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A comparative study of low and high resolution infrared cameras for IoT smart city applications

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ABSTRACT

The goal of smart cities is to improve efficiencies, enhance sustainability, advance quality of life and reduce energy consumption. One of the key factors to accomplish a smart city involves the use of IoT and information technology infrastructure which can be described as the foundation of a smart city. Its effective implementation will allow the city to meet its wide range of requirements while being able to respond to innovations, such as advanced sensors, analytic tools, measurement, and artificial intelligent based solutions. This paper investigates and compares between the use of low and high resolution infrared sensors as part of the Internet of Things (IoT) to estimate crowds in cities to enhance and optimise the efficiency of the transportation process and other public services for low density scenarios. A case study was conducted in Nottingham city at one of the tram stops. An experimental methodology is used where different number of people are captured and the results are compared using different image processing techniques. The findings show that both technologies are useful in the estimation of crowd density, however, the high resolution camera has been found to be more accurate in estimating the number of people albeit it is more expensive for the integration into infrastructures. The practical implication is that low-cost and low resolution infrared cameras could provide reasonable results. However, for higher accuracy, high resolution infrared cameras will be needed; and they are potentially more expensive. So a compromise might be needed between cost and performance to encourage the installation of more IoT systems using infrared technologies.

1. Introduction

Several cities around the world are aspiring to be smart cities of the future. To achieve this, however, it is imperative to implement a plan with the involvement of both public and private sectors, product vendors, IT infrastructure providers and research institutions. The goal of smart cities is to improve efficiencies, economic development, sustainability, and quality of life for their residents. [22,2,3]. Economic development, social development, and environmental protection are all part of the urbanization process. Therefore, the urban population percentage is becoming increasingly important as the urban population is expected to reach 66 % by 2050. For these populations to meet their basic needs, such as adequate energy and clean water, as well as food safety, sustainable development must be guaranteed while ensuring social, economic, and environmental sustainability [15].

Al-Habaibeh has defined an intelligent city as being "*a city with changeable characteristics that can respond with minimum human interference to change in the external and internal environments for the benefit and comfort of its inhabitants taking into consideration safety, financial perspective and reduction in energy use*" [12]. To achieve this, however, it is imperative to implement a plan with the involvement of many stake holders. One of the key factors to achieve a smart city involves the use of information technology infrastructure and IoT. Its effective implementation will allow the city to meet its wide range of requirements while being able to respond to innovations such as advanced sensors and instrumentations, analytic tools, measurement, and artificial intelligence. Subsequently, its potential benefits include improved sustainability,

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effective disaster prevention, business, enhanced public safety, better transportation systems and improved standard of living [14,10,18].

In cities, pedestrians and crowds are a common sight. Therefore, city management involves managing, monitoring, and planning for crowds. Due to this, crowd management is a vast area of research and development that encompasses theoretical models, simulation tools, as well as a variety of support systems. Additionally, crowd monitoring techniques employing computer vision systems have been highly popular [6,5]. However, in the context of the development of smart cities, the issue of crowd management is not considered to be a priority as it is given insufficient attention. According to Bock [7], understanding the impact of crowds mobility and their behaviour would be a facilitator in the development of smart cities. This would therefore benefit various sectors such as transportation sector, tourism sector, and the public safety. Several studies suggest that the use of IoT technologies can encourage development in sectors which include transportation services [28], tourism [8], and public order [9]. Other applications would include health and safety. For example, Wuhan was reported to be the first places where the SARS-CoV-2 virus was identified for the first time in December 2019 which is the virus that causes COVID-19 [20]. Jayaweera, Perera, Gunawardana and Manatunge, [13] established that droplets ejected by sick people spread the virus to others. Therefore, the COVID-19 virus calls for the enforcement of restrictions at crowded events, aimed at containing the spread of Covid-19. Therefore, a distributed and feasible IoT technology is needed for crowd monitoring, including situations with low visibility due to darkness.

1.1. Motivation

Sensors are essential components that enable intelligent control systems to become aware of their environment and improve their processes accordingly. They utilise data collection techniques that provide data for the operation of smart cities. Using these variables, smart cities can adjust their operational settings according to the environment [16]. According to Mobus and Kolbe [19], the steady technological development of sensors will help driving innovation while simultaneously enabling small scale devices to generate ample processing power. Hence, this should support the IoT and the concept of smart cities.

A critical aspect of surveillance is estimating the number of people in a particular area. However, the most widely used device to achieve this is the video camera. Regardless of its effectiveness, it consumes considerable storage space and communication bandwidth [11]. It could also be affected by conditions such as illumination. Schif et al., [21] also identified the challenges with video cameras which include its inability to precisely detect objects in dark environments where the difference between foreground and background images becomes not clear [17]. However, this could be resolved using infrared (PIR) sensors [27]. Due to their low cost [25], compact size [29], and stability under changing temperatures [30], they are commonly used to identify, detect, and track individuals. Regardless, the use of the appropriate infrared camera is of paramount importance. This involves, normally, the implementation of high-resolution infrared cameras as opposed to low resolution infrared cameras [24,23,1,26].

1.2. Contribution

This paper will investigate the difference in using low-resolution and high resolution infrared cameras in detecting the number of people at night in dark environments towards developing smart or intelligent cites to estimate the number of people at a specific location. This paper used a Nottingham tram strop for this purpose. This paper aims to investigate the ability of a high resolution infrared camera and low resolution infrared camera in counting people as shown in Fig. 1, assuming it is a low density crowd situation. For this comparison we are using a low-cost 16x16 pixels infrared canera (IRI 1002); and FLIR E25 for the high resolution option. Humans at normal body temperature radiate infrared radiation. Normal body temperature can vary and it is dependent on different factors such as type of food, clothing, exercise, sleeping and the time of the day. Infrared cameras can detect infrared radiation between 7.5 up to 13μm. The question is: can we use a low resolution infrared camera to detect the number of people from a distance with similar accuracy as the high resolution? Similar work has been used previously to look at density and count people with high success in elevators [4]. But can we do the same in open areas with low density? In this case the aim is to count the number of people from the thermal images and compare the results against the actual number of people, for both high and low resolution infrared imagers. Other researchers have done previously high densities of people using low-resolution infrared technology with high success rate, please see for example [26]. However, the focus here is on low density of people in open area.

1.3. The paper's structure

This paper included the introduction in section 1 above. Section 2 includes the methodology and the algorithms' flowcharts used to estimate of the number of people from the infrared images. It includes examples of the captured images and the flowchart of the methodology. Section 3 presents in detail the image processing techniques and the obtained results, namely average heat, background threshold (pixels) and edge detection (pixels). The discussion and conclusion sections are then presented.

2. Methodology and experimental work

The experimental setup is designed to count the number of people coming and leaving from a tram stop. In this experiment, the idea is to compare between the accuracy of a high resolution infrared imager and a low resolution infrared imager. After the experimental work is conducted, different digital image processing and other mathematical techniques are applied to predict actual number of people in an image. Fig. 1 presents the visual image and the two infrared images. For the high resolution camera and from a distance, body heat is very clear as shown in Fig. 2. In this research, the idea is to detect the number of people at a tram stop by using a high and low resolution IR systems. High resolution infrared images are shown in Fig. 2. While Fig. 3 presents the data from the low cost and limited resolution infrared imager. Although it is a low resolution, 16 X16 pixel, the thermal imager it can be used to display images of up to 128X128 pixels using bilinear or bicubic interpolation. The interpolation process estimates values of intermediate components of continuous function in discrete samples.

An interpolation technique does not add extra information into the image but can provide better thermal images for human perception. For the bicubic interpolation, the output pixel value is the weighted average of the pixels in the nearest 4X4 neighbourhood as shown in Fig. 3-a.

Fig. 4 presents the flowchart of the proposed methodology. Three main techniques are in this case for comparison between the two systems:

Average heat in the form of infrared radiation, measured in (temperature ^{o}C).

As described further in section 3.1, this method is based on calculating the average values of the pixels of the infrared image as a

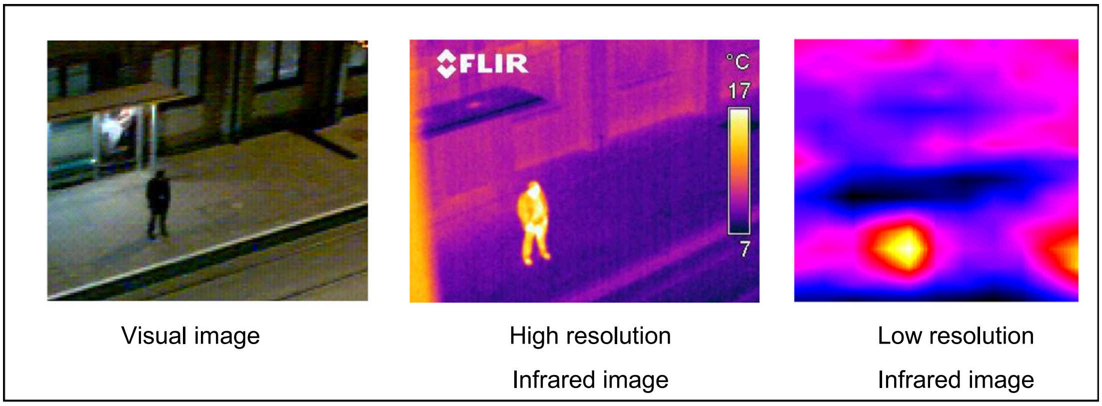


Fig. 1. The low resolution infrared image, high resolution infrared image and the associated visual image.

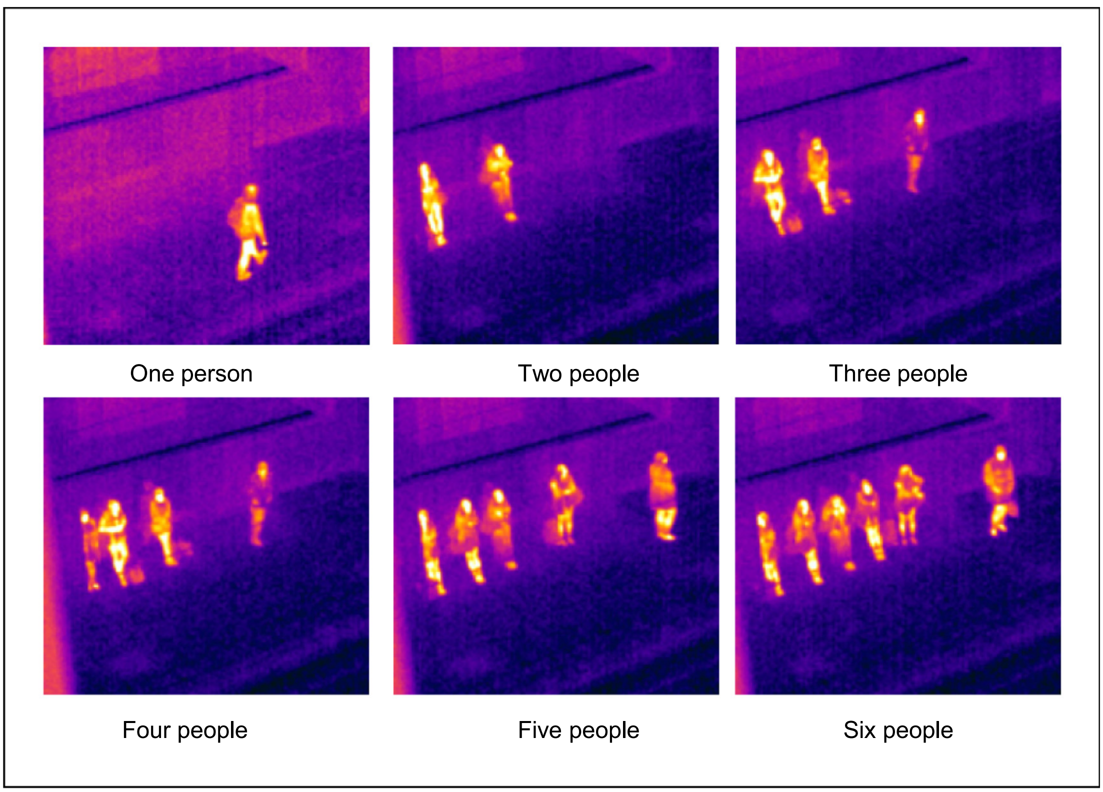


Fig. 2. High resolution infrared images of people waiting at night near the tram stop.

temperature sensor on the assumption that a higher number of people (i.e heat source) would mean more heat.

- *Background threshold* (pixels). In this technique, see section 3.2, the background is separated from the foreground via thresholding and then the number of white pixels (people) are counted as an indication of the number of people.
- *Edge detection* (pixels). As described in section 3.3, this technique is based on edge detection algorithm to identify the people's profile from the background and then counting the pixels as a measure of the number of people in an image.

An experimental work to count people at low density has been performed. In this case up to six people are used in the analysis. The temperature of a person is generally higher than the background, usually between 19 and 32°Celsius. The average heat of the background depends on the outside temperature.

3. Results

This section includes the three image processing techniques, in three separate sub-sections, that have been implemented. This includes also examples of data, the detailed analysis flowchart and the obtained results.

3.1. Using average heat to estimate the number of people

One way to look at the number of people is to calculate the average heat (temperature) as described in equation (1). The math-

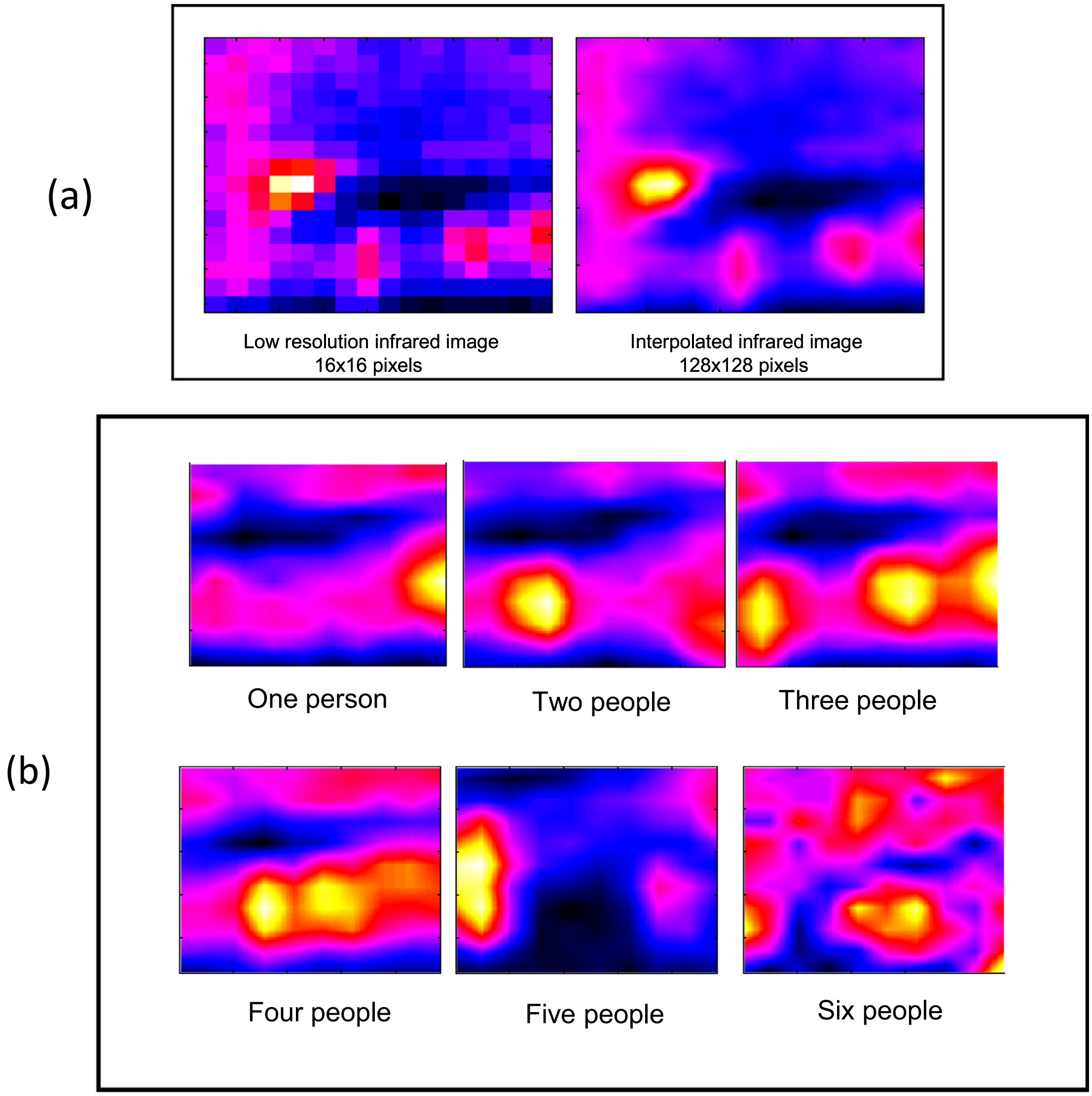


Fig. 3. (a) A low resolution infrared image (16x16 pixels) and its interpolation; (b) the interpolated low resolution infrared images for different number of people.

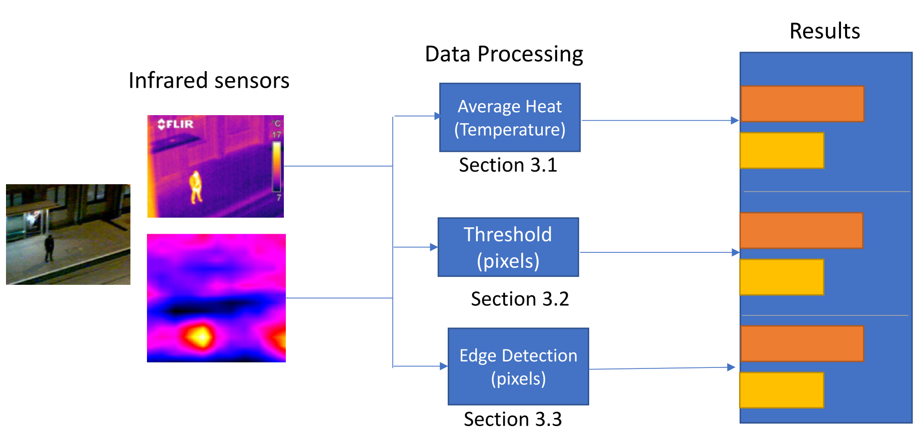


Fig. 4. The flowchart of the proposed methodology.

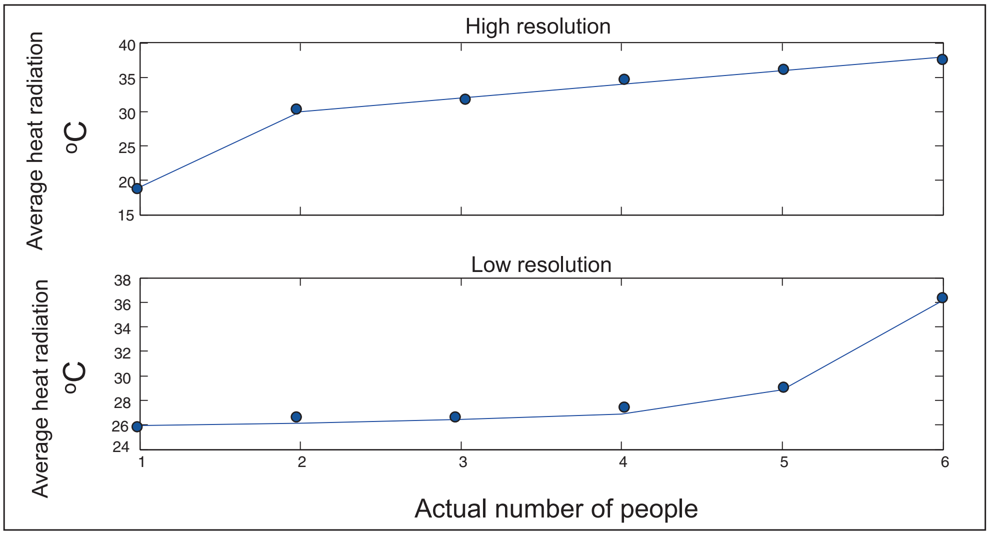


Fig. 5. The comparison between high and low infrared images using average heat values (Temperature °C).

Table 1
The comparison between the number of people and the average temperature.

Actual number of People	Average temperature (C°) (Low resolution)	Average temperature (C °) (High resolution)
0	25.2940 (empty)	10 (empty)
1	25.9567	19.5142
2	26.1605	31.2734
3	26.4670	31.3175
4	26.9173	34.7801
5	28.8457	37.3547
6	36.1933	38.3672

ematical representation of the average temperature (heat) can be expressed as:

$$\text{Average temperature} = \frac{\sum pixels}{(\text{pixels width}).(\text{pixels height})} \quad (1)$$

Fig. 5 presents the average heat of high & low infrared cameras based on equation (1).

As shown below in Table 1, the comparison between the number of people in an infrared image and the average temperature.

As the number of people increases in a thermal image, the average temperature also rises. It can be seen from Fig. 6-a that the system is able to count up to six people in an image. The percentage error is shown in Fig. 6-b.

3.2. Using threshold values for estimating the number of people

One idea that can be derived from the previous analysis is to count the infrared pixels in a an infrared image. The results of the threshold values can be seen in Fig. 7-a and Fig. 7-b for the high and low infrared images respectively.

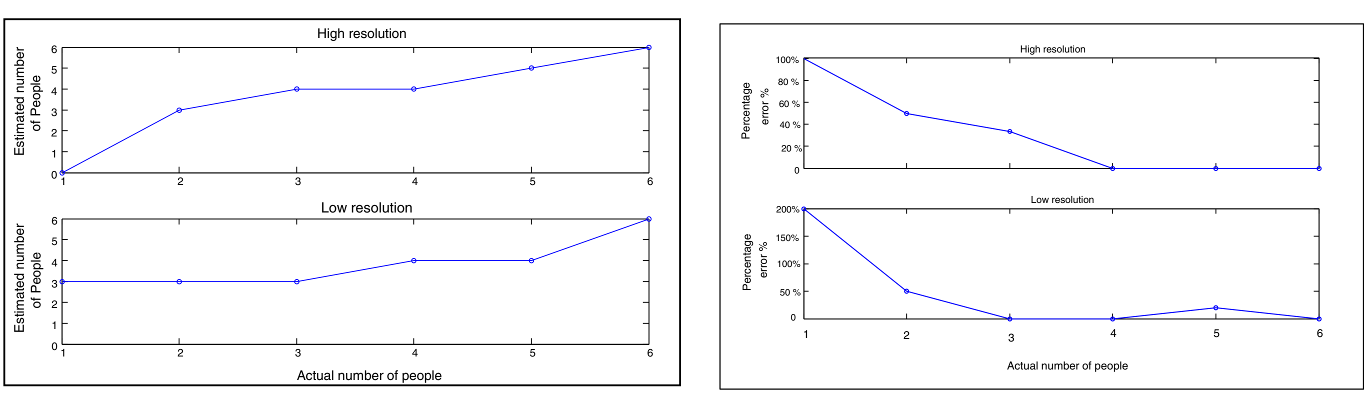
The average value in this experiment is 15 °C, however this value is dependent on the distance, ambient temperature and the geometry of the view; in addition to other factors such as emissivity. As the number of people increases, the number of infrared pixels also increases.

For the thresholding process, infrared images are processed using equation (2). Let x be an element (pixel) of the infrared image (matrix) of 241x241 elements from infrared imager.

Hence,

$$[n]_{(j,k)} = \begin{cases} 1 & if \quad x \geqslant 15 \\ 0 & if \quad x < 15 \end{cases} \quad (2)$$

where j = 241; k = 241.



(a) (b)

Fig. 6. (a) The comparison between average heat and number of people; (b) High and low average heat error (%).

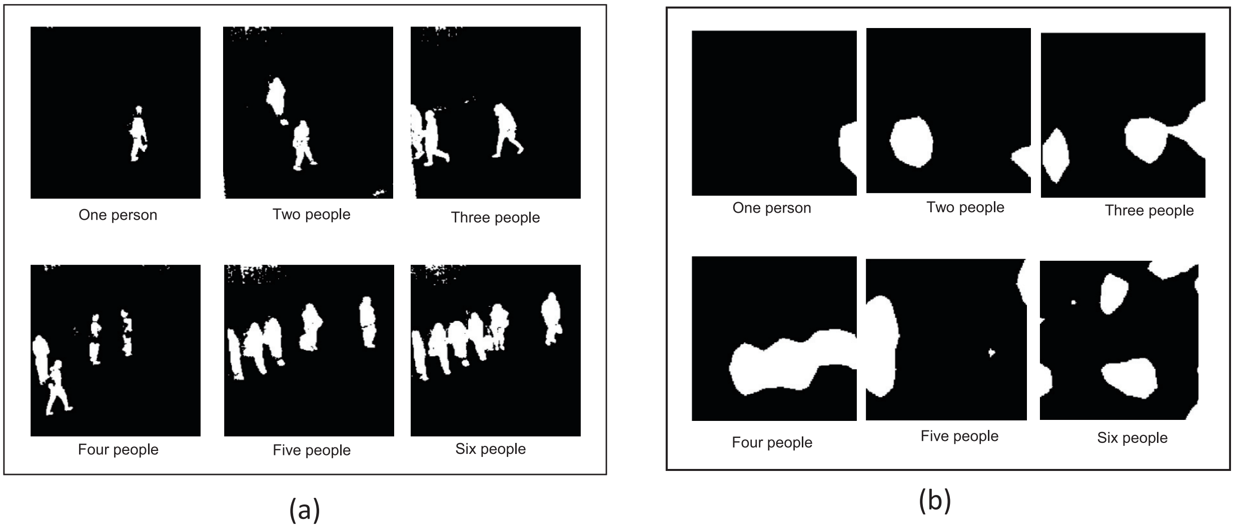


Fig. 7. (a) Infrared images after thresholding; (b) low resolution Infrared images after interpolation and thresholding.

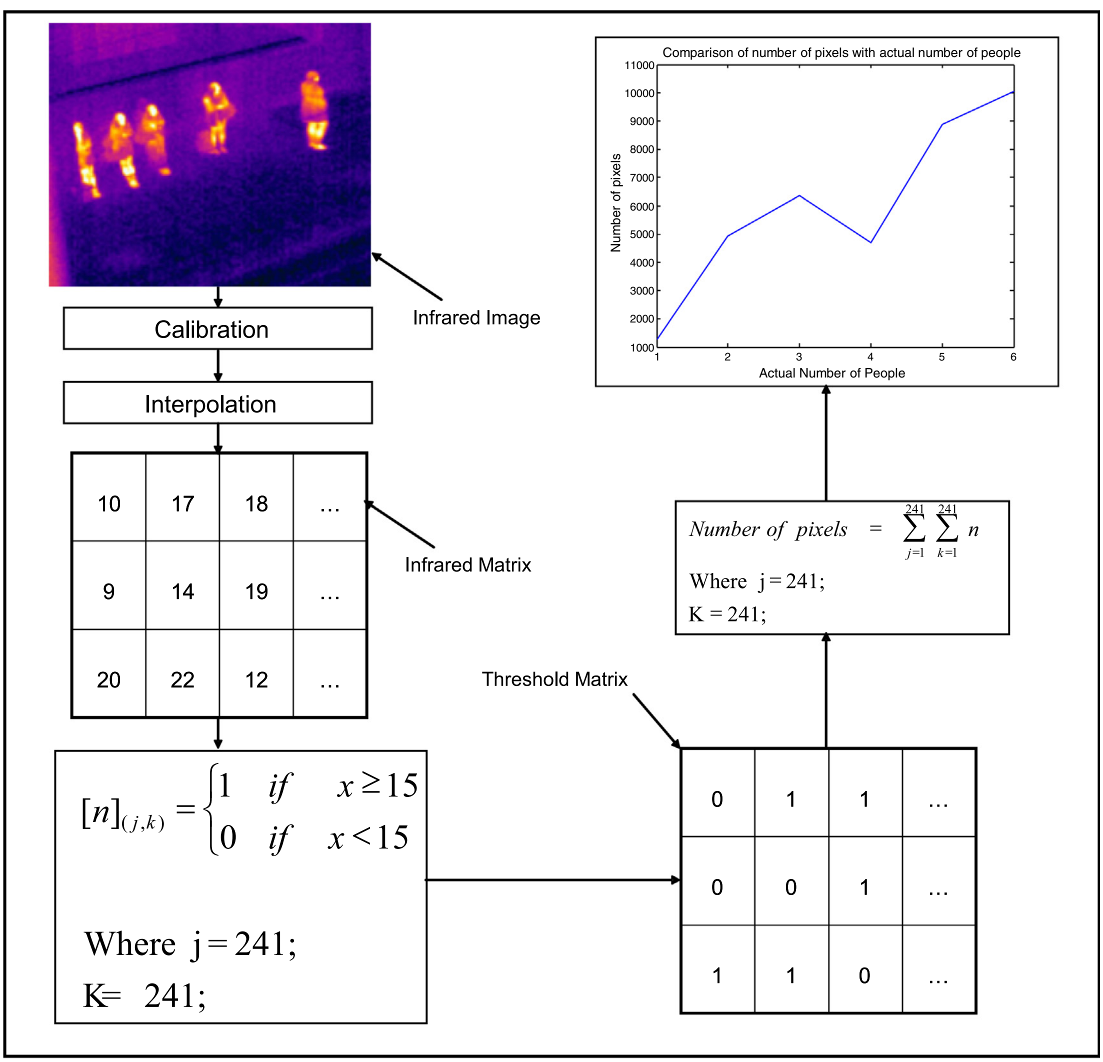


Fig. 8. The algorithm used to calculate the number of pixels that represent people.

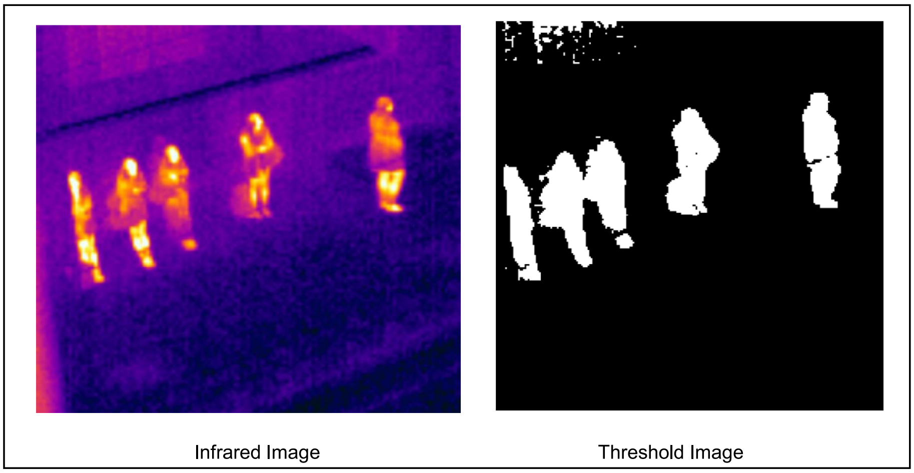


Fig. 9. An axample of a high resolution image thresholding and background subtraction.

In equation (2), n is the number of infrared pixels. Hence for these experiments because they are conducted in an open environment, 15 °C is the average human temperature used as a threshold value. Afterwards thresholding for each image is processed using the following equation:

$$Number\ of\ pixels = \sum_{1}^{241}\sum_{1}^{241} n \quad (3)$$

where 241x241 is the number of pixels of the infrared image. Fig. 8 presents the flowchart of the implemented image process technique.

After plotting the resulting images, distinguishable results are obtained. For example, six people make around 10,000 pixels using a high resolution infrared imager, and 21,584 pixels using a low resolution thermal imager. Fig. 8 shows the flowchart of the algorithm used to calculate the number of pixels that represent people. Fig. 9 presents an example of the thresholding process of an infrared image.

Table 2
The comparison between the number of pixels and the number of people (thresholding).

Number of people	Number of infrared pixels in an image (High resolution)	Number of infrared pixels in an image (Low resolution)
0	889	0
1	1275	804
2	4931	1632
3	6358	2855
4	4686	4175
5	8881	5430
6	10,044	21,584

The results are shown in Fig. 10 in relation to the number of pixels and the actual number of people in the image. Table 2 represents a comparison between the number of people and the number of infrared pixels in the threshold signal processing of the infrared images.

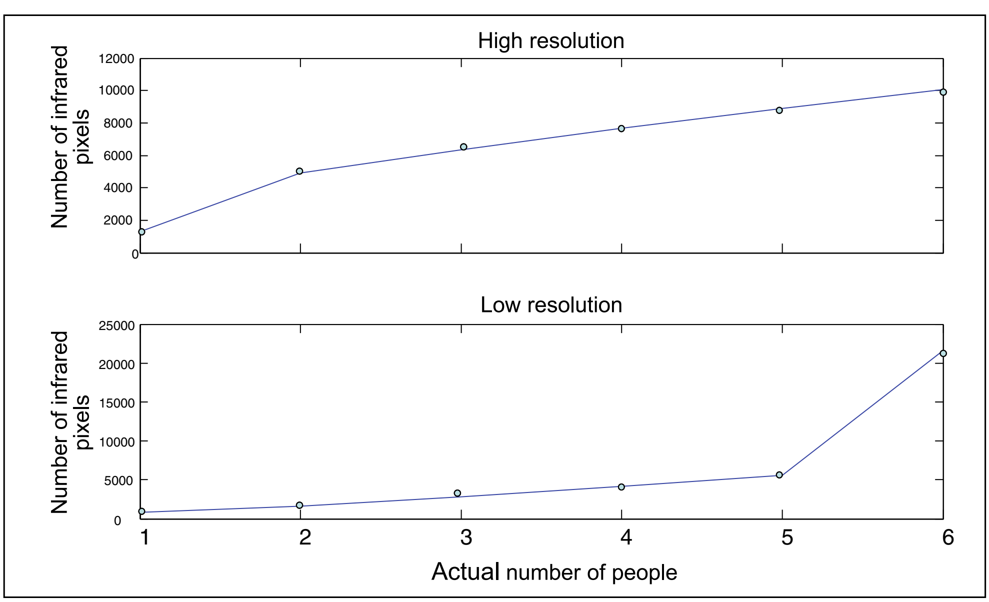


Fig. 10. The comparison between number of infrared pixels and number of people for the high and low resolution imagers when thresholding algorithm is used.

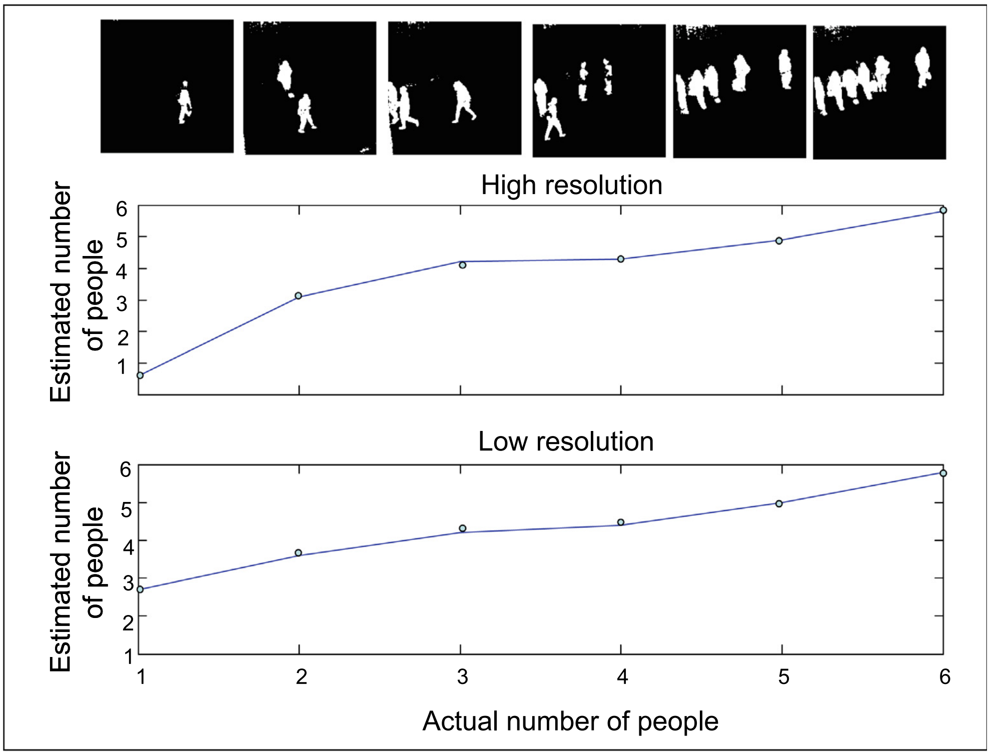


Fig. 11. The estimation of people's number using the thresholding technique.

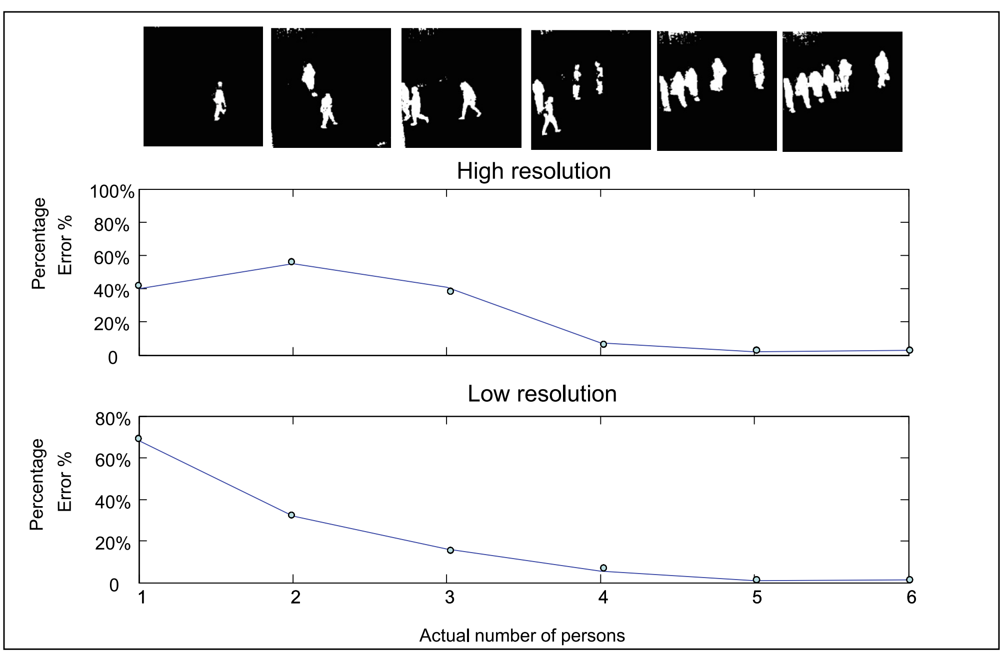


Fig. 12. The % error of the high and low resolution infrared images using the thresholding technique.

In order to change from number of pixels to estimating the number of people, equation (4) is used. Pixel counting N_{pixels} of 'white' pixels, see Fig. 9, has been found to be a useful technique for predicting people's count. The calibration of number of pixels N_{pixels} in relation to the number of people is expressed by equation (4):

$$People\ Density = \frac{(N_{pixels} + D)}{\beta}; \quad (4)$$

where D and β are selected to achieve a specific target of values to minimise the error between the calculated density/count and the actual density/count. Equation (4) ignores the effect of noise from the change in light intensity.

Fig. 11 presents the high resolution infrared image and the image with thresholding estimation using equation (4) to estimate the number of people. The original captured infrared images are 241×241 pixels. As shown in Fig. 11, the infrared number of pixels successfully present that number of people standing at the tram stop. The percentage error is shown in Fig. 12.

The high resolution infrared images at dark time after thresholding give a distinguishable result of up to 75.25 % average accuracy that can be used for human object recognition, while it is just up to 48.61 % accuracy in the case of low resolution infrared imager. As the number of people increases in the image, the correlation coefficient of the graph indicates the increment of people in the image and is able to distinguish reliably between them. As shown in Fig. 12, the error tends to decrease as the number of people counted in the scene increases. Thus the algorithm used in this analysis is reliable for high number of people.

3.3. Using edge detection for estimating the number of people

The edge detection process is implemented in order to enhance and detect sharp changes in the infrared image's brightness that is related to the people's number in the image. Edges are those places in an image that correspond to object boundaries. Edge detection also reduces the size of the memory needed for image processing steps. An example of a high resolution and low resolution infrared images after interpolation and edge detection are shown in Fig. 13.

Examples of high resolution and low resolution infrared images and the corresponding images after edge detection are shown in Fig. 14-a and Fig. 14-b.

The number of pixels after edge detection process is proportional to the number of people waiting at the tram stop. Pixel counting is used which is then transferred to a people number estimation. The concept here is that more white pixels will mean more edges and hence more people at the tram stop. The number of pixels acquired from the infrared data is shown in Table 3.

As shown in Table 3, the number of pixels successfully represents the actual number of people. Equation (4) has been implemented to find the estimated number of people from the number of pixels, as shown in Fig. 15.

It can be seen from the result of edge detection of high and low resolution infrared images in Fig. 15 that it can successfully repre-

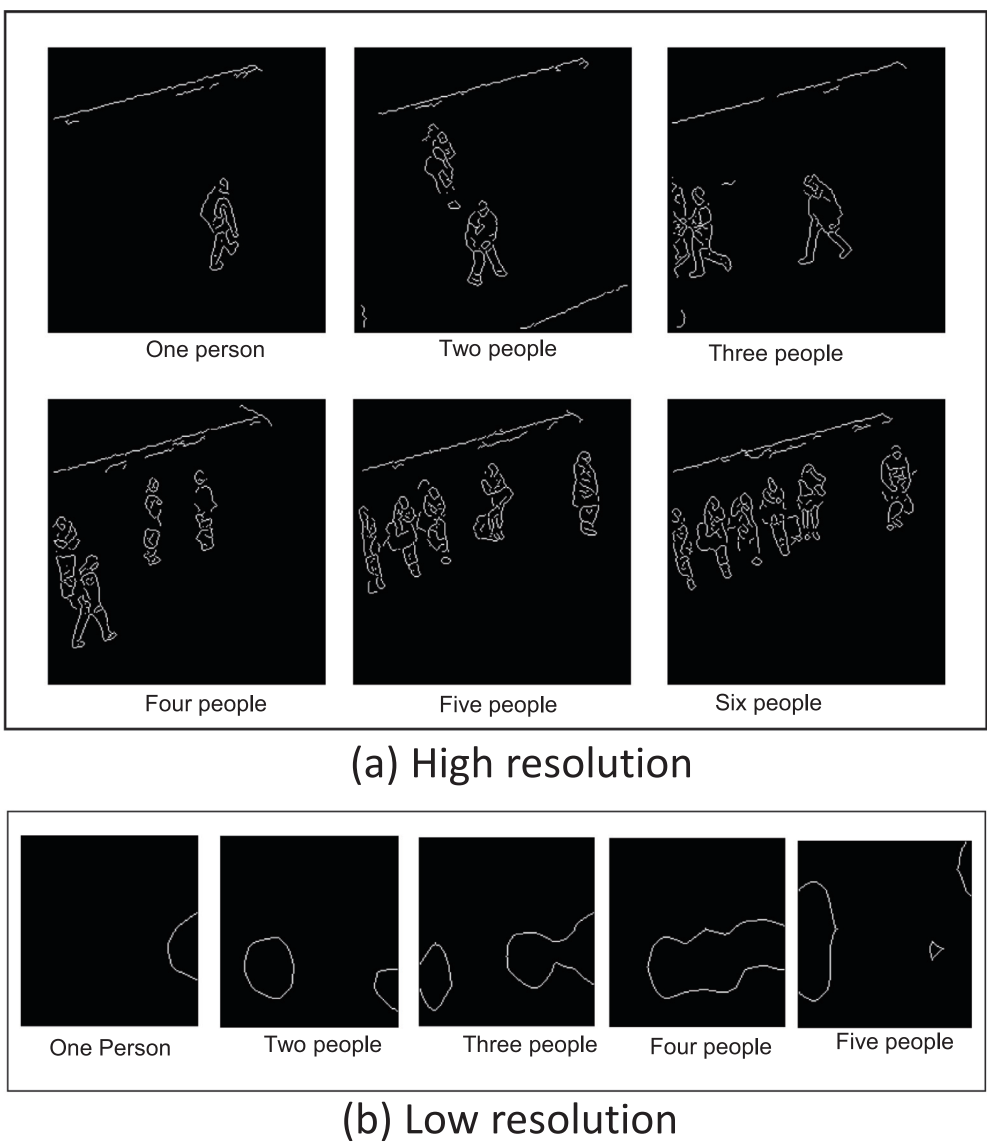


Fig. 13. (a) The high resolution infrared images after interpolation and edge detection; and (b) the low resolution infrared images after interpolation and edge detection.

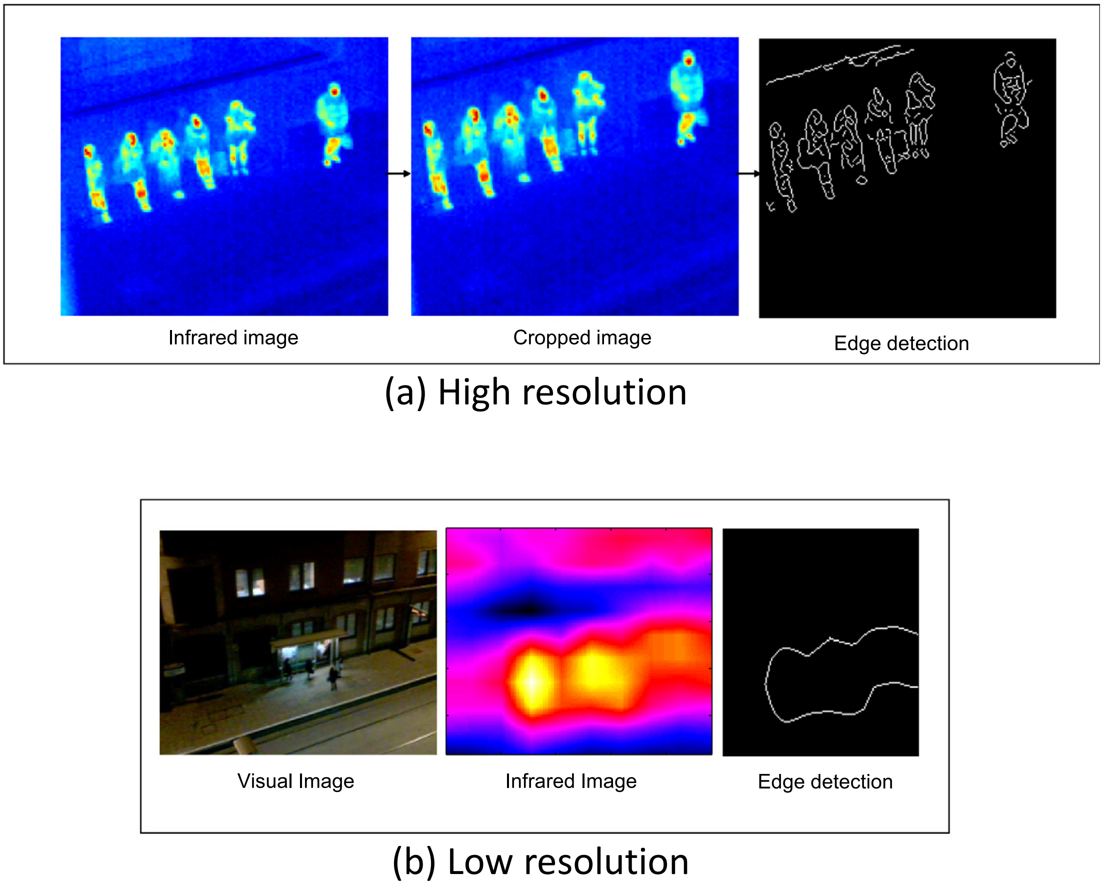


Fig. 14. (a) A high resolution infrared images before and after applying edge detection; (b) a low resolution infrared image before and after applying edge detection.

Table 3
The comparison between the number of people at the tram stop and the number of pixels (edge detection technique).

Number of people	Number of white pixels in an image (High resolution)	Number of white pixels in an image (Low resolution)
0	252	0
1	536	188
2	809	387
3	1055	463
4	1214	594
5	1333	406
6	1630	601

sents the people number of the corresponding image. The actual people's number in these images are estimated by an expert person. The error tends to decrease as the number of people at the tram stop increases as shown in Fig. 16.

The high resolution infrared images at dark time after edge detection gives a distinguishable better result of up to 96 % average accuracy that can be used for human object recognition, while it is just up to 52.39 % accuracy in the case of low resolution infrared imager. But this is true only for small number of people as with the area under consideration gets crowded then the algorithm becomes more reliable. Further techniques will be used in future analysis to address this situation.

4. Discussion

This paper has investigated the ability of the high resolution infrared thermal imager and low resolution thermal imager in estimating the number of people waiting for public transportation. A comparison between the accuracy of FLIR-E25 high resolution thermal imager and IRISYS (1002) low resolution has been conducted in estimating the number of people. Fig. 17 presents the results of comparing between high and low resolution infrared images and the tested techniques. As shown, the maximum percentage error has been reduced to 4 % in the case of the high resolution infrared camera with edge detection, while it is reduced to 47 % only in the case of the low resolution imager. But would 4 % or 47 % error be acceptable? This will depend on the required application and the cost of the system. As high resolution infrared cameras are more accurate, but more expensive and the low resolution infrared cameras are less accurate for low density monitoring of crowd, but inexpensive. As shown in Fig. 17, both the high resolution infrared imager and low-cost infrared imager perform well in low intensity light at night after edge detection giving distinguishable results, albeit at different error levels. For the low cost

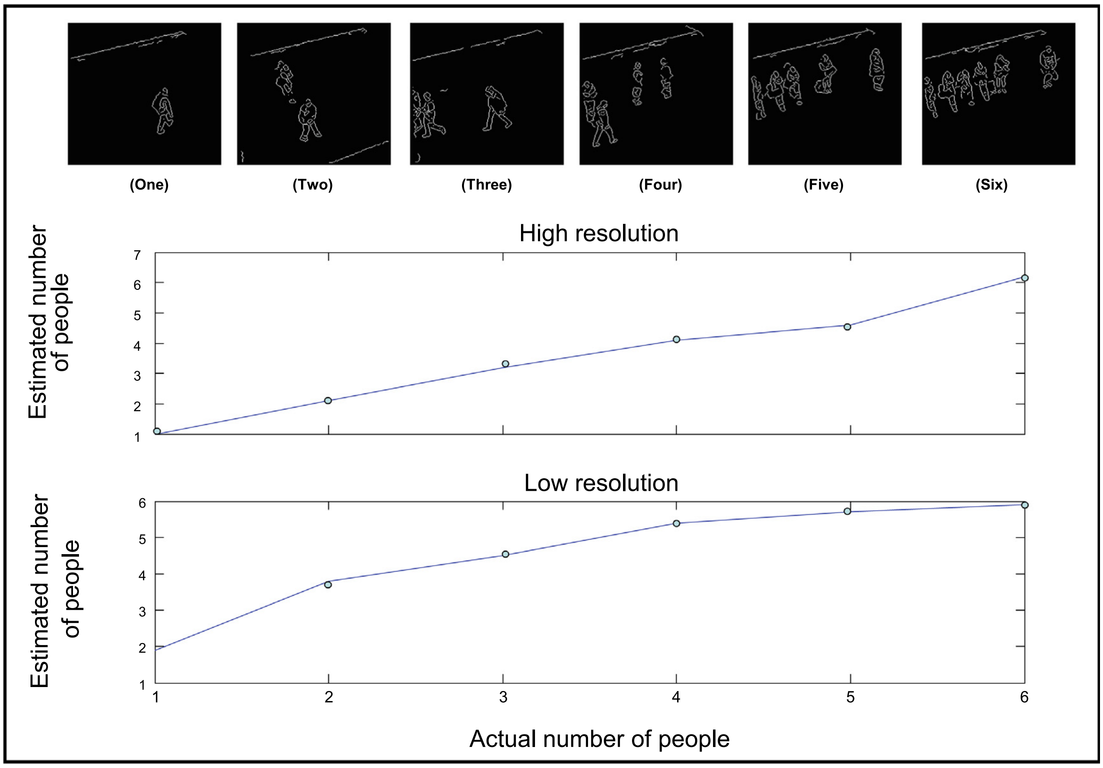


Fig. 15. Estimating the number of people from infrared images using edge detection.

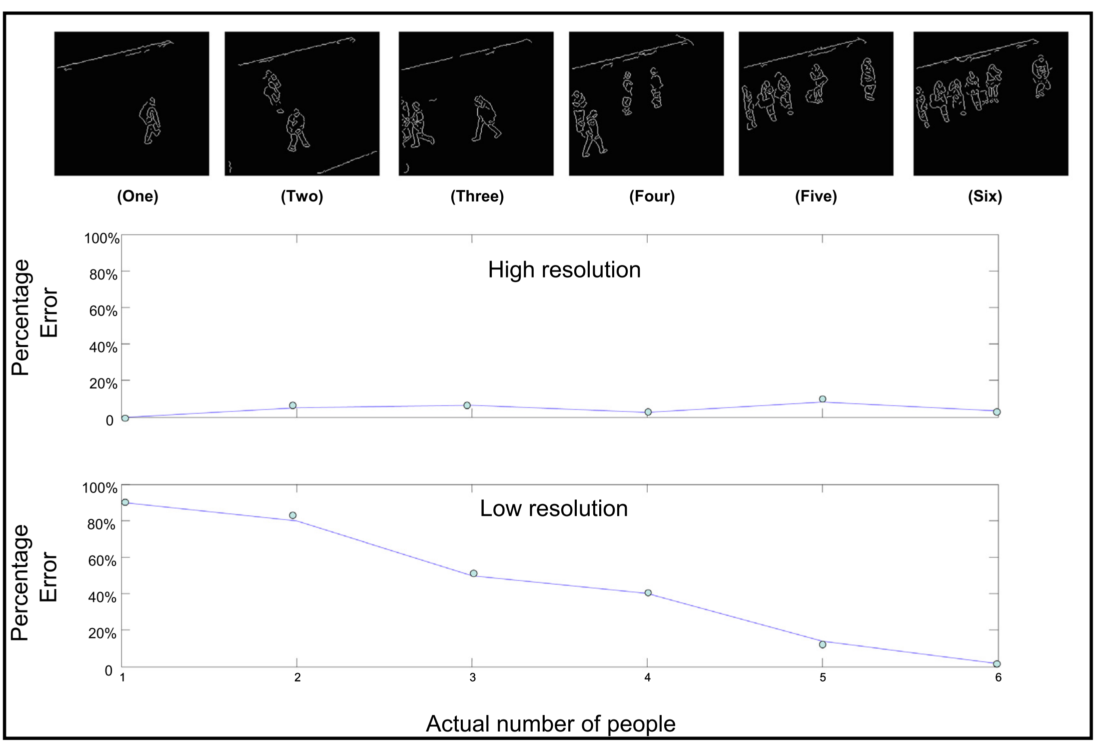


Fig. 16. The error (%) for using edge detection in estimating the number of people.

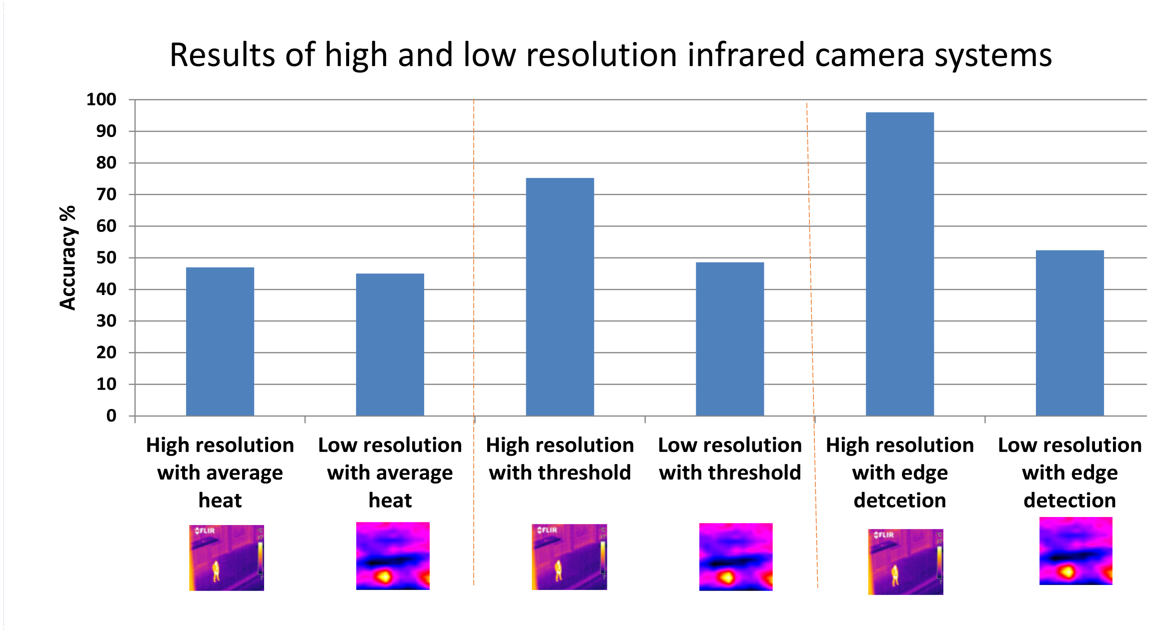


Fig. 17. A comparison between the high and low resolution infrared cameras for the suggested image processing techniques of infrared images.

infrared imager, the average error tends to decrease as the number of people increases. This indicates that the low resolution infrared imager can be used for human object recognition. Further techniques will be used in future analysis to address this further. The results of this paper prove that infrared cameras can provide density or number estimation of people which could help in the design of safety systems for crowd monitoring and management in smart cities.

5. Conclusion and future work

The costs and capabilities of crowd monitoring systems are essential in crowd monitoring application. The aim is, not only to produce a successful crowd monitoring system, but also to keep the system as inexpensive as possible in order to be economically justifiable. In order to keep the monitoring system as inexpensive as possible, the utilisation of sensors in the system should be kept relatively high. Therefore, using the low-cost infrared camera could provide an inexpensive and autonomous methodology for crowd density mapping or number estimation. The high resolution infrared camera has a high relative cost and has a high accuracy. On the other hand, the low resolution infrared camera has a much lower cost with a reasonable accuracy that is improved at higher densities. Therefore, future work will be based on the low resolution infrared camera as the main source of infrared data due to its low cost and reasonable accuracy at higher numbers. Future work will include the integration of artificial intelligence and deep learning for the estimation of people's number.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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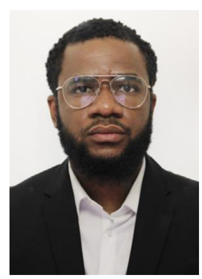

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