Turning Over Detecting Using Low-Resolution Thermal Sensor

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***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 turning over while sleeping with low-resolution thermal sensors. To improve the accuracy of detection, we fuse the data from multiple sensors and use SRCNN to enhance the resolution. We also propose a method to reduce the noise caused by the residual body temperature on bed after turn over while detect the pose and turning over. The accuracy of pose detection is 65%, and the turning over detection has 50% recall rate and 83% precision.**

I. Introduction

The turning 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 information, but not reveal too much privacy like the RGB camera.

Contribution

In this work, we deployed multiple low resolution thermal cameras to monitor the turning over frequency while sleeping. We propose a data fusing and enhancement method to fuse multiple Grideye thermal sensors into a low-resolution thermal image, and use Super-resolution techniques to enhance the resolution. With our pose detection method, we have 65% accuracy of pose detection, and 50% recall rate and 83% precision of turning over detection.

II. Background

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

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.

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	$\pm 2.5°C$	-
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].

B. Thermal cameras

In this work, we use two different resolution thermal cameras to play the role of low-resolution and high-resolution cameras. For low-resolution camera, we use Grid-EYE thermal camera. Grid-EYE is a thermal camera that can output 8×8 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.

III. 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 data from Grideye sensors into a low-resolution image, since the resolution of a single Grideye sensor too low to make a decision. 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, to reduce the noise and effect cause by the residual heat on bed after turning over. We remove the noise by median

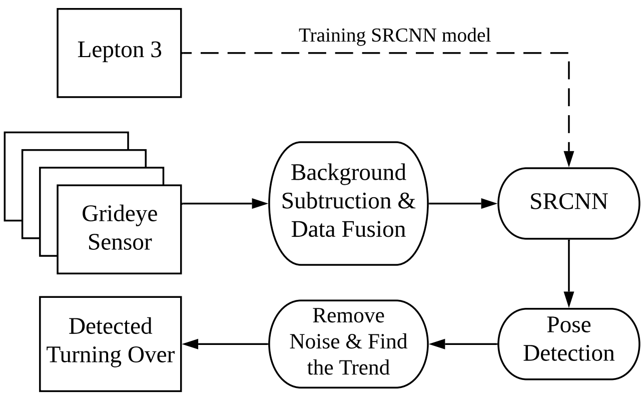


Fig. 1: Illustration of Proposed Method.

Fig. 2: Residual heat on bed.

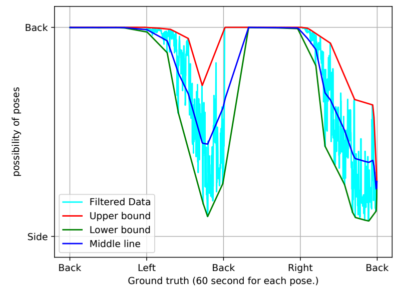
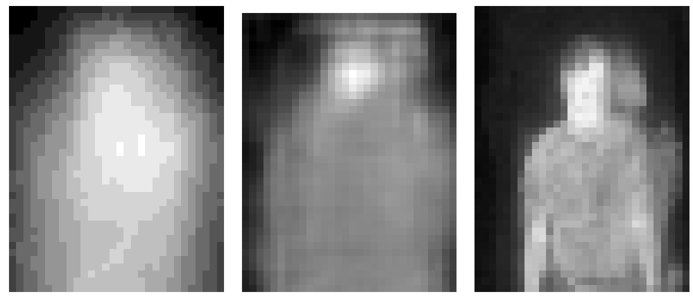


Fig. 3: Trend of pose.



(a) Grideye Image

(b) SR Image

(c) Downscaled Lepton Image

Fig. 4: Result of SRCNN.

filter, and determine the current pose according to the trend of the possibility from recognition network.

A. 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 8×8 Grideye images to 64×64 by bilinear interpolation and then merge them dependence on the distance between thermal-box and bed, distance between sensors and the FOV of Grideye sensor. In our case, D_B is 150 cm, and D_s is 10 cm.

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) $Overlap = 64 - 64 \times (\frac{D_s}{2 \times D_b \times tan(\frac{F}{2})})$

B. Turning Over Determination

We train a SRCNN model by the fused Grideye image and downscaled Lepton 3 image, and use it to enhance all following Grideye frames to SR frames. We labeled some SR frames into two categories, lay on back and 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 turn 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. Then, 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, and regrad it as the trend of the pose changing. Figure 3 shows the filitered 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, or the trend is going up, it is a lay on back. If it is at the bottom one fifth, or the trend is going down, it is a lay on side. If there are three continuously same poses, and different from the last turning over, it will be count as another turning over.

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.

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 minute. The pose is repeating lay on back, lay on left, lay on back and lay on right. Our method will output the current pose every 10 seconds and detect the turning over. 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 propose a data fusing and enhancement method to fuse data from multiple low-resolution thermal sensors and use the SRCNN to enhance resolution, the result shows that it can improve the accuracy of single frame pose detection by 5%. We also propose a turning over detection method using multiple frames to reduce the noise and considering the trend of pose change to deal with the residual heat. The result shows that The accuracy of pose detection is 65%, and the recall rate and precision of turning over detection is 50% and 83%.

REFERENCES

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