks, thus it can generate more diversified signal patterns for different thermal sources. (3) The simple modulation model of the conventional pyroelectric choppers is difficult to interpret in physical model. The modulation of our mask is closely tied with the Buffons Needle model, which provides an elegant, accurate physical explanation of the collected thermal signals.

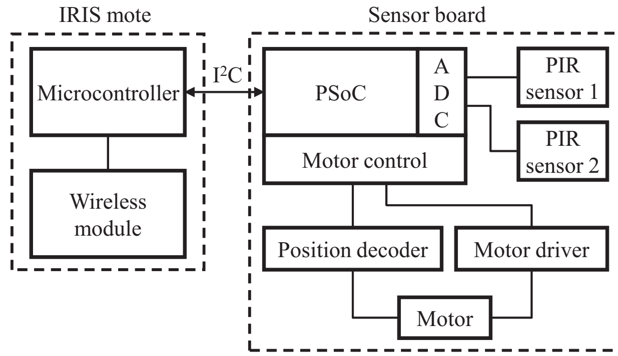


Fig. 2. Hardware diagram of PIR sensor with servo control.

In our previous work [22], we presented a compressive gait sensing system based on passive PIR binary sensors, and developed statistical geometric models for gait information acquisition using several bit streams. Our previous work provides the insights upon the physical parameters of gait configuration, and demonstrates the high intra-subject biometric invariance under different experimental conditions.

In this work we will utilize integral geometry for the target modeling and feature extraction. With the novel active sampling method, we are able to measure the static targets.

## III. PIR Sensor System and Sensing Model

Our active PIR sensor hardware consists of an IRIS wireless mote and a sensor board. The IRIS mote is used for the signal processing and wireless networking. The sensor board includes a programmable system-on-chip (PSoC), an amplification circuit, and our invented motor drive unit. The PSoC reads the ADC data from the sensor and controls the motor. All the data (sensor signal, amplification gain, rotating angle, etc.) is sent to IRIS mote via PSoC through $I^2C$ protocol for wireless transmission. The hardware architecture of the sensor node is shown in Fig. 2.

The PSoC adds certain *intelligence* to the sensor: it can change the amplification gains of the sensor when the target-to-sensor distance is changing. It can also control the sensor's orientation for calibration purpose, as shown in Fig. 3. In our system, there is an angle sensor in the mini motor. PSoC reads the angle data and determines how to rotate the sensor or the mask according to the pre-programmed operation modes.

### A. Model of Human Target

Binary sensors can achieve highly data-efficient sensing and captures the intrinsic geometric information of the target. Direct use of binary data for scenario classification is feasible. But we may also want to understand the meaning of the binary data in addition to classifying them for scene identification purpose. If we could create a physical model that relates the

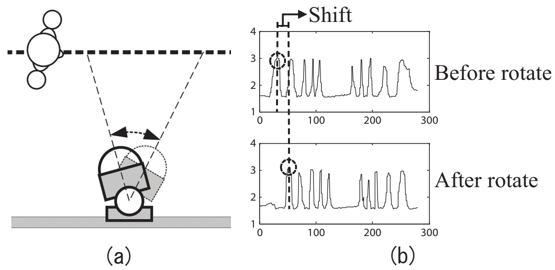


Fig. 3. (a) Setup for calibration. (b) PIR sensor signals before and after sensor node rotation.

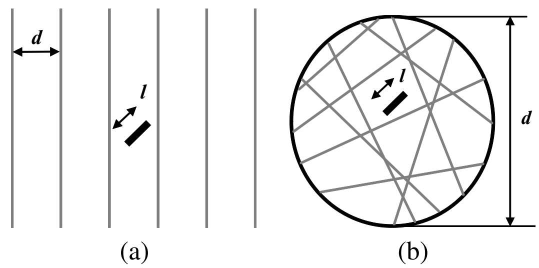


Fig. 4. The sampling structures of (a) parallel lines, and (b) pseudo-random lines.

geometric meaning to the binary data, we may be able to explain the generated sensing signals. To recover the geometric target information from the binary data, we start by building the physical model of the human target, such that we can know the size or geometric distribution of the target.

To model the motion of human target, we utilize the Buffon's Needle model from the field of integral geometry, where the human target is modeled as a moving needle in the FOV of sensors. The probability of the target triggering the detection by the sensor can be calculated by the math operation of integration [23]. Two cases are considered here, as shown in Fig. 4:

(1) In the first case, the traditional sampling structure of parallel lines are used. The probability of the target touching the parallel lines is given by [23]:

$$p_c = \frac{2l}{\pi d}, \tag{1}$$

where the $l$ is the length of the needle, and $d$ is the distance between two lines.

(2) In the second case, the probability of the target touching the pseudo-random lines is given by [23]:

$$p_{rc} = 1 - (1 - \frac{2l}{\pi d})^N, \tag{2}$$

where $d$ is the diameter of the circle, and $N$ is the number of the lines in the area. The probability of target triggering the sensor is the probability of having ‘1’ in the generated sensory data. Buffon's Needle model thus can establish the relation between the geometric information and the binary sensor data.

## B. Statistical Features of Binary Sensors

The statistics of binary data can represent the static and dynamic features of the target. However it usually has a non-Euclidean geometric structure [24], which means that the general statistic features are not independent.

We have extracted the statistical features from the binary sensor's data streams, as shown in Fig. 5. For the 1-bit PIR sensory data stream, two features can be generated: (1) temporal correlation $\theta$, and (2) intersection probability or marginal density $\eta$. They have the following relationship:

$$\begin{aligned} \eta &= \frac{\rho_{10} + \rho_{01}}{2} + \rho_{11}, \\ \theta &= \log\left(\frac{\rho_{00}\rho_{11}}{\rho_{01}\rho_{10}}\right), \end{aligned} \tag{3}$$

where $[\rho_{00},\ \rho_{01},\ \rho_{10},\ \rho_{11}]$ are the joint probabilities of each group of two consecutive bits in a binary data stream.

For a 2-bit PIR sensory data stream, the third feature, spatial correlation $\theta_{12}$, can be calculated as

$$\theta_{12} = \log\left(\frac{p_{00}p_{11}}{p_{01}p_{10}}\right), \tag{4}$$

where $[p_{00},p_{01},p_{10},p_{11}]$ are the joint probabilities of the two sensors on the same node.

Those three statistical features are orthogonal to each other [24], and they can be obtained from the decomposition of a higher-order Markov chain. They can be used for the scenario recognition. For the passive PIR sensors, the temporal correlation is related to the temporal transition of the thermal source; the marginal density is related to the size of thermal sources; and the spatial correlation is related to the spatial distribution of the thermal source. The above 3 parameters have the following features:

(1) On temporal correlation: As shown in Fig.5, suppose we use 2 sensors in one wireless node. Those two sensors are arranged in a vertical direction. The top sensor and bottom sensor each generate a series of sensing results (‘1 means ‘detected, and ‘0 means ‘missed). We define the temporal correlation (formed by $l_{ij}$) as the ‘1 / ‘0 signal transition pattern in each row (i.e., a particular sensors results). These ‘1’ and ‘0’ sensor signals are generated from left to right along the time dimension, so it is called temporal correlation. It reflects the geometric information of the thermal source in the ‘horizontal direction. (2) The marginal density is the probability of signal ‘1’. Generally speaking, a larger thermal source would trigger more ‘1’ signals. (3) The spatial correlation formed by $p_{ij}$ represents the ‘1’ and ‘0’ signal pattern between two (or more) sensor data streams in the vertical direction. Generally, a thermal source with bigger size in vertical direction would more easily trigger “11 pattern (for a two-sensor case) and may not trigger “00 pattern. Thus the spatial correlation reflects the geometric distribution of the thermal source in the vertical direction. We can deploy those two sensors in a vertical direction with some distance between them (say 1 foot). Thus the upper sensor can capture the moving patterns of the upper limbs and the lower sensor captures the lower limb movement patterns.

## C. Compressive Sampling Principle

We have created a multi-mask for the PIR sensor based on compressive sensing/sampling principle. Such a multi-mask

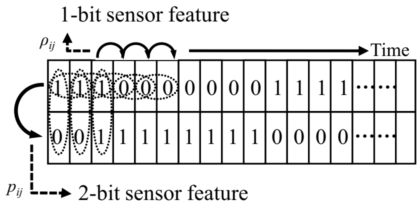


Fig. 5. The statistical features of binary sensors.

plays a critical role in sensing process since it can use special lens architecture to generate rich sensing patterns. Without the multi-mask, the sensor just generates a simple, smooth analog signal curve. Below we briefly introduce the mathematical model of the compressive sampling.

In general, a signal measurement process can be represented as:

$$s = \Phi x, \tag{5}$$

where $s$ is the measurement data matrix $\in R^{M\times 1}$, $\Phi$ is the sensing system coefficient matrix $\in R^{M\times N}$, and $x$ is the original (raw) signal $\in R^{N\times 1}$. In conventional sensing, $\Phi$ is a strict diagonally dominant matrix or diagonal matrix, and it has $M \leq N$. In compressive sensing, the sparse signal can be measured at a much lower sampling rate than the traditional Nyquist rate by using random sampling technique. Here $\Phi$ is a random matrix and it could be $M \ll N$. For compressive sensing, the random sampling is an important mechanism that guarantees the success of signal reconstruction [25].

The human scenario signals can be treated as sparse signals in thermal distribution space. The human postures can be modeled as a set of moving sticks, and has much less intrinsic degree-of-freedom than the mega pixels of video signals. This makes the scenario recognition easy to achieve via the PIR sensors. The compressive sensing indicates that random sampling can better preserve the main features of the target. Thus we apply pseudo-random sampling design for our PIR sensors:

- For PIR sensor with rotating mask: we use multiple random coded masks.
- For wearable PIR sensor: we use 3-dimensional random sampling with arm movement.

The efficiency of these random sampling designs is verified in our experimental results in Section V.

Our compressing sensing based sensor design significantly reduces the hardware and software complexity. To see the benefit of using compressive sensing in our PIR design, lets quickly take a look at the original application of compressive sensing. In the initial study of compressive sensing, people found that by just using one-pixel camera lens with a reconfigurable mask pattern in the front of the lens, we can capture the image of the surrounding scene with high resolution. The mask keeps changing its grid patterns each time (some holes blocked, some open). And the camera software then reconstructs the original high-resolution image by combining those pixels from different mask patterns. Without using the above compressive sensing based pixel system, the camera must have numerous one-pixel lens to form an array in order to capture the entire scene within only one single shot. Obviously, this significantly increases the hardware manufacturing cost.

By using the similar principle, our proposed PIR compressive sensing system can measure the human scenarios or posture information with only one or two pyroelectric sensors in the chip, after using our manufactured multi-mask that is equipped in the front of the sensors. Without such a multi-mask, the same sensing accuracy can only be achieved by using a huge sensor array with numerous sensors. Thus the biggest benefit of using compressive sensing is to reduce the hardware cost. It also saves much energy consumption due to much less sensor operations. It significantly reduces the calculation complexity due to much less sampling data collections, which is critical in any wireless sensor network with constrained CPU and memory resources.

Our design here is superior to conventional compressive infrared sensing [26] due to its important feature as follows: it does not perform signal reconstruction for scenario recognition. As we know, compressive sensing systems typically need to reconstruct the original signals from the sparsely sampled signals. Such a reconstruction is often based on high-complexity $L_1$ or $L_2$ normalization (or other optimization algorithms). The conventional systems then use such a reconstructed signal to perform pattern analysis. However, our system here does not need to perform signal reconstruction, and we build machine learning algorithms to directly analyze the compressive signals from multi-masks. We use classification schemes to find out which human scenario it belongs to. Due to the avoidance of complex signal reconstruction, our system has ultra-low computation overhead. This is important to real-time applications.

## IV. Active Sensing Systems

In this section, we will present our three active sensing implementations: (1) rotating sensor, (2) sensor with multi-mask, and (3) wearable sensor. They can complement with each other to form a more powerful sensing system. For example, the rotating sensor and multi-mask sensor can be integrated in one system to achieve active, compressive sampling.

### A. Rotating Sensor

The rotating PIR sensor has a mini motor. The node has two tiny thermal sensors, which are assembled above the motor. There is an angle sensor in the motor that sends back the angle information to the sensor node, such that the PSoC knows how much it has rotated and determines how much more to rotate next. At least two sensor nodes are required to count the number of people by scanning the room. A single node is not able to achieve that when the subjects are standing in line with the node, as shown in Fig. 6. In Fig. 6, the number of people is counted as one for Node 1 and two for Node 2. When more sensor nodes are used together, ambiguous situations can be identified more accurately. In this sensor design, the mask of the sensor uses parallel line sampling structure, as shown in Fig. 6.

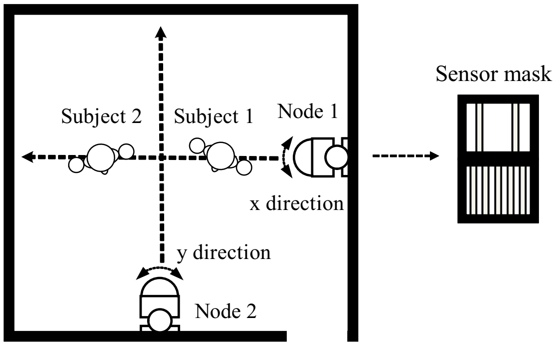


Fig. 6. Human scenario scanning.

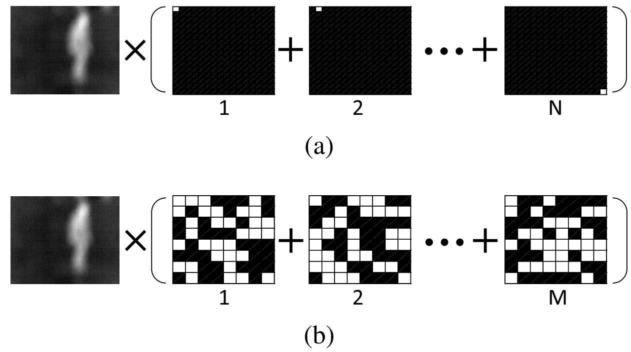


Fig. 7. The sensing procedure of thermal image: (a) conventional measurement; (b) compressive measurement.

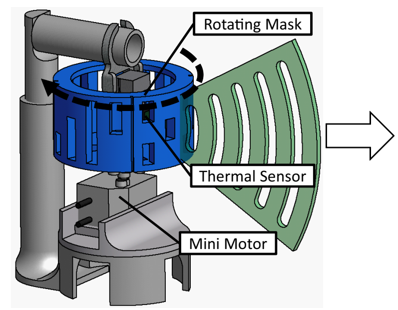


Fig. 8. The active PIR sensor with rotating multi-mask.

### *B. Sensor with Multi-mask*

With limited number of PIR sensors, we may not obtain enough information for accurate human posture recognition. Increasing the number of sensors with different masks is an approach to extracting more comprehensive target information. However, the deployment of many sensors is inconvenient. Compressive sensing provides a promising solution.

The compressive sensing of thermal images with just one pixel is demonstrated in [26]. A comparison between conventional sensing and compressive sensing of a thermal image is shown in Fig. 7. In conventional sensing shown in Fig. 7 (a), the target is measured with $N$ measurements, and each measurement captures a small part of the target. While in compressive sensing shown in Fig. 7 (b), the target is measured with $M$ measurements, and each measurement is a sum of the whole target. The underlying theory of compressive sensing says that such measurement can reconstruct the target even $M \ll N$.

PIR sensor measures the overall thermal change in the FOV, and is a good candidate of compressive sensing. The proposed PIR sensor uses a PSoC-controlled servo to change the mask of the sensor, such that one sensor can measure the target with different masks, in order to obtain different measurements based on the principle of compressive sensing. Without the need of reconstructing the entire human target shape, our design can use just one PIR sensor to detect the shape features of the target.

The proposed PIR sensor is shown in Fig. 8. It has a reconfigurable multi-mask set with four different masks applied to the sensor when it rotates. These masks divide the FOV of the sensor into 4x3 areas, as shown in Fig. 9. Higher resolution of the mask is not needed here because our design targets a low-cost PIR sensor architecture, which does not have high sensitivity to fit such a high-resolution mask.

Different mask architectures could generate different measurements for the same target, and the same mask architecture may also generate different signals for various targets, as shown in Fig. 10. In Fig. 10, the thermal subject moving along “up, middle and down” directions can make the multi-mask sensor generate different numbers of wave peaks. Thus the shape of the subject can be measured after one round of mask rotation, based on the signals detected by the four masks. Note that in Fig. 10 we regard that each thermal subject consists of multiple hot spot sources, and each of those hot spots is called a ‘target. From this point of view, we are actually testing different targets. The reason we can capture the movement pattern of those different hot spots (i.e., targets) in the same humans body is because that we used ‘sensor array for a single wireless PIR node. For instance, in vertical direction we can use two sensors (see Fig.5). Those two sensors may have 1 foot of gap between them. Thus we can capture the gesture of two targets (one is arm target and the other is leg target). Since the arms can be seen as a hot spot (target), we can let a target move along “up, middle and down directions to study different geometric distribution of the target.

### *C. Wearable Sensing for Situation Perception*

The wearable sensor is useful for blind people who would like to detect other people around them. The sensor node uses similar hardware units as the sensor with servo control but without a motor. And it is specially designed to fit the hand

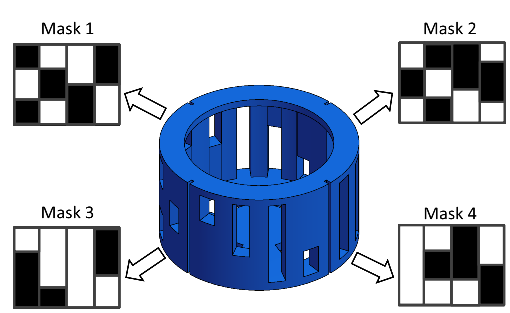


Fig. 9. Pseudo-random coded multi-mask design.

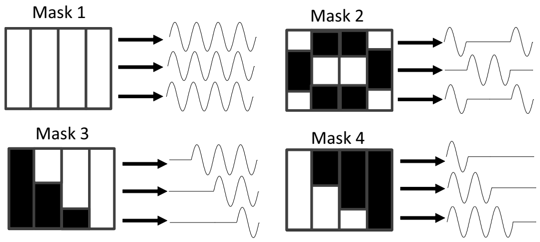


Fig. 10. Different masks generate different measurement for different targets.

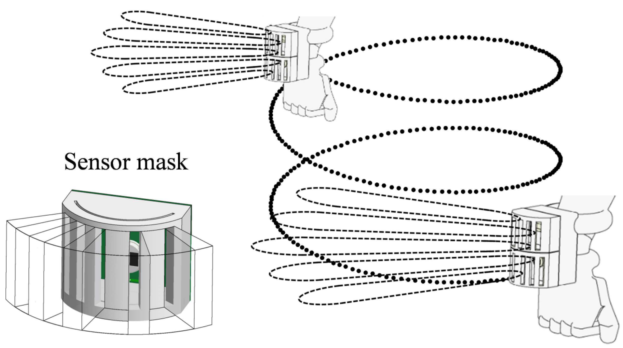


Fig. 11. The random three-dimensional sampling.

wrist. It can be tied with a cell phone armband, as shown in Fig. 11. Its mask also uses parallel sampling structure, and a pseudo-random sampling can be actually generated from the natural, random arm movements.

The PIR sensor is capable of detecting thermal sources in motion, but it cannot detect static targets. Fortunately it is a wearable sensor. As long as the arm with the sensor moves just a little bit, (which happens each time the person walks or just slightly swings the arm), the sensor is able to generate the detection signals. The blinded can use them to perceive the situations of surrounding human subjects.

During the measurement process, the user's arm swings a little to detect the static targets. In order to achieve better recognition rate and to alleviate the impacts from different target distances and orientations, we further propose the pseudo-random 3-dimensional (3D) sampling. In this sampling, the sensor is swung left and right, up and down, back and forth randomly, such that it could sample more information of the target, and meanwhile it is insensitive to target distance and orientation in a certain scope. Such a 3D hand movement aims to find any thermal objects around the user. The 'back and forth' sampling will generate different signal patterns for the 2D target, and it also helps to alleviate the variance introduced by the distance to the same target. However, since the generated sensor data is still based on '2D space coding', the data is still '2D measurement. In other words, we use '3D sampling to perform '2D measurement. Such random sampling structure can be represented by Buffon's Needle model, already shown in Fig. 4. The similar sampling process is used by the mouse which can use its whiskers to sense the geometric shape of the target.

Fig. 12. The experiment set up for the human scenario.

## V. Experiments and Discussions

The experiment setup for the human detection scenario is shown in Fig. 12. One person or two people standing in different positions are tested in the experiment with active PIR sensors. We have tested several scenarios for each of the three sensing devices. Some human subjects participated in the experiments: (1) In the scenarios where the rotating sensor is used to count people, the subjects stand together, and each scenario lasts about 10 seconds. (2) In the scenarios where the sensor with rotating mask is used for posture recognition, each scenario lasts about 60 seconds in which the subject performs three postures (standing, sitting, and squatting), each for several times. (3) In the scenarios of the wearable sensor, the human subjects to be detected stand or sit in front of the user wearing the sensor. Each scenario lasts about 25 seconds, and the worn sensor scans both of the human subjects and the warm computer/TV screen.

In the experiments, the subjects perform the three postures (sitting, standing, and squatting), not in a sequential manner. Instead, they perform those postures randomly.

Our designed and fabricated active PIR sensor nodes and the sensor board with servo control are shown in Fig. 13.

### A. Performance of Target Counting

In the first sensor design (with the rotating motor), the sensor board generates the logic signal "0 0", "1 0" and "0 1" to control the motor for stopping, rotating forward, and backward operations. The control circuit's voltage output for the motor is shown in Fig. 14 when the motor is rotating back and forth. Such a figure is directly taken from the oscilloscope. The driving voltage is about 2 volts. This output drives the motor to rotate back and forth to scan the targets nearby.

When two people are standing in a line with one of the sensors, the sensor signal is shown in Fig. 15. The sensor mask can help to distinguish the signals from different numbers of people. The statistical feature of the target counting is shown in the feature space, as illustrated by Fig. 16. It can be seen that the scenario of one person has a higher temporal correlation $\theta$, since one person has a simpler shape and the sensed signals are more correlated with each other during the process of scanning the room.

### B. Sensor with Rotating Mask

First, a hot soldering iron is used to test the impulse response of the PIR sensor with a rotating mask. The detected

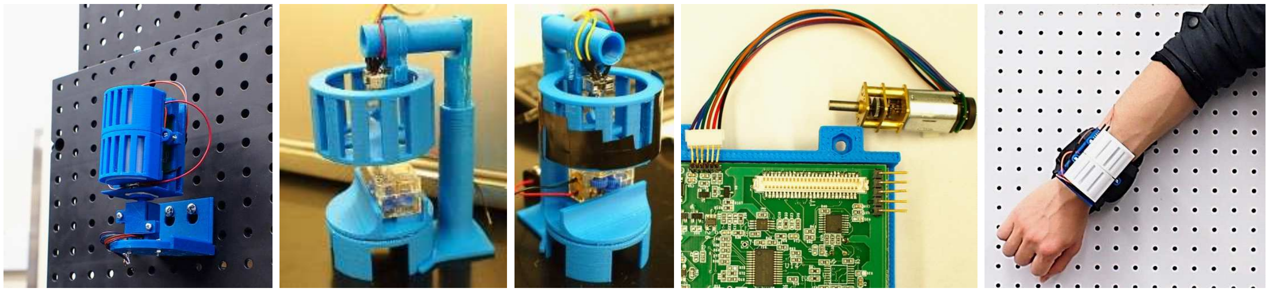

Fig. 13. The PIR sensor nodes.

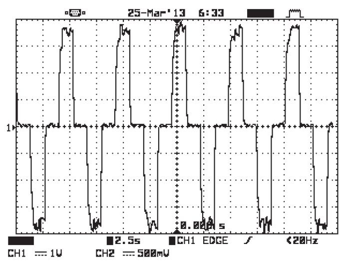


Fig. 14. Motor control signal when scanning the room (voltage captured by oscilloscope).

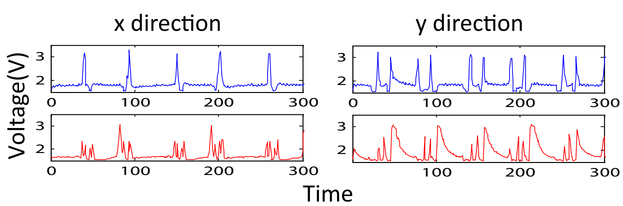


Fig. 15. Signals of two PIR thermal sensor nodes in two direction of scanning two static human subjects.

signal is shown in Fig. 17. The hot soldering iron stays in different locations to generate various signals. This result verifies the functions of active sensing with rotating mask.

In the next experiment, the PIR sensor with a rotating mask is used to detect the static target's postures, such that the system can infer whether the target is reading books or sleeping, etc. A comparison between the parallel-coded and random-coded masks is given in Fig. 18. It can be seen that

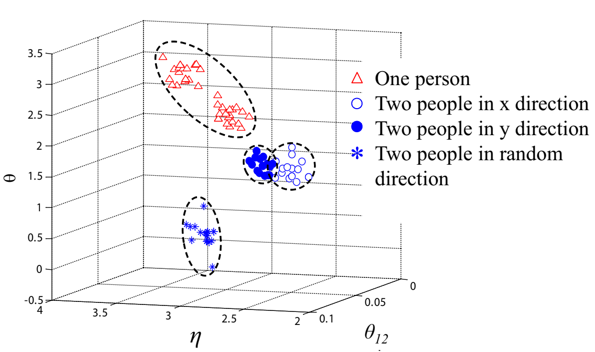


Fig. 16. Scanning results of counting people represented in feature space.

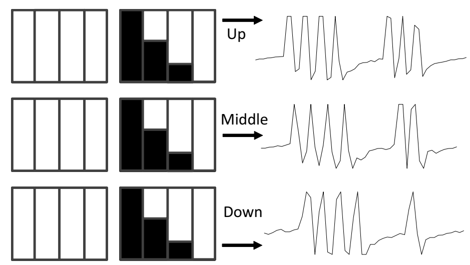


Fig. 17. The hot spot test for the rotating multi-mask along different trajectories.

for parallel-coded mask, different postures generate the same signal. Thus they cannot be distinguished from each other. However, for the case of pseudo-random coded mask (already shown in Fig. 9), the sitting posture can be easily distinguished from the standing posture, even just using the raw signal. This can be seen from Fig. 18.

The comparison between different gesture recognition results is shown in Fig. 19. The recognition of three basic postures is tested: standing, sitting and squatting. Two statistical features $\theta$ and $\eta$ are used for the recognition because only 1-bit binary stream is generated from the PIR sensor with the rotating mask.

It can be seen from Fig. 19 that from standing to squatting, the $\eta$ 's value, which represents the overall size of the target, decreases obviously because the actual target size decreases from the standing, sitting to squatting posture.

The $\theta$ 's value represents the target shape correlation. We can see that the standing posture has a larger $\theta$ variance but the global distribution of $\theta$ is smaller than the squatting gesture. The $\theta$ of the sitting posture is obviously smaller than squatting, which again proves that the target with the smaller shape has a larger shape correlation $\theta$.

In summary, the statistical features $\theta$ and $\eta$ are able to represent the geometric information of the targets.

### *C. Wearable Sensor Test*

An environment setting may consist of both human and non-human thermal sources. Then how do we distinguish the non-human thermal source from human sources? In this experiment, the thermal features of TV screen, computer screen, standing or sitting human subjects are extracted through our designed wearable PIR sensor node.

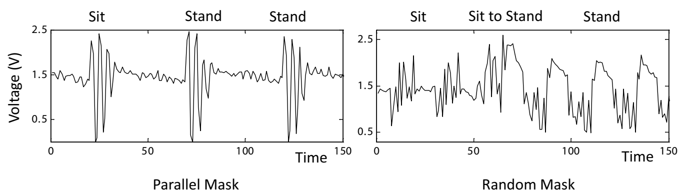


Fig. 18. The analog signal of active sensor with rotating mask of parallel coded mask and random coded mask.

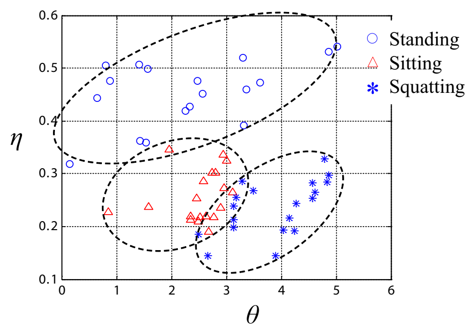


Fig. 19. The human posture recognition by active sensor with rotating mask represented in feature space.

The recognition results of different thermal sources detected by the wearable sensor are shown in Fig. 20. The wearable sensor node has two PIR sensors and outputs 2-bit binary data. Thus three statistical features $\theta$, $\eta$ and $\theta_{12}$ are used. The non-human thermal sources such as the TV screen (40") and PC screen (21.5"), all have a larger width than the human thermal sources. Thus they have larger $\eta$. And their shapes are also simpler than human body. Thus they also have a higher shape correlation $\theta$ than humans. $\theta_{12}$ is the shape correlation in another dimension, and the non-human thermal sources have a larger $\theta_{12}$ due to their simpler shapes. The clusters of different thermal sources can be better distinguished in 3D feature space than in 2D space.

The experiment for testing different sampling methods is also performed, and the results are shown in Fig. 21. It can be seen that the features of different thermal sources may not be easily distinguished from each other when the signal is collected by swinging the arm along a fixed path. This is because that the sampling method performed along the fixed path is not invariant with respect to the thermal source location and orientation. There is also a difference in terms of $c_{12}$ , which can be seen if we change the perspective angle of Fig. 21. Thus their differences could be due to the size of the target and the posture (the subjects with different standing postures may generate very different $c_{12}$).

By comparison, the 3D random sampling method is insensitive to the locations and orientations of thermal sources and different users. Different thermal targets can be better recognized in the feature space. The geometric information represented by the three statistical features $\theta$, $\eta$ and $\theta_{12}$ accords well with the practical truth.

The recognition of different scenario contexts including different amount of people, different human postures or different thermal sources, can be easily achieved by using the

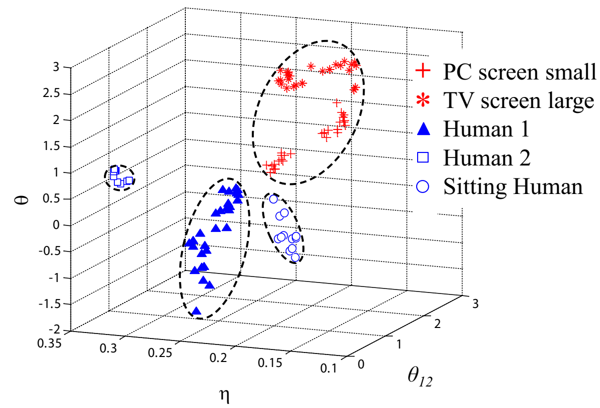


Fig. 20. Wearable sensor results of human and non-human thermal sources.

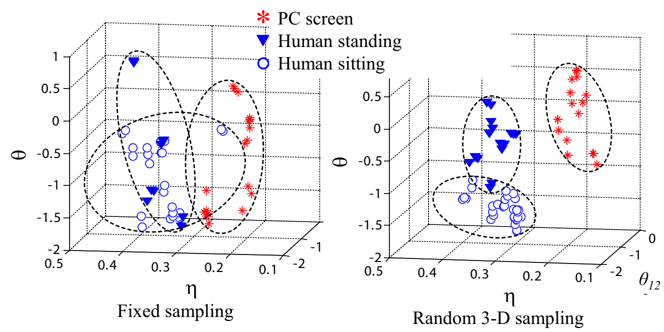


Fig. 21. The comparison of fixed sampling results and 3-D random sampling results.

above statistic features. Since those features reflect the intrinsic geometric information of the target, the simple classification method can be used: (1) First, we use the training samples to obtain a set of features, and we calculate the center and the covariance matrix of these features. (2) Then we calculate the Mahalanobis distance between the training sample feature center and the testing sample features using the covariance matrix. (3) The Mahalanobis distance to the training sample center can be used to determine the class of the testing samples.

For the amount of people, 20 training samples for each class are collected. For the classification of human postures, 60 training samples for each class are collected. For the classification of thermal sources, 30 training samples for each class are collected.

Here we further compare the recognition performance for our 3 sensor designs. The recognition performance of the three proposed active PIR sensor designs, in the form of receiver operating characteristic (ROC), is shown in Fig. 22. It can be seen that the rotating sensor has the best performance, because it uses two nodes with 4 sensors, and the signal from different numbers of people is quite different from each other. The sensor with rotating multi-mask has the worst performance among the three designs because it uses only one sensor for the posture recognition. But its performance is still satisfactory, with 92% true-positive (TP) rate at 7% false-positive (FP) rate.

Regarding to the noise (decibels) of our motor design,

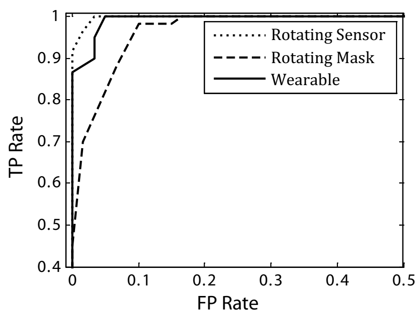


Fig. 22. The ROC curve of recognition performance of the three active PIR sensing systems.

our tests show that it is much smaller than the building air conditioning units. It does not bother the users at all. Moreover, the motor does not rotate as long as the PIR sensor can detect any thermal targets. Only when the sensor cannot detect any thermal signals for over a certain time (the time threshold can be set up based on the application preferences), the motor will wake up and scan only once to detect any possible ‘static thermal objects.

Regarding the energy consumption, the PIR sensor network consists of both traditional ‘passive sensors and ‘active sensors. As usual, we let all passive sensors turn on all the time to detect any possible moving thermal objects. However, we let all active sensors go to ‘sleep status. They are triggered to wake up only when all nearby passive sensors cannot detect any thermal objects. Due to such a trigger-based wake-up scheme, our active sensors will have very low energy consumption.

## VI. Conclusions

This paper has presented a wireless active PIR sensing system with three concrete implementations. The PIR sensors are enhanced to measure the static human targets with the servo control and arm movement. They complement with each other for human scenario recognition and enable the recognition of complex human situations.

The active compressive sampling scheme for the PIR sensor with reconfigurable multi-mask is designed. This tiny sensing board with only one sensor has accurate human posture recognition. The wearable PIR sensor for blind user is proposed. The pseudo-random 3D sampling method is developed for the wearable sensor to obtain the invariant geometric features of the static targets. The blind users can use it for indoor or outdoor applications. They can even use it to detect the coming cars when crossing the street.

In the future work, these active PIR sensors will be integrated to form a distributed sensor network for a better information fusion. PIR sensor node with reconfigurable multi-mask and two sensors, will be designed to obtain 2-bit binary data, and the multi-mask assembled with different Fresnel lenses will also be tested to obtain different sensor detection distances and FOVs. The work of 2-bit PIR sensor with multi-mask and multi-lens will provide more information and improve the performance for complicated human posture recognition.

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