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Calibration of low-resolution thermal imaging for human monitoring applications

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Abstract—Thermal imaging has recently come to light to measure high human body temperature (fever) in responses to the global public health issues. This is normally achieved by very expensive high-resolution thermal cameras. Lately, there has been a new commercial low-resolution Thermal Sensor Array (TSA) that have gained growing interest in indoor human monitoring applications due to their low-cost and human privacy-preserving claims. However, there has not been sufficient independent empirical calibration of low-resolution TSA and high-resolution images for human-centred applications. This letter provides empirical calibration of low- and high-resolution thermal imaging techniques in terms of their visible outputs, accuracy in temperature values and stability. Besides, this letter assesses the claimed privacy-preserving feature of TSA by experimentally validating the possibility of revoking the human identity from the TSA's output. Thus, this letter aims to understand better the advantages, limitations, and future trends of using TSA in human monitoring applications.

Index Terms—sensor calibration, privacy-preserving, thermal sensor array, human-centered AI, neural network, regression

I. INTRODUCTION

Thermal imaging has emerged in several human-body temperature monitoring applications and recently became popular through utilising them to identify individuals with fever in public places (e.g. one of the COVID-19 disease symptoms) [1], [2]. The thermal imaging process relies on capturing the infrared radiations emitted by the environmental objects above absolute zero to form a thermal image called thermograms. A primary advantage of thermography over conventional imaging is its ability to work with or without light since all objects with a temperature emit infrared radiation. Recently, there has been a growing interest in utilising low-resolution Thermal Sensor Array (TSA) in indoor human-centric applications [3]–[10]. The motivation behind using TSA rather than high-resolution thermal imaging is due to several claimed features, including privacy-preserving and low-cost capabilities. Like any high-resolution thermographer, the spectrum of TSA radiation is entirely determined by the temperature alone as no wavelength is selectively emitted. Thus even a colourless object could still appear in TSA's thermograms. On the other hand, the utilised sensing technologies for human monitoring devices can be classified into three main categories: First, wearable-based sensors, which usually require the users to wear or carry a device perpetually. This is often inconvenient for the older adults [11], and it is even more challenging to manage by older adults with Dementia, as there is a high probability of forgetting to carry these devices. Second, the conventional vision-based systems provide high-performance but violate users privacy in indoor environments, e.g., home settings. Third, ambient sensing devices such as Passive Infra-Red (PIR) sensors installed in a home environment. Such devices preserve privacy but do not generally perform well in multi-occupancy home environments. Nevertheless, PIR can only detect temperature changes within the sensors' Field of View (FoV) and therefore cannot be used reliably to detect, for example, different states of human [4]. TSA overcomes the challenges of detecting stationary objects and their orientation within the sensor's FoV by utilising multiple IR sensor elements, referred to as IR array, that works together instead of a single sensing element. Therefore, the primary use of TSA sensors is to fine-tune the trade-off between privacy and performance in domestic human-centred applications.

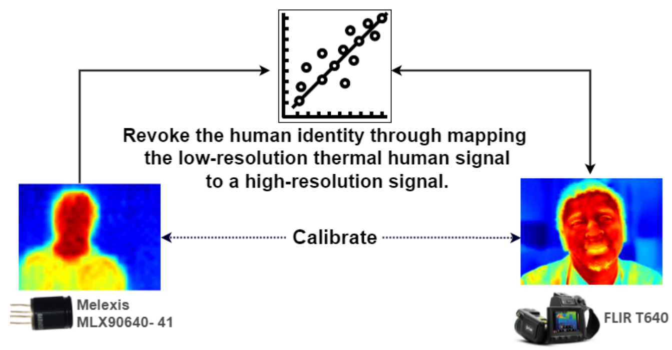

Fig. 1: Graphical visualisation of this letter objectives to calibrate between thermal imaging and assess the privacy of low-resolution TSA output.

The TSA's low-cost feature is evident compared to high-resolution thermographers. For instance, the price of a commercial Melexis TSA[1] is about 0.00125 of the price of the FLIR T6XX[2] camera, the high-end "gold standard" thermal camera. However, there has not been sufficient independent empirical calibration of the performance of TSA and high-resolution thermal imagers for human monitoring applications. Also, an assessment of TSA's privacy-preserving feature

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[1] The sensor details can be obtained from the Melexis website: https://www.melexis.com/en/product/MLX90640/

[2] More details about the camera is available from FLIR website: https://www.flir.co.uk/support/products/t640/

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in cloud-based human-centric applications has been missed in the previous work to experimentally validate the advantage of TSA over ordinary and high-resolution thermal imagers to maintain human privacy in indoor environments.

This letter aims to provide a better understanding of the advantages, limitations and future trends of using TSA in human-centred applications by addressing the following specific objectives.

- to perform a visual thermal calibration of a high-resolution and high-cost imager with low-resolution and low-cost TSA;
- to perform temperature accuracy and stability calibration for various TSA sensors and high-resolution thermal imager;
- to validate the claimed privacy-preserving feature of TSA in cloud-based human monitoring applications.

The above study objectives, which have been visually illustrated in Fig. 1, have been achieved using four thermal imagers, one TSA with the resolution of 16×12, two TSAs with the resolution of 32×24, and one high-resolution thermal imager with the resolution of 640×480. A detailed description of their experimental calibration is provided below.

II. VISUAL THERMAL CALIBRATION

Thermal imagers capture the thermal energy of objects in the FoVs and output as a temperature matrix. The temperature matrix visualisation is performed by applying a colour mapping scheme to create a visual image. Thus, thermal imagers could be considered as an image converter from the radiant thermal energy to the visible images. Therefore, there are specific attributes for determining the quality of the image: Accuracy, constant pattern noise and thermal sensitivity.

Figs. 2(a), 2(b), and 2(c) show a visual calibration on the obtained temperature matrices post applying the same colour map scheme using TSA with 16×12 and 32×24 resolution versus high-resolution imager with 640×480 resolution, all captured at the same distance. Remarkable observations can be deduced from this visual calibration. First, the edges of the objects in the TSA output were not well preserved compared to the high-resolution imaging output. Second, the warmest region (maximum temperature values) that appears in all visual calibrations is the human face. However, the scale of temperature variations drops when the image resolution decreases. This is due to the fact that each temperature value (pixel) in the imaging output represents the average temperature of a wider inspection area for a lower resolution imager. This justifies the clear appearance of the human face in the high-resolution image and its high accuracy even in the detection of a small heat bump under the human lips in Fig. 2(c).

The noise affecting thermography in indoor human-centred applications can be classified into two categories: (1) external noise, e.g. a cup of warm tea or ice cream, (2) thermal noise induced by the human movement. Although external noises affect the colour map scale of both high and low thermal images, human-induced noise appears to be more serious in low-resolution thermal imaging. Fig. 3 demonstrates two types of human-induced noise on the TSA output. The first is caused by a swift human movement that can be seen around the thermal human presence, while the second noise affects both low and high-resolution thermal images as it is caused by prolonged human contact with environmental objects such as a chair.

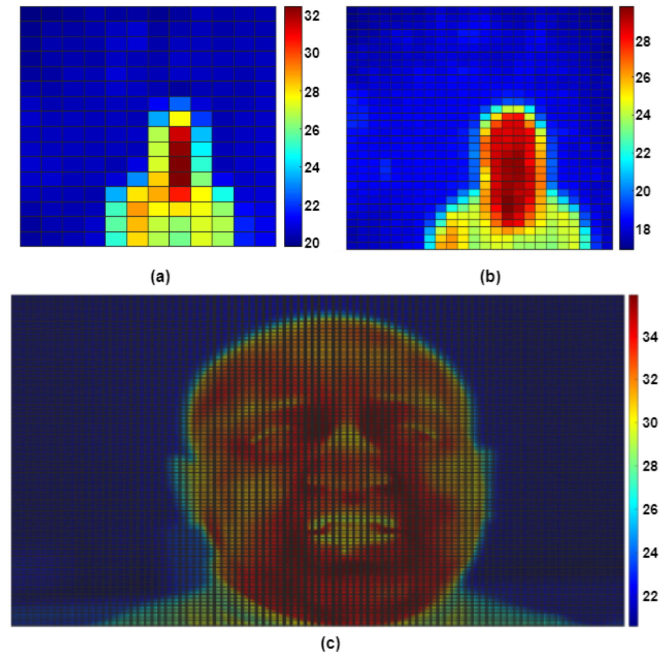

Fig. 2: A visual calibration on colour mapped temperature matrices obtained using different thermal imaging resolutions, (a) TSA with 16×12 resolution, (b) TSA with 32×24 resolution, (c) high-resolution imager with 640×480.

Fig. 3: TSA is sensitive to thermal noise induced from a recent human movement and prolonged human contact with environmental objects such as a chair.

III. TEMPERATURE VALUE CALIBRATION

The visual calibration demonstrated the potential of low and high-resolution thermal imaging in stationary and moving human detection. However, thermal imaging provides more useful information than conventional imaging, which is human temperature. This section investigates the reliability and accuracy of the human temperature acquired using different TSA resolutions. Fig. 4 shows an experimental calibration of human skin temperature accuracy using different resolution thermal imagers placed at the same human to sensor distance. The first calibration shown in Fig. 4(a) is concerned with assessing the stability of the same TSA resolution. In particular, two TSAs with the resolution of 32×24 have been used with a human

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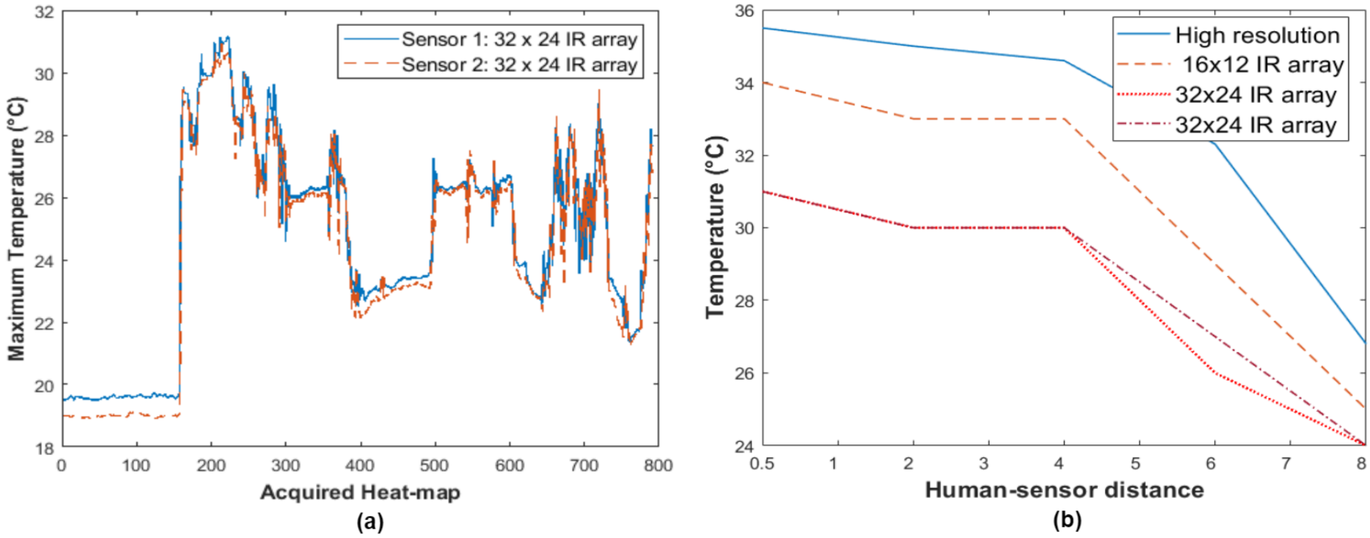

Fig. 4: An empirical calibration of acquired human skin temperature using, (a) same TSA resolution, (b) different TSA resolution with a high-resolution thermal imager on a different human to sensor distance.

moving in their FoVs. It can be observed from Fig. 4(a) that the TSA is a well-stabilised sensor in acquiring the temperature value.

In the second calibration experiment, a high-resolution imager has also been used with a human moving from a close human to sensor distance to a far distance in the sensors' FoVs in addition to two different TSA resolutions. The result of this experiment are illustrated in Fig. 4(b). It can be concluded from these results that there is a linear relationship between all of the thermal imagers regardless of their resolution. Specifically, the lower resolution TSA has a higher temperature value of $2°C$ in a linear relationship. Moreover, the lowest resolution TSA seems to be more accurate than the higher resolution one with reference to the result of the high-resolution thermal imager. Besides, the acquired temperature values vary with the distance between the object and the sensor positions on all the used thermal imagers.

IV. PRIVACY ASSESSMENT OF LOW-RESOLUTION THERMAL IMAGING

Unlike high-resolution thermal imagers, identifiable human information is not clear enough to identify human identity in the TSA's output. Therefore, it has been claimed that TSA is a privacy-preserving sensing approach. An empirical privacy assessment has been conducted to verify the possibility of reconstructing the low-resolution thermal image to invoke identifiable human information from the TSA's output.

The analysis performed to validate the privacy-preserving feature of TSA is based on exploring if there is a relationship between low-resolution and high-resolution imaging. Thus, low-resolution images can be converted using this relationship to high-resolution images. Technically, to perform a regression analysis to estimate the relationship between independent variables (low-resolution images) and dependent variables (high-resolution images). In this letter, a two-layer feed-forward neural network is trained to solve this regression problem. The network input is the low-resolution data, while the output is the high-resolution data. The weight of the network is updated using Levenberg-Marquardt optimisation [12].

Given a set of m pairs (x_i, y_i) of low-resolution image and high resolution image. The primary goal of the optimisation algorithm is to find the parameters β of the network model $f(x, \beta)$ to minimise the sum of the squares of the deviations $S(\beta)$ as follow:

$$\hat{\boldsymbol{\beta}} \in \operatorname{argmin}_{\boldsymbol{\beta}} S(\boldsymbol{\beta}) \equiv \operatorname{argmin}_{\boldsymbol{\beta}} \sum_{i=1} \left[y_i - f\left(x_i, \boldsymbol{\beta}\right)\right]^2 \tag{1}$$

where $\hat{\beta}$ is is the estimate of parameters β.

In the first experiment, a dataset of 916 low-resolution images and 916 high-resolution images were collected simultaneously for various indoor environmental thermal objects, including human subjects who move within the imagers FoV while facing the imagers. Each subject presents in the imagers' FoV separately at the time of acquisition. To have the same size of input and output network layers, high-resolution images resized to 32×24, the TSA output resolution. Further, the thermal images have also been converted from matrix to vector form. The data set was divided randomly into 70%, 15%, and 15% for training, validation, and testing. The R-value is used as a network evaluation matrix to report the extent to which the regression model can convert low-resolution images to high-resolution images and was 0.93691, 0.74869, 0.7128 and 0.85879 for training, validation, testing, and all of them, respectively.

The results above demonstrate the ability of the method to convert a low-resolution thermal signal into a high-resolution thermal signal. However, the result of the testing subset were 0.7128, which is not as good as the performance of the training subset. On the other hand, the aim of this experiment is to validate the claimed privacy-preserving feature of the TSA for human-centred applications. Therefore, a second data set was collected in the presence of a human in all the acquired scenes. The dataset contains 96 low-resolution images and 96 high-resolution images. The regression model achieves R-values of 0.93912, 0.93287, 0.92174 and 0.93287 for training, validation, testing, and all of them, respectively. Fig. 5 shows the regression plots of the relationship between the acquired human presence in the low and high-resolution thermal images. Building on top of this, the identifiable human information may not be as private as claimed

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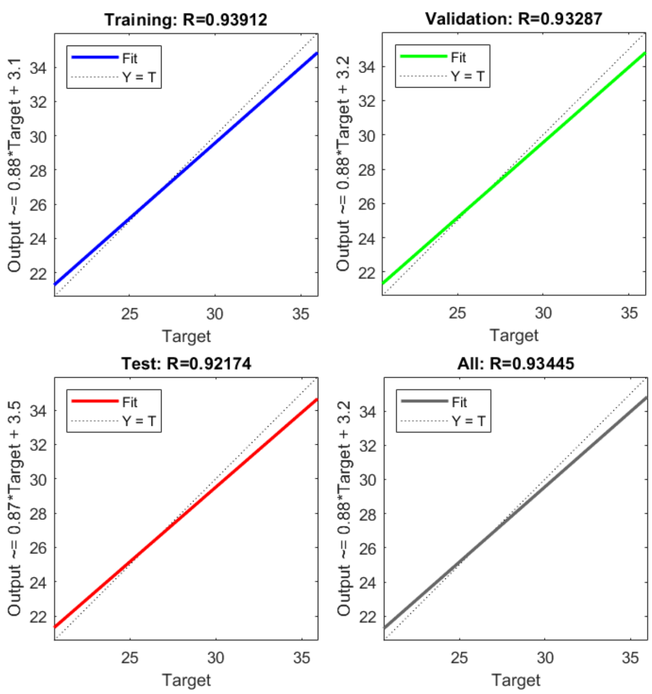

Fig. 5: A visualisation of the regression model for the training, validation, and testing data sets shows the relationship between the low and high-resolution thermal images.

since it can be revoked after the low-resolution thermal signal is enhanced into a high-resolution signal.

V. DISCUSSION AND FUTURE OF WORK TRENDS

TSA shows a promising imaging approach for human-centred applications through overcoming challenges observed in other sensing approaches for human monitoring applications. For example, TSA does not require the human to wear or carry a device and thus could be more suitable for supporting older adults to live independently in their own homes. Also, the raw TSA output does not contain specific identifiable information compared to a regular- or high-resolution thermal imagers.

The experimental calibrations of acquired human temperature show that human temperature values vary with imaging resolution in a linear relationship and human to sensor distance. Therefore, future work should take into account this variation in applications where the acquired human temperature is important for system decisions, e.g. human fever detection. Furthermore, the TSA output appears to be more sensitive to thermal noise, and thus it is very important to consider appropriate pre-processing techniques that are specifically suited to this sensing methodology.

This letter raises serious privacy concerns regarding TSA deployment in indoor human monitoring applications. Accordingly, the letter recommends not to take TSA privacy for granted since a third party could reconstruct the human thermal image from a low-resolution signal to a high-resolution signal. Thus identifiable human information could be revoked.

From an engineering point of view, TSA would be a better choice than high-resolution imagers due to the low cost and development integration for large-scale deployment of indoor human monitoring applications. Nevertheless, high-resolution imagers provide richer thermal information than TSA and could be more useful in controlled-based applications such as human medical diagnostic systems or energy efficiency applications.

VI. CONCLUSION

The letter results confirm the potential of Thermal Sensor Array (TSA) in human monitoring applications due to its low cost and development integration compared to commercial high-resolution thermal imagers. However, potential thermography-based human monitoring applications should consider the human temperature variance acquired using different imaging resolutions and human to imager distance. On the other hand, TSA is more sensitive to thermal noises, and thus, it is essential to perform robust pre-processing techniques suited explicitly to this sensing methodology.

A regression model that uses an artificial neural network to fit the low-resolution thermal signal to the high-resolution signal has also been proposed to ensure the TSA's privacy-preserving capability. It can be concluded that identifiable human information can be invoked from TSA's output, and therefore security measures should be in place to ensure users' privacy in cloud-based applications. The proposed regression model is also valid to enhance the low-resolution thermal signal in potential human-centred applications.

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