# Turning Over Detecting Using Low-Resolution Thermal Sensor

Jyun-Jhe CHOU*, and Chi-Sheng SHIH†
Embedded Systems and Wireless Networking Lab
†Graduate Institute of Networking and Multimedia
Department of Computer Science and Information Engineering
National Taiwan University
Email: *f03922104@csie.ntu.edu.tw, †cshih@csie.ntu.edu.tw

***Abstract*—A low resolution infrared camera can use to collect the data of our daily activity, and protect privacy. However, pose detection on an extremely low resolution image will be a big challenge to deal with. Many researches show that Super-resolution may improve the accuracy of object detection on low resolution images. In this work, we detect the turn over while sleeping. To deal with low resolution image, we fuse the images from multiple infrared cameras, and enhance the resolution by SRCNN. The noise not only from the sensor itself but also the residual body temperature on bed after turn over.**

## I. INTRODUCTION

The turn over frequency while sleeping is an important index to quantify the health of elderly. Many wearable devices can also achieve the same purpose, but many study show that the elderly feel uncomfortable with wearing such devices all days.(source?). By the low resolution thermal camera, we can obtain the daily activities informations, but not reveal too much privacy like the RGB camera.

**Contribution**

In this work, we deployed multiple low resolution thermal camera to monitor the turn over frequency while sleeping. With multiple thermal camera, Super-resolution techniques, and our method, we can have 50% recall rate and 83% precision on turning over detection.

The remaining of this paper is organized as follow. Section II presents background for developing the methods. Section III presents the system architecture, and the developed mechanisms. Section IV presents the evaluation results of proposed mechanism and Section V summaries our works.

## II. BACKGROUND

This section describes background of Super-resolution technique, and the sensors we are using in this work.

### A. Background

*a) Super-Resolution Convolutional Neural Network:* C. Dong et al. [1] proposed a deep learning method for single image super-resolution (SR). Their method learns how to directly map the low-resolution image to high-resolution image. They show that the traditional sparse coding based SR methods can be reformulated into a deep convolutional neural network. SRCNN consists three operations.The first layer of SRCNN model extracts the patches from low-resolution image. The second layer maps the patches from low-resolution to high-resolution. The third layer will reconstruct the high-resolution image by the high-resolution patches.

### B. Thermal cameras

In this work, we use two different resolution thermal camera to play the role of low-resolution and high-resolution camera. For low-resolution camera, we use Grid-EYE thermal camera. Grid-EYE is a thermal camera that can output $8 \times 8$ pixels thermal data with $2.5°C$ accuracy and $0.25°C$ resolution at 10 fps. For the high-resolution one, we use Lepton 3. The specification of them are shown in Table I.

| Specification | Grid-EYE | Lepton 3 |
|---|---|---|
| Resolution | 64 pixels (8x8) | 120x160 |
| FOV-horizontal | 60° | 49.5° |
| FOV-vertical | 60° | 61.8° |
| Frame rate | 10Hz | 8.7Hz |
| Detect temperature range | $-20$°C to 80°C | 0°C to 120°C |
| Output format | Absolute temperature (Celsius) | 14-bits value which is relative to camera temperature |
| Temperature accuracy | ±2.5°C | - |
| Temperature resolution | 0.25°C | - |
| Bits per pixel | 12 | 14 |
| Data Rate | 7.68 kbps | 2.34 mbps |

TABLE I: Specification of Grid-EYE [2] and Lepton 3 [3].

## III. METHOD NAME

### A. System Architecture

We designed a thermal-box to collect the data. It has four Grideye sensors on the corners of a 10 cm square and a Lepton 3 at the central. Figure 1 shows the system of our method. It consists four parts. The first part is to fuse multiple Grideye image, since the resolution of singel Grideye sensor only has 64 pixels. The second part, we train the SRCNN model with fused Grideye image as low-resolution and downscaled Lepton 3 image as high-resolution image. The third part, we use the Super-resolution image to train a neural network model for recognizing current pose is lay on back or lay on side. The last part, because of noise and the residual heat on bed after turn over, it is difficult to figure out the current pose. We remove the noise by median filter, and determine the current pose according to the trend of the possibility from recognition network.

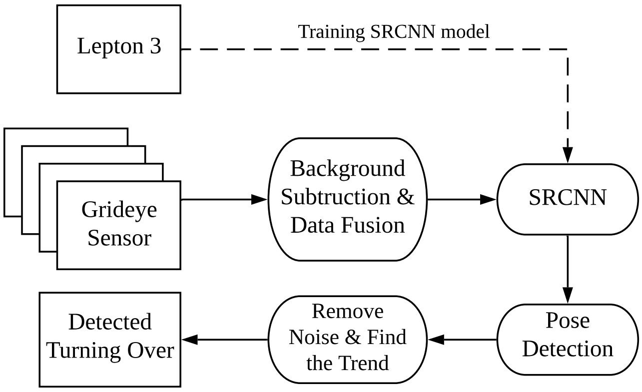



Fig. 1: Illustration of Proposed Method.

### B. Grideye Data Fusion

On the thermal-box, there are four Grideye sensors. At the beginning, we let the thermal-box faces to an empty bed and records the background temperature. All the following frames will subtract this background temperature. After that, we resize four $8 \times 8$ Grideye images to $64 \times 64$ by bilinear interpolation and than merge them dependence on the distance between thermal-box and bed, width of sensor square and the FOV of Grideye sensor.

1) $D_b$ is the distance between bed and thermal-box.
2) $D_s$ is the width of sensor square also the distance between adjacent sensors.
3) $F$ is the FOV of Grideye sensor which is about 60 degree.
4) $Overlap = 64 - 64 \times (\frac{D_s}{2 \times D_b \times tan(\frac{F}{2})})$

### C. Pose determination

We train a SRCNN model by the fused Grideye data and downscaled Lepton 3 image, and use it to upscale all following frames to SR frames. We labeled some SR frames to two categories. One is lay on back and the other is lay on side. Since the input data is very small, we use a neural network consist one 2D convolution layer, one 2D max pooling, one flatten and one densely-connected layer. The possibility of output has a very large various just after turning over because the model cannot distinguish the residual heat on bed and the person as Figure 2 shown. This situation will slowly disappear after one or two minutes.

To determination the pose, first we use a median filter with a window size of five to filter out the noise. Than, find the curve hull line of the upper bound and lower bound of the data. Finally calculate the middle line of upper bound and lower bound. Figure 3 shows the data and these lines.

We divide every data into 10 second time windows. If the middle line of the time window is at the top one fifth, it is a lay on back. If it is at the bottom one fifth, it is a lay on side. If the trend of line is going up, it is lay on back. Otherwise, it is lay on side. To guarantee the confidence of result, we will only trust the pose if there are three continuously same output.

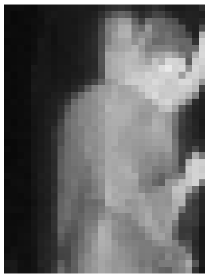


Fig. 2: Residual heat on bed.

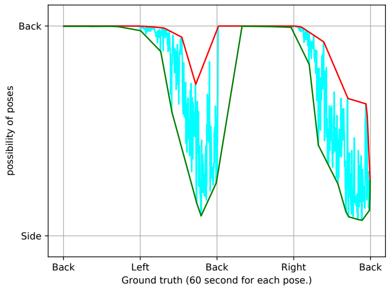
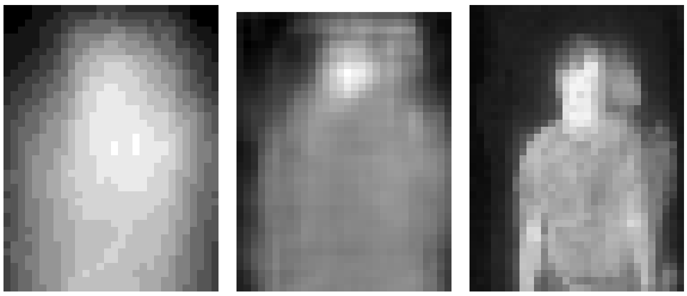



Fig. 3: Trend of pose.

## IV. Performance Evaluation

This section presents the evaluation results for the proposed method, and how we collect the dataset.

For training SRCNN model, we let a person lay on bed and randomly change pose or move his arms and legs. Collect the about 600 images from Grideye sensors and Lepton 3, and align them at the same timestamps. Figure 4 shows the result of SRCNN model.



(a) Grideye Image

(b) SR Image

(c) Downscaled Lepton Image

Fig. 4: Result of SRCNN.

For training the pose recognition model, we collect 200 images of lay on back and 400 images of lay on right or left side. The result shows that the accuracy of single frame detection can be improved about 5% by SRCNN.

We let a person lay on bed and change his pose every minutes. The pose is repeating lay on back, lay on left, lay on back and lay on right. Our method will output the currect pose every 10 seconds and check if the pose changed. The accuracy of pose detection is 65%, and the turning over detection has 50% recall rate and 83% precision.

## V. Conclusion

In this paper, we use the SRCNN to improve the resolution of thermal sensor, and detect the pose of each frame. The result shows that Super-resolution can slightly improve the accuracy of pose detection. We develop a method to detect the turning over. It has about 50% recall rate and 83% precision.

## REFERENCES


[1] C. Dong et al. “Image Super-Resolution Using Deep Convolutional Networks”. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 38.2 (Feb. 2016), pp. 295–307. ISSN: 0162-8828. DOI: 10.1109/TPAMI.2015.2439281.

[2] *Infrared Array Sensor Grid-EYE (AMG88) Datasheet*. https://datasheet.octopart.com/AMG8833-Panasonic-datasheet-62338626.pdf.

[3] *FLIR LEPTON®3 Long Wave Infrared (LWIR) Datasheet*. https://groupgets-files.s3.amazonaws.com/lepton/Lepton-3-Engineering-Datasheet.pdf.